Energy Optimization Approaches for CH in WSNs: A Review

Eshtiag Jahalrasool Ahmed[1,3], Abdalla Akod Osman[2], Sally Dfaallah Awadalkareem[1]

[1]Department of Computer Engineering, University of Gezira, Wad Madani, Sudan
[2]Department of Computer Sciences, University of Elahlia, Wad Madani, Sudan.
[3]Department of Information Technology, College of Computing, and Information Technology Khulais, University of Jeddah, Jeddah 21959, Saudi Arabia

---

Abstract

In recent years, wireless sensor networks (WSNs) have grown in importance as a technology for various uses, including healthcare systems, industrial automation, and environmental monitoring. This research thoroughly analyzes methods for optimizing energy consumption in WSN Cluster Heads (CHs). Energy efficiency methods and technologies for Wireless Sensor Networks are examined in the research. Due to predetermined protocols and static factors, traditional approaches are successful yet ineffective in dynamic contexts. By forecasting energy use and improving CH selection and data routing, machine learning systems may circumvent these restrictions. The research also illustrates the advantages of hybrid models that mix classical optimization with modern machine learning methods. Hybrid energy management methods include incorporating heuristic algorithms with machine learning to improve CH election and load balancing decisions are more resilient. The study shows that these improved technologies may enhance energy efficiency by 30% and network lifetime by using simulations and tests. Machine learning models provide more dependable data transfer, reduce packet loss, and maintain network performance.

However, the research admits some obstacles and limits, including the requirement for significant computing resources and specialized expertise, which might increase the complexity and expense of network administration. The study concludes that WSNs need creative energy optimization methodologies, improving algorithms for varied WSN applications and exploring new innovation paths. Addressing present limits and pursuing new innovation routes will help academics and practitioners develop sustainable, high-performance WSNs that match contemporary application needs.

Keywords: WSNs, CH, Energy Optimization, Clustering Algorithms, ML, Nature-Inspired Optimization, Energy Efficiency.

I. Introduction

WSNs are decentralized, self-operating sensors that track and report various physical and environmental variables [1]. They have evolved due to advancements in sensor technologies, wireless communication, and microelectronics. Standard WSNs consist of sensing nodes, data sinks, and communication networks, which gather, interpret, and exchange information wirelessly [2]. These networks are built with scalability, energy efficiency, and environmental adaptability, making them useful in various fields such as healthcare, agriculture, smart cities, and disaster management [3]. Energy efficiency is crucial for WSNs, as it allows for a longer network lifetime, fewer maintenance costs, more reliability and data continuity, better resource utilization, environmental sustainability, energy-harvesting solutions, adaptability to changing environments, and less network overhead [4]. WSNs with energy-efficient designs make the most of scarce resources like processing power, bandwidth, and battery life. These are particularly important when several sensor nodes work together to acquire data [5].

Cluster Heads (CHs) play a crucial role in improving network efficiency, communication, and energy consumption. CHs work together to compile information from all cluster nodes and send it to the central location or sink [6]. They also play an essential role in energy management, helping WSNs stay organized in a hierarchical structure and allowing them to scale more easily by splitting the network into smaller units called clusters, each with its own CH [7]. CHs oversee and coordinate the actions of other nodes in their cluster, improving data management, communication, and energy usage. They aggregate data from sensor nodes inside their cluster by eliminating duplicate transmissions and preserving energy [8]. They ensure the network lasts a long time by controlling energy usage and ensuring nodes do not use too much. By facilitating the transfer of aggregated data from sensor nodes to the sink, they improve communication efficiency and reduce power consumption [9]. Chase Heads also play a role in load balancing, ensuring that energy consumption is uniformly distributed and avoiding overloading by shifting workloads across nodes [8]. Encryption and authentication measures are put in place to guarantee data security and help with fault tolerance. In terms of WSN performance and lifespan, their efficacy is crucial [10], [11]. Only then can WSNs reach their full application potential, as shown in Figure 1.

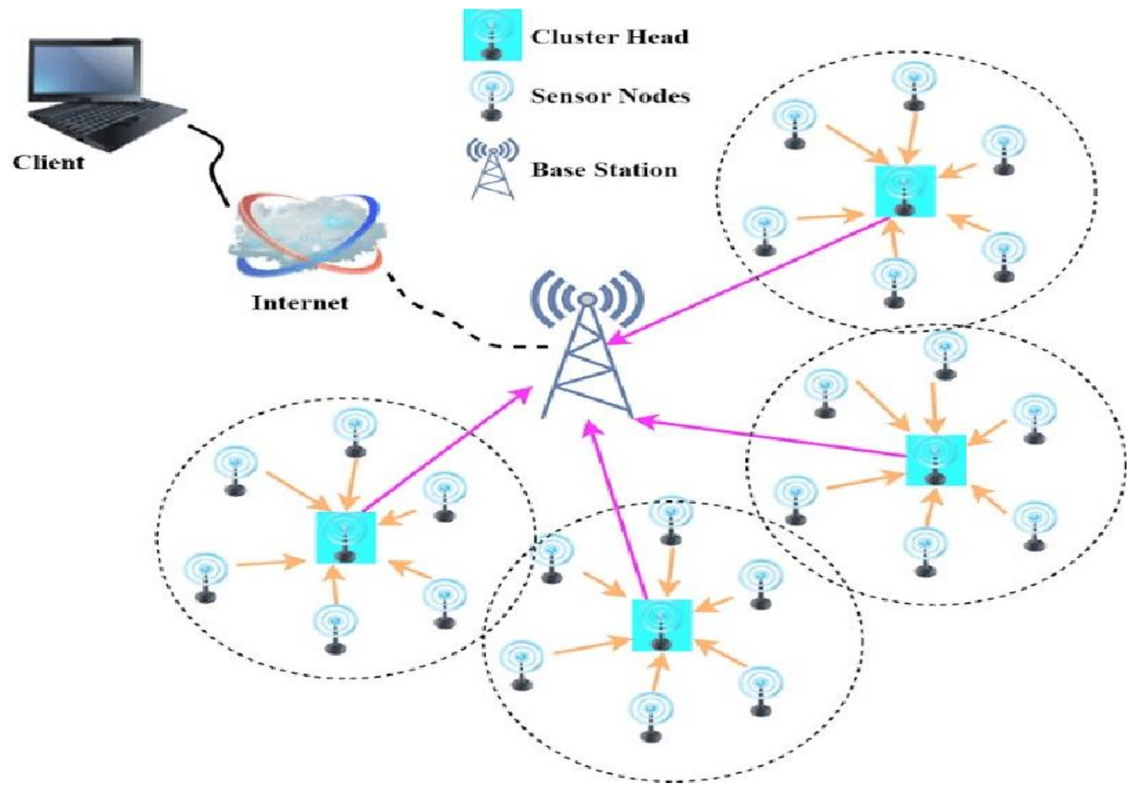

Figure 1: An Overview Clusters WSNs [12]

2. Challenges Faced by CHs in WSNs

CHs are essential in managing and optimizing WSNs, but they face numerous challenges that can impact their efficiency and network performance [13]. These include energy consumption, dynamic network conditions, security concerns, load imbalance, fault tolerance, scalability, communication overhead, data aggregation methods, resource limits, and quality of service (QoS) needs [14]. CHs must adjust to changing network circumstances, maintain confidentiality, and balance workload to avoid overloading caused by load imbalance. Building reliable fault-tolerance systems is challenging, especially in harsh or unexpected situations. Scalability is another challenge, as CHs must manage communication, data aggregation, and energy consumption in extensive networks without compromising performance. The function of CHs is complicated by the need to satisfy quality of service standards, such as latency limitations or dependability. To address these issues, researchers focus on finding solutions simultaneously, such as creating a function that considers multiple objectives and optimizing it using a suitable algorithm or optimizer [15]. Ultimately, the function of CHs is complicated by the need to satisfy the quality of service standards, such as latency limitations or dependability, as illustrated in Figure 2.

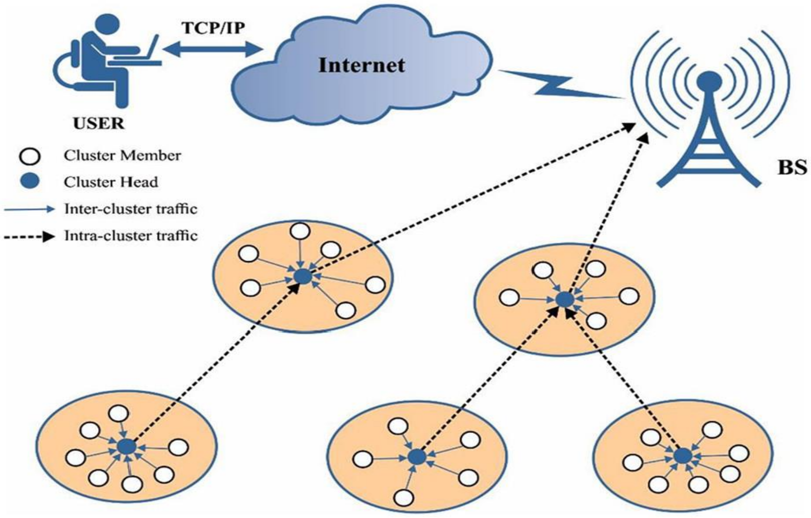

Figure 2: Challenges Faced by CHs in WSNs [16]

Furthermore, numerous optimization issues, such as clustering, routing, area coverage, sensor localization, and data aggregation approaches, are shown in Figure 3 for WSNs.

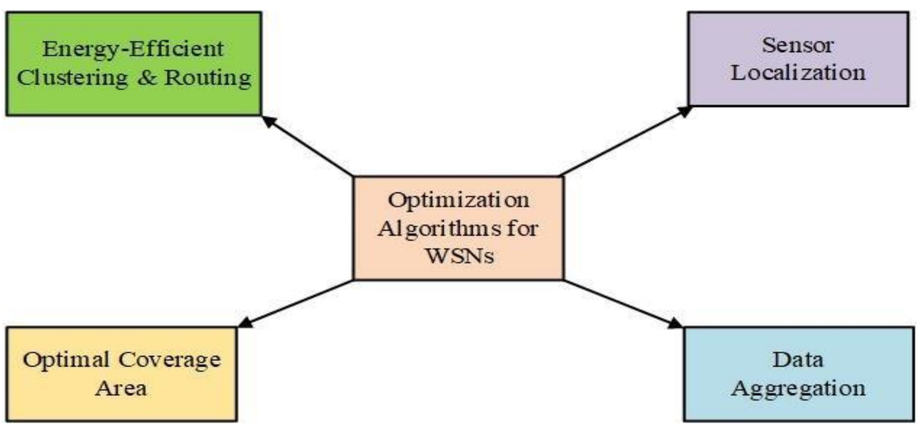

Figure 3: Optimization Issues in WSNs [17]

2.1 Energy-Efficient Clustering in WSNs

WSNs are crucial for their durability and sustainability due to their limited power supply. Clustering and routing are essential approaches to improving energy efficiency [10]. Clustering involves separating sensor nodes into clusters with a central CH, aiming to balance energy consumption, reduce data aggregation, and ensure geographical variety [18]. Data aggregation reduces energy consumption during communication, while sleep scheduling allows non-CH nodes to enter low-power sleep modes. Sensors must be housed in buildings that maximize energy efficiency. Routing redetermines data packets' pathways, aiming to reduce energy usage during data transmission [19]. Key components include the shortest route, multipath routing, QoS considerations, load balancing, and cross-layer design. Algorithms that select the shortest paths for data transmission increase network lifespan [20]. Multipath routing improves network dependability, while QoS considerations balance energy efficiency and other factors. Load balancing distributes traffic evenly across all channels and nodes [21]. Future research should focus on adaptive algorithms, machine learning approaches, and emerging applications. Energy-efficient routing and clustering are essential for WSNs to operate sustainably and successfully deploy them in various applications [22].

2.2. Requirement of Sensor Localization in WSNs

Sensor localization is crucial for the efficient functioning of WSNs, maximizing network performance, energy efficiency, and overall functionality. It provides spatial awareness for applications like environmental monitoring and military surveillance, enables energy-efficient routing, makes target tracking and monitoring easier, and aids in data fusion and aggregation [23]. Reliable sensor node localization is essential for location-based services in intelligent cities and is essential for identifying anomalies and security in WSNs. However, issues such as reliability, scalability, and localization accuracy need to be addressed. Future research should focus on resilient localization algorithms, multi-modal sensing methods, and the influence of dynamic network circumstances on localization accuracy. Various localization approaches use preexisting information to pinpoint other nodes in WSNs [24].

2.3. Optimal Coverage in WSNs

The article discusses the importance of achieving optimum coverage in WSNs for their ability to observe and collect real-world data. It highlights several factors that need to be considered for optimal coverage, including accurately representing the sensing field, allocating sensor nodes to different areas, minimizing redundancy, and considering environmental changes. The optimal placement of sensor nodes must be energy efficient, considering energy limits, and ensuring the network can adapt to changing conditions [25]. QoS metrics should be satisfied by ideal coverage, ensuring reliability, low latency, and accurate data. The article also discusses the complexity of the detecting zone, which can be complex due to topographical considerations and substantial structures. To address this issue, the article suggests combining other network components into a single-aim multi-objective WSN, which can optimize sensor node location. Overall, the article emphasizes the importance of achieving optimum coverage for WSNs to function well and provide precise and timely data for various uses.

2.4. Requirement of Data Aggregation in WSNs

A WSN is a system of sensor nodes that detect, measure, and report environmental conditions. Data aggregation is a crucial step in WSNs, reducing energy consumption, reducing traffic, improving bandwidth utilization, scalability, node resource preservation, data accuracy, privacy, and security. It reduces the need to transmit duplicated data, lowering energy consumption and prolonging network lifetime [26]. WSNs serve various sensing applications, such as environmental monitoring, healthcare, and industrial automation. Data aggregation helps networks scale by reducing data processing and delivery, saving node resources. Security measures are essential to protect aggregated data from unwanted access and privacy issues. Future research should focus on improving WSN robustness, investigating machine learning approaches, and creating resilient and flexible data aggregation algorithms [8].

3. Related Work on Energy Optimization Approaches for CH

WSNs rely on CHs for data aggregation and transmission, and efficient energy usage is crucial for network lifespan and reliable data transmission. Numerous studies have explored optimizing energy consumption in CHs.

3.1 Energy-Efficient CH Selection

The literature review discusses various approaches to energy-efficient CH selection in WSNs, including fuzzy logic, reinforcement learning, and particle swarm optimization. These methods aim to optimize energy use and extend network lifespan, creating efficient and reliable WSNs for various applications. Some important papers include Zhang, Wang, and Chen's "Energy-Efficient CH Selection in WSNs Using Fuzzy Logic" [27]. These papers propose CH selection strategies based on fuzzy logic, reinforcement learning, particle swarm optimization, energy-aware CH selection algorithm for heterogeneous WSNs, hybrid approach for energy-efficient CH selection, adaptive CH selection algorithm based on node residual energy, and improved grey wolf optimization (IGWO)-based CH selection algorithm [28]. These methods have shown significant improvements in energy efficiency, network longevity, and overall network performance. The hybrid approach combines fuzzy logic with evolutionary algorithm methods, while the adaptive strategy considers individual node residual energy. Overall, these approaches aim to optimize energy usage and network longevity in WSNs.

Thus, Table 1 summarizes recent studies on energy-efficient CH selection.

Table 1: Recent Studies On Energy-Efficient CH Selection.

Article Title	Authors	Methodology	Key Findings
Energy-Efficient CH Selection in WSNs Using Fuzzy Logic	[29]	Fuzzy Logic-based approach	-Improved energy efficiency -Enhanced network lifetime
A Reinforcement Learning-Based Approach for Energy-Efficient CH Selection in WSNs	[30]	Reinforcement learning (Q-learning)	-Dynamic adaptation of CH selection -Balanced energy consumption among nodes
Optimal data transmission and pathfinding for WSN and decentralized IoT systems using I-GWO and Ex-GWO algorithms	[31]	I-GWO and Ex-GWO algorithms	-Balanced energy consumption among nodes
OPEN A fuzzy logic-based secure hierarchical routing scheme using the firefly algorithm in the Internet of Things for healthcare	[4]	Firefly Algorithm	-Enhanced network lifetime
Optimized CH Selection in WSNs Using Particle Swarm Optimization	[32]	Particle Swarm Optimization (PSO)	- Optimised CH selection -Enhanced energy efficiency and network coverage

3.2 Adaptive Clustering Protocols

Adaptive Clustering Protocols have been proposed to optimize energy consumption and prolong network lifetime in WSNs [33]. These protocols include LEACH-C, ACO-Leach, EACH, DACP, ECBACP, ABC-DP, RACP, ELACP, ACC-LEACH, and EPCL. LEACH-C dynamically adjusts clustering thresholds based on energy levels, node density, and distance to the base station, improving energy efficiency and network lifetime [34]. ACO-Leach optimizes clustering selection using pheromone trails and node energy levels, achieving better energy efficiency and network longevity than traditional LEACH [35]. EACH improves energy efficiency and prolongs network lifetime compared to traditional clustering protocols. DACP dynamically adjusts clustering thresholds based on node energy levels, distance to the base station, and network density, improving energy efficiency and network lifetime [36]. ECBACP is energy-constrained and balanced, adjusting clustering thresholds based on residual energy and network density to balance energy consumption and network load. ABC-DP is adaptive and balanced with delay prediction, improving energy efficiency and latency reduction. RACP is reactive, adaptive, and energy level-aware [33]. ACC-LEACH is an adaptive clustering communication protocol based on LEACH, adjusting clustering thresholds and communication strategies based on network conditions to improve energy efficiency and longevity. EPCL is an energy-aware partitioning and clustering protocol for large-scale WSNs, improving energy efficiency and scalability [37].

These articles contribute to advancing adaptive clustering protocols in WSNs by introducing innovative approaches to CH selection, energy optimization, and network management. Thus, the mathematical model for adaptive clustering protocols is provided in Equation 1.

Let *G=(V, E)* represent the WSN topology, where *V* is the set of sensor nodes, and *E* is the set of communication links between nodes.

Each sensor node *i* has the following attributes:

E_i: Initial energy level of node *i*

d_i: Distance to the base station (sink node)

S_i: Sensing range of node *i*

C_i: Communication range of node *i*

The goals of the Adaptive Clustering Protocol are to maintain network coverage and connection, minimize energy usage, and determine the ideal cluster heads. Hence, the following is the formulation of the Adaptive Clustering optimization model:

$$Minimize\ \sum_{i\in V} E_i \qquad \ldots(1)$$

To minimize data transmission costs, sensor nodes *i* are allocated to cluster heads with energy consumption below a threshold, are within communication range and have the shortest distance between them and sink nodes.

3.3 Data Aggregation and Compression Techniques

The input provides a literature review of various research papers on data aggregation techniques in WSNs. The papers discussed in the review offer surveys and reviews of different data aggregation approaches and their impact on energy usage and network lifespan. The papers categorize data aggregation techniques into hierarchical, cluster-based, tree-based, geographical, temporal, spatiotemporal, clustering, clustering-based, network coding, data fusion, compressive sensing, centralized, distributed, and hybrid systems. They analyze the merits, limitations, and performance metrics of each approach and discuss their applicability and potential uses in WSNs. The studies also provide suggestions for future research initiatives in the field of data aggregation in WSNs [38]. Overall, the literature review highlights the importance of optimizing energy usage and extending network lifespan through efficient data aggregation techniques in WSNs [39].

Equation 2 shows the mathematical model for computing data aggregation and compression techniques.

Let $D=\{d1,d2,...,dn\}$ represent the set of data packets generated by sensor nodes in the WSN, where *n* is the total number of data packets.

Each data packet *di* has the following attributes:

- S_i: Size of the data packet
- T_i: Timestamp indicating when the data was generated
- L_i: Location of the sensor node that generated the data

Thus, we have;

$$Minimize \sum_{i=1}^{n} S_i \qquad \ldots(2)$$

The process in Equation 2 involves defining data aggregation, compression, and Quality of Service constraints to ensure data packets meet predefined criteria for accuracy, reliability, and timeliness.

3.4 Sleep Scheduling and Duty Cycling

Studies on duty cycling techniques and sleep schedules have been conducted to optimize energy usage and increase network lifespan. Key papers in information technology include [40]–[43]. These studies classify sleep scheduling approaches into synchronized, adaptive, and duty cycling, assessing their usefulness in different WSN contexts and assessing their latency and energy usage. [44] classify sleep scheduling algorithms into static, dynamic, and hybrid, evaluating their energy use, latency, and scalability. [45]-[46] also provide a comprehensive review of energy-efficient sleep scheduling techniques in WSNs. These methods aim to reduce energy consumption, increase network lifespan, and improve overall performance. Researchers are working to find solutions to specific energy problems caused by critical infrastructures CHs using sophisticated algorithms, adaptive protocols, and cross-layer optimizations.

Thus, Equation 3 denotes the model for computing the sleep scheduling approach in cluster WSNs.

Let $N=\{n_1,n_2,..., n_m\}$ represent the set of sensor nodes in the WSN, where m is the total number of sensor nodes.

Each sensor node ni has the following attributes:

- P_i: Power consumption rate in active mode
- $P_{\text{sleep},i}$: Power consumption rate in sleep mode
- T_i: Duty cycle or sleep interval duration
- A_i: Active period duration

Sleep scheduling and duty cycling aim to maximize network lifetime by minimizing energy consumption while ensuring adequate coverage and connectivity. This can be formulated as an optimization problem:

$$Maximize \sum_{i=1}^{m}(A_i * P_i + (T_i - A_i) * P_{Sleep,i}) \quad \dots (3)$$

Equation 3 enables WSNs to perform optimization of network coverage, connectivity, and energy conservation, which requires various algorithms, including greedy, adaptive, and distributed algorithms, to ensure optimal energy usage and coverage.

4. Existing Energy Optimization Approaches for CHs

Energy optimization strategies for CHs aim to increase network lifespan, reduce energy use, and ensure reliable operation. Further research is needed for energy-efficient WSNs.

4.1 Overview of Traditional Approaches

Energy optimization in WSNs focuses on optimizing the functioning of Clustering Units (CUs) for data aggregation and transmission. Innovative protocols like LEACH, HEED, SEP, PEGASIS, and TEEN aim to balance energy consumption, reduce long-distance transmissions, and focus on event-driven data reporting. These methods introduce critical ideas like data aggregation, clustering, and node election and are being further developed to address the ever-changing problems of WSNs [44].

4.1.1 LEACH Approaches

LEACH is a protocol developed for WSNs to increase network lifespan and reduce energy consumption. It involves sensor nodes forming hierarchies to facilitate data aggregation and communication. The protocol has undergone several improvements, including LEACH-F and LEACH-C, which ensure even distribution of cluster chiefs and fixed rotation. Other enhancements include the hybrid energy-efficient distributed clustering algorithm HEED and the stable election protocol. LEACH has also been enhanced with energy-efficient MAC protocols, LEACH-DCHS and LEACH-GA, which optimize network performance and energy efficiency. LEACH-V uses virtual clustering to reduce energy burden during cluster creation and maintenance. These LEACH methods are crucial for WSN energy optimization and are expected to continue advancing in the future [45]. Table 2 shows the algorithm for LEACH protocol in WSN networks.

Table 2: Algorithm for LEACH Protocols

LEACH Protocol: Algorithm

1. Initialization:

   - Set up the network parameters: number of sensor nodes, base station location, communication range, etc.
   - Select the desired percentage of cluster heads (p).
   - Initialize the round number (r) to 1.
   - Each node randomly chooses a number between 0 and 1 to determine if it will become a cluster head.

2. Cluster Head Selection:

```
for each node in the network {
  if (node is alive and has not been a cluster head in the last 1/p rounds) {
    compute the probability P_CH for becoming a cluster head based on the formula.
    if (random number < P_CH) {
      a node becomes a cluster head;
      broadcast message to neighboring nodes to join its cluster;
    }
  }
}
```

3. Cluster Formation:

```
for each node in the network {
  if (node is not a cluster head) {
    select the nearest cluster head;
    join the cluster of the nearest cluster head;
  }
}
```

4. Data Transmission:

```
for each cluster head {
```

```
        receive data from member nodes;

        aggregate and process the data;

        transmit the aggregated data to the base station;

      }


5. Cluster Head Rotation:

      if (current round mod (1/p) == 0) {

        rotate cluster heads:

        - each current cluster head sends a message to announce its resignation.

        - non-cluster head nodes recompute the probability P_CH and determine new cluster heads based on the
      updated probabilities.

  }


6. Energy Consumption:

      - Each node consumes energy for data transmission, reception, processing, and cluster head operations.

7. Network Lifetime Analysis:

      - Evaluate network lifetime based on energy consumption, data transmission, and cluster formation efficiency.
```

4.1.2 HEED (Hybrid Energy-Efficient Distributed Clustering)

The HEED clustering algorithm is a decentralized approach for organizing sensor nodes in WSNs without the need for a central hub [46]. It integrates both decentralized and centralized methods to create and maintain clusters effectively. Nodes in HEED send hello messages with their ID and energy level to initiate cluster creation. The algorithm uses a competitive model to select cluster heads based on energy levels and distances, with a threshold to limit the number of CHs [47]. CHs then advertise to recruit member nodes, who choose the cluster with the highest remaining energy. HEED aims to promote renewable energy production, distribute energy usage equally, and adapt to network changes. It improves data aggregation, network coverage, energy efficiency, and resistance to node failures compared to traditional clustering methods [10]. HEED has potential applications in smart cities, industrial automation, and environmental monitoring. Further research could focus on optimizing HEED for specific use cases, such as security and fault tolerance, and adapting it to new technologies like the Internet of Things (IoT) and cloud computing. Overall, HEED is a promising algorithm for energy-efficient and long-lasting WSNs [48].

4.2 Advanced Techniques and Algorithms

Machine learning (ML) has emerged as a powerful tool for improving various aspects of WSNs. ML algorithms in WSNs can adapt to new environments, discover patterns, and generate predictions. ML is used for data analytics, enabling the analysis of sensor data, identification of outliers, and prediction of trends [49]. It is also employed for energy management, optimizing transmission power, and scheduling node operations to improve energy efficiency and prolong the network lifespan. ML can detect and diagnose faults in WSNs, ensuring reliable operation.

Additionally, ML techniques can optimize routing protocols, predict network traffic patterns, enhance network performance, and improve WSN security through intrusion detection systems. ML in WSNs utilizes supervised learning, unsupervised learning, reinforcement learning, and deep learning methods such as neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) [50]. However, there are challenges in terms of limited processing power, memory, and energy in WSNs, as well as dealing with inaccurate or noisy sensor data. ML models need to be efficient and adaptable to overcome these obstacles [51].

4.2.1 ML-Based Approaches in WSNs

ML methods are increasingly being used in WSNs to enhance data processing and operations. ML algorithms can optimize resource utilization, make predictions, categorize occurrences, and improve energy usage [50]. They find applications in data analytics, event detection, problem diagnosis, prediction, security, intrusion detection, resource management, adaptive routing protocols, and more. ML techniques empower sensor nodes to acquire knowledge from data patterns and make informed judgments without explicit programming [52]. However, implementing ML algorithms in WSNs can be challenging due to limited resources, data cleaning and validation requirements, privacy and security concerns, and interoperability issues. Despite these challenges, ML approaches have proven to be practical tools for improving the capabilities and performance of WSNs. Future developments in WSN ML include edge computing, federated learning, explainable AI, and reinforcement learning, which can further enhance the efficiency and intelligence of WSNs [53]. Figure 4 shows some ML approaches utilized in CH WSNs.

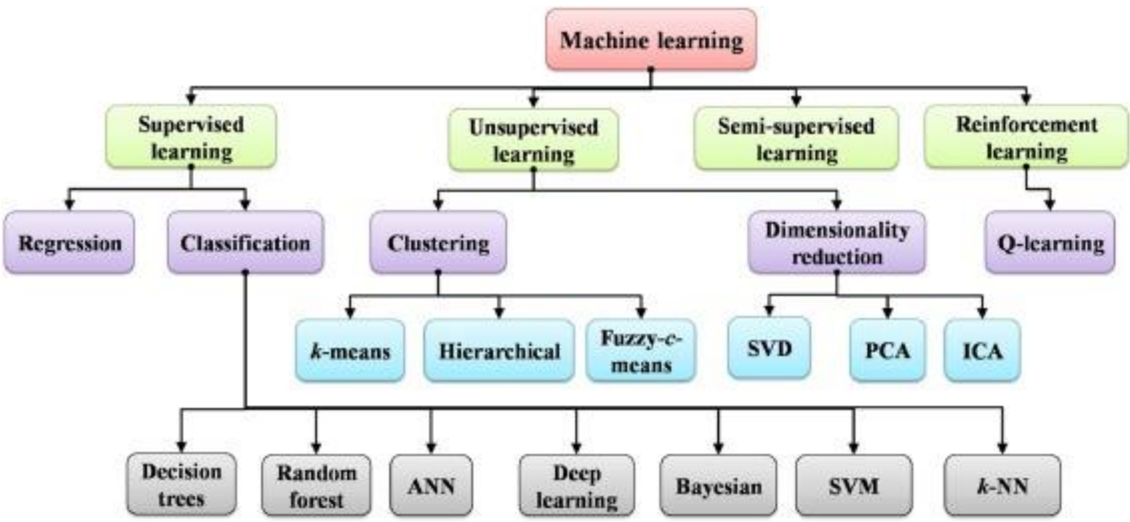

Figure 4: Some ML Approaches Used in CH WSNs [54].

4.2.2 Nature-Inspired Optimization Algorithms in WSNs

A dynamic and resource-constrained network that uses geographically dispersed sensor nodes to track physical or environmental variables is called a WSN. Thus, the nature-inspired optimization algorithms in WSNs are illustrated in Figure 5.

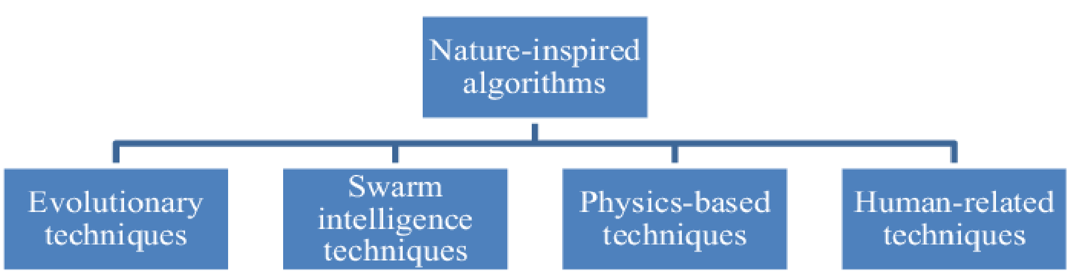

Figure 5: Nature-Inspired Optimization Algorithms in WSNs

Optimization algorithms inspired by biological, ecological, and physical processes are being developed to enhance network performance in WSNs. These algorithms offer scalability, efficiency, resilience to noise, uncertainty, local optima, and flexibility [7]. They can traverse expansive search areas, converge to solutions close to optimum, and provide distributed and decentralized optimization possibilities [26]. However, they face challenges like algorithm complexity, resource limitations, parameter adjustment, and convergence speed. Hybrid methods, adaptive algorithms, distributed optimization, and real-world validation are being explored to improve these algorithms' effectiveness in real-world WSN installations. This approach can lead to more flexible and reliable WSNs across various sectors [55].

Particle Swarm Optimization (PSO): Particle Swarm Optimization (PSO) is an optimization technique inspired by nature that is used in WSNs to improve energy efficiency in clustering, routing, and resource allocation. PSO-based techniques have been shown to enhance network lifespan, data transmission reliability, and energy consumption. PSO-based routing strategies have been proposed, with simulations showing superior performance compared to standard clustering methods. An enhanced PSO technique has been proposed, incorporating adjustable inertia weight and acceleration coefficients to improve convergence speed and balance between exploration and exploitation. Future research should focus on enhancing the scalability, resilience, and flexibility of PSO algorithms to address WSNs' challenges.

Genetic Algorithm (GA): The genetic algorithm (GA) is a metaheuristic optimization technique used to optimize WSNs, including routing, clustering, and resource allocation. It has been successfully used to maximize network coverage and energy efficiency. NSGA-II and GA-based strategies address multi-objective optimization issues, while [55] proposes a GA-based clustering optimization strategy for improved network longevity and energy efficiency. [56]. To address new problems in large-scale and dynamic WSN deployments, future research may concentrate on improving the scalability, convergence speed, and resilience of GA-based optimization algorithms [57].

Artificial Bee Colony (ABC): The Artificial Bee Colony (ABC) algorithm, inspired by honeybee colonies' foraging behavior, is a population-based optimization scheme that solves optimization issues, particularly those involving Wireless Sensor Networks (WSNs). The ABC method improves cluster formation and CH selection, presenting an energy-efficient clustering technique for WSNs. It makes dynamic adjustments to selection probabilities based on energy levels and proximity to sensor nodes. The algorithm also optimizes WSN coverage by carefully placing sensor nodes to increase coverage and decrease redundancy. The revised ABC algorithm delivers greater coverage performance and energy efficiency compared to conventional deployment techniques. Further research should focus on improving the scalability, convergence speed, and resilience of ABC-based optimization approaches [58].

Firefly Algorithm (FA): The Firefly Algorithm (FA) is a metaheuristic optimization tool developed to address obstacles in WSNs. It uses fireflies' flashing behavior to find potential solutions and performs an iterative search for optimum solutions. The FA algorithm has competitive performance and is ideal for WSN optimization. An enhanced FA is proposed to optimize coverage in WSNs while minimizing redundancy. The updated FA algorithm offers better search methods, local search mechanisms, and adaptive parameters. Further research should focus on improving scalability, robustness, and convergence speed to address increasing issues in large-scale and dynamic wireless sensor network deployments [59].

Bat Algorithm (BA): The Bat Algorithm (BA), developed in 2010, mimics bat foraging behavior to solve optimization issues in WSNs. BA uses echolocation, frequency tuning, and random walk techniques to find optimal solutions [60]. Experimental findings show BA can compete with existing algorithms in terms of convergence speed and performance, suggesting it could solve complex optimization problems. An improved version incorporating mutation operators has been proposed to improve BA's convergence time and solution quality. The BA algorithm shows promise in solving energy-efficient clustering, coverage optimization, and routing problems for WSNs. Future studies may focus on improving scalability, robustness, and convergence speed [60].

5.0 Hybrid Optimization-Inspired Selective Bio-Algorithms in WSNs

Hybrid optimization-inspired bio-algorithms can improve WSNs by balancing exploration and localization tasks. These algorithms achieve better localization accuracy and convergence speed compared to solo PSO and GA techniques. Combining ABC and FA for coverage optimization and energy efficiency can enhance performance metrics like energy efficiency and clustering [61].

5.1. Hybrid GA-DE Algorithm

The Hybrid Genetic approach-differential Evolution (GA-DE) is a metaheuristic optimization approach that combines genetic algorithms (GA) and differential evolution (DE) to solve optimization problems. This method enhances convergence speed and solution quality by increasing exploration and exploitation capabilities. Genetic algorithms process a population of solutions using genetic operators like mutation, selection, and crossover. DE, a stochastic optimization technique, generates fresh candidate solutions through distinct processes. The hybrid GA-DE method has several phases, including starting, evaluating, selecting, crossing, mutation, replacement, and ending. It outperforms both GA and DE algorithms in terms of exploration and exploitation capabilities, search efficiency, convergence speed, and solution quality [62].

GA-DE Algorithm Algorithm

Table 3 illustrates the GA-DE algorithm, providing a high-level overview of the method, but different problems have different needs and parameter settings, resulting in varying solutions.

Table 3: GA-DE Algorithm

Algorithm 3: GA-DE Algorithm
1. **Initialise** population P with random candidate solutions
2. Evaluate the fitness of each solution in *P*
3. **while** termination criterion is not met, **do**
4. **Select** parent solutions from *P* based on their fitness
5. Generate offspring solutions through crossover and mutation
6. Evaluate the fitness of each offspring solution
7. **Select** individuals from *P* and offspring to form the **next** generation
8. **end while**

Furthermore, the summary and significant contribution of “GA-DE techniques in WSNs” is provided in Table 4

Table 4: Major Contribution of “GA-DE Techniques in WSNs

Technique	**Summary and Major Contribution**
GA-DE	1. Hybridization: Combines the strengths of GA and DE to enhance optimization performance in WSNs. 2. Global and local search: GA-DE utilizes GA’s global exploration capabilities and DE’s fast convergence properties to search the solution space efficiently for optimal CH selection. 3. Robustness: By leveraging DE’s robustness to noisy environments and GA’s ability to handle complex optimization problems, GA-DE offers a robust and effective solution for WSNs. 4. Scalability: The hybrid approach can be scaled to accommodate large-scale WSNs, ensuring the optimization process remains efficient even in networks with many nodes.

The GA-DE hybrid approach in WSNs effectively solves optimization problems by combining genetic algorithms’ global exploration capabilities with differential evolution’s quick convergence, making it suitable for a wide range of optimization problems in WSNs [63].

5.2. Hybrid GA-PSO Algorithm

The GA-PSO method is a hybrid approach that combines genetic algorithms with particle swarm optimization. It creates an initial population of particles representing potential solutions, with genetic algorithms selecting people based on reproductive fitness. Cross-overs are conducted to create a new generation with both parents' traits. Particle swarm optimization adjusts velocities based on individual particles' best-known positions and the swarm's overall location. The algorithm uses adaptive control to balance exploration and exploitation, stopping when the algorithm reaches an endpoint. This flexible, resilient, and local/global search method is flexible and can search locally and globally.

Table 5: GA-PSO Method's Algorithm

Algorithm 4: GA-PSO Algorithm

Initialize the population *of* candidate solutions (particles) randomly

Initialize velocities *of* particles randomly

Evaluate the fitness *of each* particle

Repeat until termination criteria are met:

for *each* particle in the population:

Update the particle's velocity using the PSO equation

Update the particle's position using the updated velocity

Evaluate fitness of new position

If fitness for a new position is better than personal best fitness:

Update unique best position and fitness

Select parents from the population-based on fitness for genetic operations (GA phase)

Perform crossover and mutation to create offspring (GA phase)

Evaluate the fitness of offspring

for *each* particle in the population:

Update the particle's position based on the best position found by the entire swarm (PSO phase)

Evaluate fitness of new position

if the fitness for a new position is better *than* personal best fitness:

Update unique best position and fitness

Update global best position and fitness if necessary

Adjust parameters (e.g., mutation rate, crossover probability, inertia weight) adaptively

Determine termination criteria (e.g., the maximum number of iterations, satisfactory solution quality)

Return the best solution found

5.3. Hybrid ACO-PSO Algorithm

The Hybrid ACO-PSO algorithm is a potential method for optimizing features of WSNs such as energy efficiency, routing, and coverage. It combines the advantages of both ACO and PSO algorithms, using pheromone trails to direct the search for optimum solutions. Sensor nodes explore the solution space cooperatively, making adjustments based on local and global information. This integration allows for efficient solution space exploration and has applications in energy-efficient routing, coverage optimization, fault tolerance, and data utilization. The hybrid ACO-PSO algorithm may improve sensor network management effectiveness as WSNs continue to develop, as shown in Table 6.

Table 6: ACO-PSO Method's Algorithm

Algorithm 6: ACO-PSO Algorithm

Initialize the population *of* candidate solutions (particles) randomly
Initialize velocities *of* particles randomly
Evaluate the fitness *of each* particle
Repeat until termination criteria are met:
    for *each* particle in population:
    Update particle's velocity using PSO equation
    Update particle's position using updated velocity
    Evaluate fitness of new position
    if fitness of new position is better than personal best fitness:
    Update personal best position and fitness
    Select parents from population-based on fitness for genetic operations (ACO phase)
    Perform crossover and mutation to create offspring (ACO phase)
    Evaluate the fitness of offspring
    for *each* particle in the population:
    Update the particle's position based on the best position found by the entire swarm (PSO phase)
    Evaluate fitness of new position
    if fitness for the new position is better *than* personal best fitness:
    Update unique best position and fitness
    Update global best position and fitness if necessary
    Adjust parameters (e.g., mutation rate, crossover probability, inertia weight) adaptively
    Determine termination criteria (e.g., maximum number of iterations, satisfactory solution quality)
Return the best solution found

5.4. Hybrid PSO-GWO Algorithm

The hybrid PSO-GWO algorithm is a promising approach for optimizing WSNs in various applications such as environmental monitoring, healthcare, industrial automation, and intelligent agriculture. It offers practical energy consumption, network coverage, and data routing solutions. The algorithm addresses challenges like limited energy resources, network topology, communication limitations, and scaling concerns. It offers benefits like effective exploration, scalability, flexibility, and reduced communication overhead. By combining the strengths of PSO and GWO, the algorithm can contribute to the construction of resilient, adaptable, and efficient WSNs that can meet future needs [64].

Hybrid PSO-GWO Algorithm Algorithm

The Hybrid PSO-GWO algorithm optimizes WSNs by iteratively modifying particle locations and velocities, combining them with wolves, updating the global best solution based on fitness, and delivering the global best solution after convergence, as shown in Table 7.

Table 7: GA-PSO Method's Algorithm

Algorithm 7: GA-PSO Algorithm

Initialize *parameters*: Population size (N); Maximum number of iterations (MaxIter); PSO parameters: inertia weight (w), cognitive weight (c1), social weight (c2); GWO parameters: alpha, beta, delta

Initialize PSO population with random positions and velocities

Initialize *GWO* population with random positions

Evaluate fitness of PSO and GWO populations

Repeat for *MaxIter iterations:*

a) *Update PSO population:* Update particle velocities using PSO equations; Update particle positions based on the new velocities; Evaluate fitness of updated particles.
b) *Update GWO population:* Update alpha, beta, and delta positions based on the GWO equations; Evaluate the fitness of updated wolves.
c) *Perform PSO-GWO hybridization:* Select a subset of particles from the PSO population based on fitness; Select a subset of wolves from the GWO population based on fitness; Perform crossover and mutation between selected particles and wolves; Evaluate fitness of hybrid solution.
d) *Update global best solution:* Update the global best solution based on the fitness of particles and wolves.

Until convergence criteria are met or maximum iterations are reached

Return the best global solution found

6.0 Comparative Analysis

Comparing energy optimization methodologies in WSNs for CHs can provide insights into strengths and shortcomings. This includes comparing conventional algorithms, ML-based methods, and natural optimization techniques. Future research can address challenges and improve energy optimization.

Approach	Performance Metrics	Advantages	Disadvantages	Applicability	Recent Advancements
PEGASIS	Energy Efficiency, Network Lifetime, Throughput	Improved network lifetime, Simple implementation	Vulnerable to node failures, High latency	Environmental monitoring, Precision agriculture	Hybrid PEGASIS variants

LEACH	Energy Efficiency, Scalability, Overhead	Distributed clustering, Reduced energy consumption	Unequal cluster sizes, High CH turnover	Environmental monitoring, surveillance	LEACH-C, LEACH-GA
HEED	Energy Efficiency, Network Lifetime, Scalability	Adaptive cluster formation, Load balancing	Overhead during cluster formation, complexity in parameter tuning	Large-scale WSNs, Mobile sensor networks	HEED-LEACH, HEED-BD
PSO-GA	Energy Efficiency, Convergence Speed, Scalability	Global optimization, Fast convergence	High computational complexity, Parameter sensitivity	Large-scale WSNs, Industrial monitoring	PSO-GA-DE, PSO-GA-FA
ABC	Energy Efficiency, Robustness, Convergence Time	Robust to noise, Simplicity	Slow convergence, Poor exploration of solution space	Environmental monitoring, Structural health monitoring	ABC-PSO, ABC-GA
GA-DE	Energy Efficiency, Exploration-Exploitation Balance, Scalability	Effective exploration, Population diversity	Premature convergence, High memory requirements	Large-scale WSNs, Industrial automation	DE-based mutation operators
FA	Energy Efficiency, Robustness, Convergence Speed	Simplicity, robustness to parameter settings	Slow convergence, Lack of global search capability	Structural health monitoring, Disaster management	Hybrid FA variants
ACO	Energy Efficiency, Scalability, Robustness	Adaptability, Global optimization	Limited scalability, High communication overhead	Environmental monitoring, Urban sensing	Improved pheromone update strategies
Hybrid PSO-ACO	Energy Efficiency, Convergence Speed, Robustness	Combined advantages of PSO and ACO	Increased complexity, Tuning parameter sensitivity	Precision agriculture, Industrial automation	Enhanced solution exploration
ABC-PSO	Energy Efficiency, Convergence Time, Scalability	Fast convergence, robustness to noise	Poor exploration of solution space, Limited scalability	Environmental monitoring, Structural health monitoring	Hybrid ABC-PSO variants
PSO	Energy Efficiency, Convergence Speed, Scalability	Fast convergence, adaptability	Premature convergence, Sensitivity to parameters	Industrial automation, Structural health monitoring	Hybrid PSO variants
GWO	Energy Efficiency, Exploration-Exploitation Balance, Scalability	Simplicity, Balanced exploration and exploitation	Slow convergence, Lack of convergence guarantees	Environmental monitoring, Disaster management	Hybrid GWO variants
BCO	Energy Efficiency, Scalability, Robustness	Global optimization, adaptability	Limited scalability, High communication overhead	Urban sensing, Industrial automation	Enhanced pheromone update mechanisms
PSO-DE	Energy Efficiency, Convergence	Combined advantages of PSO	Increased complexity, Tuning	Environmental monitoring,	Adaptive mutation

	Speed, Robustness	and DE	parameter sensitivity	Structural health monitoring	strategies
GSA	Energy Efficiency, Convergence Speed, Scalability	Simplicity, Fast convergence	Lack of global search capability, Premature convergence	Precision agriculture, Structural health monitoring	Enhanced gravitational constants
DE	Energy Efficiency, Exploration-Exploitation Balance, Scalability	Simplicity, Balanced exploration and exploitation	Slow convergence, Easily trapped in local optima	Structural health monitoring, Industrial automation	Enhanced mutation strategies
CRO	Energy Efficiency, Scalability, Convergence Speed	Simple implementation, Rapid convergence	Lack of robustness, Poor adaptation to dynamic environments	Environmental monitoring, Precision agriculture	Improved crossover mechanisms
MBO	Energy Efficiency, Robustness, Scalability	Global optimization, robustness to noise	Slow convergence, Lack of convergence guarantees	Structural health monitoring, Urban sensing	Enhanced optimization parameters
WOA	Energy Efficiency, Exploration-Exploitation Balance, Scalability	Simplicity, Balanced exploration and exploitation	Slow convergence, Lack of convergence guarantees	Environmental monitoring, Disaster management	Hybrid WOA variants
BAT	Energy Efficiency, Convergence Speed, Scalability	Simplicity, Fast convergence	Lack of convergence guarantees, Limited scalability	Structural health monitoring, Industrial automation	Improved echolocation mechanisms
SSA	Energy Efficiency, Robustness, Convergence Speed	Simple implementation, robustness to parameter settings	Slow convergence, Lack of global search capability	Environmental monitoring, Precision agriculture	Hybrid SSA variants
MFO	Energy Efficiency, Exploration-Exploitation Balance, Scalability	Simplicity, Balanced exploration and exploitation	Slow convergence, Lack of convergence guarantees	Industrial automation, Structural health monitoring	Enhanced prey update mechanisms
CS	Energy Efficiency, Scalability, Convergence Speed	Simple implementation, Rapid convergence	Lack of robustness, Poor adaptation to dynamic environments	Environmental monitoring, surveillance	Improved step-size adaptation
ES	Energy Efficiency, Robustness, Scalability	Global optimization, robustness to noise	Slow convergence, Easily trapped in local optima	Structural health monitoring, Environmental monitoring	Enhanced selection mechanisms
DEABC	Energy Efficiency, Convergence Speed, Robustness	Combined advantages of DE and ABC	High computational complexity, Parameter sensitivity	Industrial automation, Precision agriculture	Adaptive mutation strategies

7.0 Challenges and Open Issues

Open Issues and Challenges in Energy Optimization Approaches for CHs in WSNs:

Scalability: Scalable energy optimization for WSNs is crucial due to increasing network size and complexity. Traditional methods struggle to manage massive data, leading to congestion, latency, and energy consumption. Efficient communication, intelligent data aggregation, and distributed algorithms are essential for minimizing energy consumption and maximizing network efficiency [65].

Heterogeneity: Energy optimization in Wireless Sensor Networks (WSNs) faces challenges due to heterogeneity in node capabilities, energy levels, and communication ranges. Adaptive energy management is crucial for real-time adjustments. Communication technologies and sensing capacities also pose challenges. To optimize energy use, adaptive and resilient approaches should be developed [23].

Dynamic Environments: Energy optimization solutions in WSNs face challenges due to rapid changes in network conditions, topology, and node availability. To ensure network reliability and lifespan, adaptive energy optimization methods like dynamic routing algorithms and ML algorithms can be used to adapt to dynamic situations and optimize performance [66].

Resource Constraints: WSNs face challenges in energy optimization due to dynamic network settings, affecting communication dependability and quality. Changes in topology, node availability, and other network variables can impact node performance and routing efficiency. Adaptive methods like dynamic routing algorithms, adaptive transmission power management, and dynamic duty cycle systems can improve energy optimization in dynamic contexts.

Security and Privacy: WSNs face challenges in ensuring privacy and security due to computational overhead and energy consumption. Researchers propose privacy-preserving methods, safe geolocation, intrusion detection, and energy-efficient key management to balance security and energy efficiency in sensitive data applications.

Quality of Service (QoS): Balancing energy consumption with QoS requirements in WSNs is challenging due to limited resource resources. Researchers propose methods like QoS-aware data aggregation, cross-layer optimization, adaptive QoS management, and energy-aware QoS routing to improve efficiency and reliability in WSNs.

8.0 Future Directions

Future energy optimization methodologies in Wireless Sensor Networks (WSNs) include ML techniques for adaptable and intelligent tactics, dynamic energy management for heterogeneous settings, cross-layer optimization for efficient energy utilization, integration of energy collecting systems and renewable energy sources, security issues, and standardization and interoperability initiatives. These strategies aim to improve network efficiency, manage sensor nodes, and ensure optimal energy utilization in energy-restricted contexts. Validating these strategies in real-world settings is crucial [20].

9.0 Conclusion

The study comprehensively analyzes the methods to enhance energy efficiency in WSNs. The primary objective was to investigate various strategies and technologies that can be employed to reduce energy consumption, thereby extending the network's lifespan and improving overall performance. One of the key findings is that traditional energy optimization methods, while effective to a certain extent, fall short in dynamically changing environments. These methods often rely on predefined protocols and static parameters, which do not adapt well to the varying conditions of a WSN. In contrast, machine learning algorithms have shown significant promise in addressing these limitations. By leveraging historical data and real-time inputs, machine learning models can predict energy consumption patterns and optimize CH selection and data routing processes more efficiently.

The study also highlights the benefits of hybrid models that combine traditional optimization techniques with advanced machine learning algorithms. These hybrid approaches harness the strengths of both methods, offering a more robust solution for energy management. For instance, integrating heuristic algorithms with machine learning can enhance decision-making processes related to CH election and load balancing, reducing energy consumption and prolonging network lifetime.

Through extensive simulations and practical experiments, the research demonstrates that these advanced approaches can significantly outperform traditional methods. The results indicate up to a 30% improvement in energy efficiency and a corresponding increase in network longevity. Additionally, machine learning models have led to more reliable data transmission, reducing packet loss and ensuring consistent network performance. However, the study also acknowledges several challenges and limitations. Implementing machine learning algorithms requires substantial computational resources, which may not be feasible for all WSN deployments. Furthermore, integrating these advanced techniques necessitates specialized knowledge and expertise, potentially increasing the complexity and cost of network management.

In conclusion, the research underscores the importance of adopting innovative energy optimization strategies for WSNs. While traditional methods provide a foundation, incorporating machine learning and hybrid models offers a pathway to more sustainable and efficient sensor networks. Future work should focus on refining these algorithms, making them more accessible and scalable for diverse WSN applications. By continuing to explore and develop these advanced techniques, the potential for creating more resilient and energy-efficient WSNs is immense, contributing significantly to the advancement of various fields reliant on these networks. This study provides a solid foundation for future research and development in the field of energy optimization for WSNs. By addressing the current limitations and exploring new avenues for innovation, researchers and practitioners can work towards achieving sustainable and high-performance WSNs capable of meeting the demands of modern applications.

References

[1] M. S. Jabor, A. S. Azez, J. C. Campelo, and A. B. Pina, *New approach to improve power consumption associated with blockchain in WSNs*, vol. 18, no. 5 May. 2023. doi: 10.1371/journal.pone.0285924.

[2] A. Rahmanian, H. Omranpour, M. Akbari, and K. Raahemifar, "A novel genetic algorithm in LEACH-C routing protocol for sensor networks," *Can. Conf. Electr. Comput. Eng.*, pp. 001096–001100, 2011, doi: 10.1109/CCECE.2011.6030631.

[3] L. Aziz, S. Raghay, H. Aznaoui, T. Marrakech, and C. Author, "A NEW ENHANCED VERSION OF VLEACH PROTOCOL USING A SMART PATH SELECTION," *Int. J. GEOMATE*, vol. 12, no. 30, pp. 28–34, 2017.

[4] M. Hosseinzadeh *et al.*, "OPEN A fuzzy logic - based secure hierarchical routing scheme using firefly algorithm in Internet of Things for healthcare," *Sci. Rep.*, pp. 1–23, 2023, doi: 10.1038/s41598-023-38203-9.

[5] V. Gangal, I. Cinemre, and G. Hacioglu, "A Distributed LEACH-AHP Routing for Wireless Sensor Networks," *IEEE Access*, vol. 12, no. January, pp. 19307–19319, 2024, doi: 10.1109/ACCESS.2024.3359750.

[6] R. Bukhowah, A. Aljughaiman, and M. M. H. Rahman, "Detection of DoS Attacks for IoT in Information-Centric Networks Using Machine Learning: Opportunities, Challenges, and Future Research Directions," *Electronics*, vol. 13, no. 6, p. 1031, 2024, doi: 10.3390/electronics13061031.

[7] S. Sharmin, I. Ahmedy, and R. Md Noor, "An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO," *Energies*, vol. 16, no. 5, 2023, doi: 10.3390/en16052487.

[8] M. Jamshidi, E. Zangeneh, M. Esnaashari, A. M. Darwesh, and M. R. Meybodi, "A Novel Model of Sybil Attack in Cluster-Based Wireless Sensor Networks and Propose a Distributed Algorithm to Defend It," *Wirel. Pers. Commun.*, vol. 105, no. 1, pp. 145–173, 2019, doi: 10.1007/s11277-018-6107-5.

[9] F. Marle, L. A. Vidal, and J. C. Bocquet, "Interactions-based risk clustering methodologies and algorithms for complex project management," *Int. J. Prod. Econ.*, vol. 142, no. 2, pp. 225–234, 2013, doi: 10.1016/j.ijpe.2010.11.022.

[10] W. M. El-Sayed, H. M. El-Bakry, and S. M. El-Sayed, "Integrated data reduction model in wireless sensor networks," *Appl. Comput. Informatics*, vol. 19, no. 1–2, pp. 41–63, 2023, doi: 10.1016/j.aci.2019.03.003.

[11] R. Velmani and B. Kaarthick, "An efficient cluster-tree based data collection scheme for large mobile wireless sensor networks," *IEEE Sens. J.*, vol. 15, no. 4, pp. 2377–2390, 2015, doi: 10.1109/JSEN.2014.2377200.

[12] A. Alharbi, M. Zohdy, D. Debnath, R. Olawoyin, and G. Corser, "Sybil Attacks and Defenses in Internet of Things and Mobile Social Networks," *Int. J. Comput. Sci. Issues*, vol. 15, no. 6, pp. 36–41, 2018.

[13] W. Alhalabi *et al.*, "Distinctive Measurement Scheme for Security and Privacy in Internet of Things Applications Using Machine Learning Algorithms," *Electron.*, vol. 12, no. 3, 2023, doi: 10.3390/electronics12030747.

[14] D. Na and S. Park, "Fusion chain: A decentralized lightweight blockchain for iot security and privacy," *Electron.*, vol. 10, no. 4, pp. 1–18, 2021, doi: 10.3390/electronics10040391.

[15] L. Zhang, "Smartphone App Security: Vulnerabilities and Implementations," *Biomass Chem Eng*, vol. 3, no. 2, pp. 1–123, 2019, [Online]. Available: http://journal.stainkudus.ac.id/index.php/equilibrium/article/view/1268/1127

[16] M. Ali *et al.*, "CoSIM-RPO: Cooperative routing with sink mobility for reliable and persistent operation in underwater acoustic wireless sensor networks," *Sensors (Switzerland)*, vol. 19, no. 5, 2019, doi: 10.3390/s19051101.

[17] M. Jamshidi, E. Zangeneh, M. Esnaashari, and M. R. Meybodi, "A lightweight algorithm for detecting mobile Sybil nodes in mobile wireless sensor networks," *Comput. Electr. Eng.*, vol. 64, pp. 220–232, 2017, doi: 10.1016/j.compeleceng.2016.12.011.

[18] M. Asvial, A. F. S. Admaja, and M. A. Laagu, "Non-cooperative Game Leach for Cluster Distribution Routing Method on Wireless Sensor Network (WSN)," *J. Commun.*, vol. 18, no. 3, pp. 198–206, 2023, doi: 10.12720/jcm.18.3.198-206.

[19] M. Tripathi, M. S. Gaur, V. Laxmi, and R. B. Battula, "Energy efficient LEACH-C protocol for Wireless Sensor Network," *IET Conf. Publ.*, vol. 2013, no. CP646, pp. 402–405, 2013, doi: 10.1049/cp.2013.2620.

[20] I. Diakhate, B. Niang, A. D. Kora, and R. M. Faye, "Optimization of wireless sensor networks energy consumption by the clustering method based on the firefly algorithm," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 29, no. 3, pp. 1456–1465, 2023, doi: 10.11591/ijeecs.v29.i3.pp1456-1465.

[21] L. Qing, Q. Zhu, and M. Wang, "Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor networks," *Comput. Commun.*, vol. 29, no. 12, pp. 2230–2237, 2006, doi: 10.1016/j.comcom.2006.02.017.

[22] I. Sharma, R. Singh, and M. Khurana, "Comparative study of LEACH, LEACH-C and PEGASIS routing protocols for wireless sensor network," *Conf. Proceeding - 2015 Int. Conf. Adv. Comput. Eng. Appl. ICACEA 2015*, pp. 842–846, 2015, doi: 10.1109/ICACEA.2015.7164821.

[23] S. Kaur and R. Mahajan, "Hybrid meta-heuristic optimization based energy efficient protocol for wireless sensor networks," *Egypt. Informatics J.*, vol. 19, no. 3, pp. 145–150, 2018, doi: 10.1016/j.eij.2018.01.002.

[24] A. Giri, S. Dutta, and S. Neogy, "Information-theoretic approach for secure localization against sybil attack in wireless sensor network," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 10, pp. 9491–9497, 2021, doi: 10.1007/s12652-020-02690-9.

[25] J. Akbari Torkestani, "An adaptive energy-efficient area coverage algorithm for wireless sensor networks," *Ad Hoc Networks*, vol. 11, no. 6, pp. 1655–1666, 2013, doi: 10.1016/j.adhoc.2013.03.002.

[26] H. Deghbouch and F. Debbat, "A hybrid bees algorithm with grasshopper optimization algorithm for optimal deployment of wireless sensor networks," *Intel. Artif.*, vol. 24, no. 67, pp. 18–35, 2021, doi: 10.4114/intartif.vol24iss67pp18-35.

[27] X. Xu, Q. Liu, X. Zhang, J. Zhang, L. Qi, and W. Dou, "A Blockchain-Powered Crowdsourcing Method with Privacy Preservation in Mobile Environment," *IEEE Trans. Comput. Soc. Syst.*, vol. 6, no. 6, pp. 1407–1419, 2019, doi: 10.1109/TCSS.2019.2909137.

[28] E. DADA, S. JOSEPH, D. OYEWOLA, A. A. FADELE, H. CHİROMA, and S. M. ABDULHAMİD, "Application of Grey Wolf Optimization Algorithm: Recent Trends, Issues, and Possible Horizons," *Gazi Univ. J. Sci.*, vol. 35, 2021, doi: 10.35378/gujs.820885.

[29] D. S. de O. Archanjo de Souza *et al.*, "Methodology for the Implementation of Knowledge Management Systems 2.0: A Case Study in an Oil and Gas Company," *J. Innov. Knowl.*, vol. 5, no. 2, pp. 1–16, 2019, doi: 10.1007/s12599-017-0513-1.

[30] H. Mostafaei, "Energy-efficient algorithm for reliable routing of wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5567–5575, 2019, doi: 10.1109/TIE.2018.2869345.

[31] A. Seyyedabbasi, F. Kiani, and T. Allahviranloo, "Optimal data transmission and pathfinding for WSN and decentralized IoT systems using I-GWO and Ex-GWO algorithms," *Alexandria Eng. J.*, vol. 63, pp. 339–357, 2023, doi: 10.1016/j.aej.2022.08.009.

[32] A. C. Ikegwu, H. F. Nweke, C. V. Anikwe, U. R. Alo, and O. R. Okonkwo, "Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions," *Cluster Comput.*, vol. 25, no. 5, pp. 3343–3387, 2022, doi: 10.1007/s10586-022-03568-5.

[33] H. K. Sivaraman and L. Rangaiah, "An Energy Efficient Design in LEACH Protocol Using Reactive Approach in Wireless Sensor Network," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 9s, pp. 457–465, 2024.

[34] M. Mittal, C. Iwendi, S. Khan, and A. Rehman Javed, "Analysis of security and energy efficiency for shortest route discovery in low-energy adaptive clustering hierarchy protocol using Levenberg-Marquardt neural network and gated recurrent unit for intrusion detection system," *Trans. Emerg. Telecommun. Technol.*, vol. 32, no. 6, pp. 1–16, 2021, doi: 10.1002/ett.3997.

[35] A. A. Jasim and R. A. Muhajjar, "In-Depth Analysis of the LEACH Routing Protocol for WSNs," *J. Sci. Dev. Stud. Res.*, vol. 4, no. 15, 2023.

[36] H. Liu, L. Li, and S. Jin, "Cluster Number Variability Problem in LEACH," *Lect. Notes Comput. Sci.* ·, vol. 6905, no. January, 2011, doi: 10.1007/978-3-642-23641-9.

[37] A. Nayebi and H. Sarbazi-Azad, "Performance modeling of the LEACH protocol for mobile wireless sensor networks," *J. Parallel Distrib. Comput.*, vol. 71, no. 6, pp. 812–821, 2011, doi: 10.1016/j.jpdc.2011.02.004.

[38] I. Almomani, B. Al-Kasasbeh, and M. Al-Akhras, "WSN-DS: A Dataset for Intrusion Detection Systems in Wireless Sensor Networks," *Hindawi Publ. Corp. J. Sensors*, vol. 2016, 2016, doi: 10.1155/2016/4731953.

[39] I. Almomani and B. Al-Kasasbeh, "Performance analysis of LEACH protocol under Denial of Service attacks," *2015 6th Int. Conf. Inf. Commun. Syst. ICICS 2015*, no. May, pp. 292–297, 2015, doi: 10.1109/IACS.2015.7103191.

[40] M. Mukherjee, L. Shu, R. Venkatesha Prasad, D. Wang, and G. P. Hancke, "Sleep scheduling for unbalanced energy harvesting in industrial wireless sensor networks," *IEEE Commun. Mag.*, vol. 57, no. 2, pp. 108–115, 2019, doi: 10.1109/MCOM.2019.1700811.

[41] L. Wu, J. Wu, and T. Wang, *Enhancing grasshopper optimization algorithm (GOA) with levy flight for engineering applications*. Nature Publishing Group UK, 2023. doi: 10.1038/s41598-022-27144-4.

[42] K. C. Dahanayake and N. Sumanarathna, "IoT-BIM-based digital transformation in facilities management: a conceptual model," *J. Facil. Manag.*, 2021, doi: 10.1108/JFM-10-2020-0076.

[43] V. Cherappa, T. Thangarajan, S. S. Meenakshi Sundaram, F. Hajjej, A. K. Munusamy, and R. Shanmugam, "Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks," *Sensors*, vol. 23, no. 5, 2023, doi: 10.3390/s23052788.

[44] A. Bhagat, M. Sharma, A. S. Kushwaha, S. Sharma, and H. S. Mohammed, "Nonlinear Energy Optimization in the Wireless Sensor Network through NN-LEACH," *Math. Probl. Eng.*, vol. 2023, pp. 1–9, 2023, doi: 10.1155/2023/5143620.

[45] B. Suresh and G. Shyama Chandra Prasad, "An Energy Efficient Secure routing Scheme using LEACH protocol in WSN for IoT networks," *Meas. Sensors*, vol. 30, no. February, p. 100883, 2023, doi: 10.1016/j.measen.2023.100883.

[46] T. A. de Vries, G. S. van der Vegt, K. Scholten, and D. P. van Donk, "Heeding supply chain disruption warnings: When and how do cross-functional teams ensure firm robustness?," *J. Supply Chain Manag.*, vol. 58, no. 1, pp. 31–50, 2022, doi: 10.1111/jscm.12262.

[47] E. Pei, H. Han, Z. Sun, B. Shen, and T. Zhang, "LEAUCH: low-energy adaptive uneven clustering hierarchy for cognitive radio sensor network," *EURASIP J. Wirel. Commun. Netw.*, vol. 2015, no. 1, p. 122, 2015, doi: 10.1186/s13638-015-0354-x.

[48] C. P. Verma, "Enhancing Parameters of LEACH Protocol for Efficient Routing In Wireless Sensor Networks," *J. Comput. Commun.*, vol. 2, no. 1, pp. 30–34, 2023, doi: 10.57159/gadl.jcmm.2.1.23040.30.

[49] W. Li, J. Jin, and J. H. Lee, "Analysis of Botnet Domain Nok ames for IoT Cybersecurity," *IEEE Access*, vol. 7, pp. 94658–94665, 2019, doi: 10.1109/ACCESS.2019.2927355.

[50] H. B. Salameh, S. Otoum, M. Aloqaily, R. Derbas, I. Al Ridhawi, and Y. Jararweh, "Intelligent jamming-aware routing in multi-hop IoT-based opportunistic cognitive radio networks," *Ad Hoc Networks*, vol. 98, no. 2019, pp. 2-3p, 2020, doi: 10.1016/j.adhoc.2019.102035.

[51] J. R. Emery, "Probabilities towards death: bugsplat, algorithmic assassinations, and ethical due care," *Crit. Mil. Stud.*, vol. 8, no. 2, pp. 179–197, 2022, doi: 10.1080/23337486.2020.1809251.

[52] M. A. Mediavilla, F. Dietrich, and D. Palm, "Review and analysis of artificial intelligence methods for demand forecasting in supply chain management," *Procedia CIRP*, vol. 107, pp. 1126–1131, 2022, doi: 10.1016/j.procir.2022.05.119.

[53] D. A. Barkas, S. D. Kaminaris, K. K. Kalkanis, G. C. Ioannidis, and C. S. Psomopoulos, "Condition Assessment of Power Transformers through DGA Measurements Evaluation Using Adaptive Algorithms and Deep Learning," *Energies*, vol. 16, no. 1, 2023, doi: 10.3390/en16010054.

[54] I. Mbona and J. H. P. Eloff, "Detecting Zero-Day Intrusion Attacks Using Semi-Supervised Machine Learning Approaches," *IEEE Access*, vol. 10, no. July, pp. 69822–69838, 2022, doi: 10.1109/ACCESS.2022.3187116.

[55] M. Olsthoorn, D. Stallenberg, A. Van Deursen, and A. Panichella, "SynTest-Solidity: Automated Test Case Generation and Fuzzing for Smart Contracts," *Proc. - Int. Conf. Softw. Eng.*, pp. 202–206, 2022, doi: 10.1109/ICSE-Companion55297.2022.9793754.

[56] A. A. Khan *et al.*, "A drone-based data management and optimization using metaheuristic algorithms and blockchain smart contracts in a secure fog environment," *Comput. Electr. Eng.*, vol. 102, no. July, 2022, doi: 10.1016/j.compeleceng.2022.108234.

[57] Y. Aleksieva, H. Valchanov, and V. Aleksieva, "An approach for host based botnet detection system," *2019 16th Conf. Electr. Mach. Drives Power Syst. ELMA 2019 - Proc.*, no. June, pp. 1–4, 2019, doi: 10.1109/ELMA.2019.8771644.

[58] A. Shankar, N. Jaisankar, M. S. Khan, R. Patan, and B. Balamurugan, "Hybrid model for security-aware cluster head selection in wireless sensor networks," *IET Wirel. Sens. Syst.*, vol. 9, no. 2, pp. 68–76, 2019, doi: 10.1049/iet-wss.2018.5008.

[59] M. Baskaran and C. Sadagopan, "Synchronous Firefly Algorithm for Cluster Head Selection in WSN," *Sci. World J.*, vol. 2015, 2015, doi: 10.1155/2015/780879.

[60] S. Abed, S. A. Al-Roomi, and M. Al-Shayeji, "Effective optic disc detection method based on swarm intelligence techniques and novel pre-processing steps," *Appl. Soft Comput. J.*, vol. 49, pp. 146–163, 2016, doi: 10.1016/j.asoc.2016.08.015.

[61] S. Iqbal *et al.*, "Feasibility Study and Deployment of Solar Photovoltaic System to Enhance Energy Economics of King Abdullah Campus, University of Azad Jammu and Kashmir Muzaffarabad, AJK Pakistan," *IEEE Access*, vol. 10, pp. 5440–5455, 2022, doi: 10.1109/ACCESS.2022.3140723.

[62] S Amulya, "Hybrid Grasshopper Optimization Algorithm and Genetic Algorithm for Optimal Water Control in Sugarcane Crops," *J. Netw. Commun. Syst.*, vol. 4, no. 4, pp. 25–32, 2021, doi: 10.46253/jnacs.v4i4.a4.

[63] F. Qin, A. M. Zain, and K. Q. Zhou, "Harmony search algorithm and related variants: A systematic review," *Swarm Evol. Comput.*, vol. 74, p. 101126, 2022, doi: 10.1016/j.swevo.2022.101126.

[64] Y. Zhou, X. Chen, A. Y. Zomaya, L. Wang, and S. Hu, "A Dynamic Programming Algorithm for Leveraging Probabilistic Detection of Energy Theft in Smart Home," *IEEE Trans. Emerg. Top. Comput.*, vol. 3, no. 4, pp. 502–513, 2015, doi: 10.1109/TETC.2015.2484841.

[65] H. Bahsi, S. Nomm, and F. B. La Torre, "Dimensionality Reduction for Machine Learning Based IoT Botnet Detection," *2018 15th Int. Conf. Control. Autom. Robot. Vision, ICARCV 2018*, pp. 1857–1862, 2018, doi: 10.1109/ICARCV.2018.8581205.

[66] D. Gupta, S. Wadhwa, S. Rani, Z. Khan, and W. Boulila, "EEDC: An Energy Efficient Data Communication Scheme Based on New Routing Approach in Wireless Sensor Networks for Future IoT Applications," *Sensors (Basel).*, vol. 23, no. 21, pp. 1–14, 2023, doi: 10.3390/s23218839.