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A Comprehensive Review of Cluster Head Selection in Wireless Sensor Networks

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Abstract:-. In the last few years, there has been a rapid expansion in Wireless Sensor Networks (WSNs) due to their capacity for data sensing, wireless communication, and efficient data processing. WSNs comprise small, little powered nodes in the sensor that autonomously configured and organized themselves to fulfil their designated tasks. Despite their affordability, ease of deployment, flexibility, and efficiency, challenges persist regarding energy efficiency and network longevity. Clustering within WSNs emerges as a dependable solution, involving the grouping of the sensor nodes into clusters with the selection of a cluster head (CH) responsible to sensing data, aggregation, and transmission to the base station (BS) of the network. However, inefficiencies in methods of CH selection and cluster formation give rise to persistent challenges such as energy holes and isolated node issues. This study provides a comprehensive review of various non-metaheuristic and metaheuristic techniques responsible for CH selection and cluster formation methods across diverse environmental parameters, aiming to elucidate how these challenges have been addressed by different researchers. Additionally, the survey outlines the parameter configurations, advantages, limitations, and future directions of these methods, accompanied by a succinct performance evaluation summary.

Keywords: *Cluster head, Network lifetime, Rouitng, Optimization, WSN.*

1. Introduction

Wireless Sensor Networks (WSN) have surfaced as a notable focus of research due to their ability to monitor and record environmental changes in various fields such as biomedical applications, habitat monitoring, military operations, and health monitoring [1]. WSNs consist of low-budget and little-power sensor nodes forming a self-organizing wireless network to monitor environments inaccessible to humans. However, effective data transmission among nodes faces challenges due to factors like limitatiions of energy, processing, and data communication capabilities of sensor nodes. Energy efficiency has garnered significant attention from researchers to extend network lifespan. Energy utilization reduction strategies encompass various aspects including services, applications, and communication[2].

The limitations of WSNs include constrained capacity of battery, small size of the memory, and short communication ranges. Energy consumption occurs continuously during sensing of data, collection, and transmission phases, with data transmission consuming the most energy. Energy efficiency challenges intensify in large-scale or remote networks where battery replacement or recharging is difficult. Efficient data transfer is hindered by mismanagement, increasing packet payload size, and consequent data packet drop probability. Early approaches like Low-Energy Adaptive Clustering Hierarchy (LEACH) aimed to optimize power consumption through clustering techniques, enhancing network lifetime by conserving energy during transmission. However, challenges such as the network hole and isolated node problems persisted. Solutions integrating clustering and multi-hop communication face issues like high relay traffic and accelerated node depletion, leading to reduced network lifespan[3].

1.1. Motivation

The motivation for this work stems from the need to provide clarity and guidance to novice researchers in selecting Cluster Heads (CHs) based on various algorithms and models in WSN. The paper aims to facilitate an understanding of CH models based on specific requirements and their applications. A survey of current meta-heuristic-based approaches is conducted to offer a quick overview.

Section 2 of this paper gives insight of various CHs approaches, recommending different models and discussing their roles. A review of optimization models primarily focuses on energy consumption and network lifespan, elucidating their features and objectives. Notably, existing literature lacks comprehensive coverage of security, load, and temperature considerations in CHs. Therefore, the paper endeavours to fill this gap by proposing a broad review of previously presented models for CHs in WSN, emphasizing their evaluation metrics. The rest of the paper is organized as follows: first, we present the basics of WSNs cluster formation. Next, we review recent related works in the field. At the en, we have presented the conclusions drawn from this comprehensive review.

2. WSNs Cluster Formation

Cluster formation is a crucial organizational strategy employed in WSNs to enhance network efficiency, optimize resource utilization, and prolong network lifetime. In the vast landscape of WSNs, where numerous sensor nodes are scattered across an area for monitoring environmental or physical parameters applications, clustering establishes a structured hierarchy facilitating streamlined communication and data management. At its core, clustering entails grouping sensor nodes into hierarchical clusters and or metrics-based, typically consisting of a designated CH and member nodes. This hierarchical arrangement fosters organized communication pathways and enables localized data processing within clusters. By centralizing data accumulation and forwarding responsibilities, cluster heads play a critical role in conserving energy and reducing communication overhead, thereby enhancing the overall energy efficiency of the network[4].

Moreover, clustering enhances the scalability and manageability of WSNs by compartmentalizing the network into manageable units. This organization not only simplifies network configuration and maintenance but also promotes efficient resource allocation and utilization. Selection of cluster heads is a critical aspect of cluster formation, often governed by sophisticated algorithms that consider factors such as node energy levels, proximity to base stations, and communication capabilities. Algorithms like LEACH, Hybrid Energy-Efficient Distributed (HEED), and Power-Efficient Gathering in Sensor Information Systems (PEGASIS) are commonly employed for this purpose, ensuring a balanced distribution of responsibilities and resources across the network. Furthermore, dynamic adaptation mechanisms are integrated into clustering algorithms to enable WSNs to respond to changing network conditions and unforeseen events such as node failures or environmental fluctuations. These adaptive strategies ensure the resilience and robustness of the network by dynamically reorganizing clusters or selecting new cluster heads as needed[5].

The cluster formation serves as a cornerstone in the architecture and operation of WSNs, offering structured organization, efficient resource utilization, and adaptability to dynamic network conditions. By embracing clustering mechanisms, WSNs can achieve optimal performance, prolonged network lifetime, and enhanced reliability in various monitoring and sensing applications[6].

Figure 1 presents an illustrative depiction of the clustering model within a WSN. The diagram showcases the hierarchical organization comprising cluster heads and cluster nodes, which collectively form the backbone of the network infrastructure. At the heart of the clustering model are the cluster heads, strategically positioned within the network to oversee and coordinate communication activities within their respective clusters. These cluster heads serve as central hubs for data aggregation, processing, and transmission, effectively managing the flow of information within the network. The cluster heads are interconnected with the base station, facilitating the seamless exchange of data between the clustered network and the centralized BS.

Additionally, the BS serves as a gateway to the external networks, possessing the capability to establish connections with the Internet and end-users[7]. This connectivity enables data dissemination beyond the confines of the WSN, allowing for remote monitoring, analysis, and decision-making.

Moreover, Figure 1 provides a comprehensive overview of the cluster model architecture in WSNs, emphasizing the roles of cluster heads, cluster nodes, and the base station in enabling efficient network operation and connectivity with external systems.

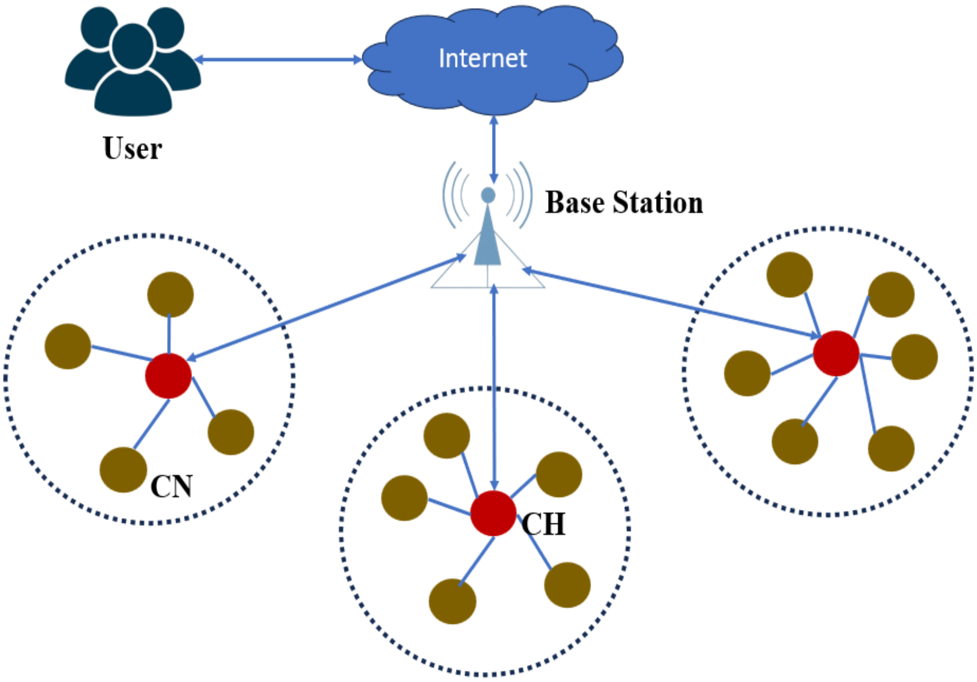

Figure 1. WSNs Cluster Model

3. CH Selection

CH selection stands as a focused phase in the clustering process within Sensor WSNs, bearing significant responsibility for efficient data transfer and aggregation. The importance of CH selection has garnered considerable attention in recent literature, as it directly impacts the total lifetime and reliability of the network[8]. Various methodologies have been employed to address this pivotal task, with recent focus extending to both Metaheuristic and Non-Metaheuristic Methods. While Metaheuristic Methods leverage heuristic solutions inspired by natural phenomena or human behavior, Non-Metaheuristic Methods rely on deterministic algorithms and mathematical models. Understanding the distinction between these approaches is essential for comprehensively evaluating clustering techniques in WSNs[9].

CH selection plays a important role in determining the efficiency and effectiveness of WSNs. Recent literature has emphasized its importance due to its direct influence on network lifetime and reliability. In Non-Metaheuristic Methods, CH selection is guided by predetermined selection criteria tailored to specific application environments. These criteria dictate the selection process and aim to identify the most convenient CHs based on predefined parameters[10]. The focus on predefined criteria in Non-Metaheuristic Methods underscores the deterministic nature of these approaches, which prioritize systematic decision-making over heuristic exploration of solution spaces.

In the process of WSNs, the optimization of CH selection and cluster formation processes plays a pivotal role in enhancing network efficiency and prolonging its lifespan. Two prominent methodologies have emerged for tackling this optimization task: Metaheuristic Methods and Non-Metaheuristic Methods. Understanding the fundamental differences between these approaches is essential for comprehensively evaluating clustering techniques in WSNs.

3.1. Metaheuristic Methods

Metaheuristic methods encompass a diverse set of problem-solving techniques inspired by natural phenomena or human behavior. These methods provide heuristic solutions to optimization problems by iteratively exploring the solution space to find near-optimal solutions. Examples of metaheuristic algorithms commonly applied in WSN clustering include Genetic Algorithms (GA)[11], Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO)[12], and Simulated Annealing (SA). Metaheuristic methods offer flexibility and adaptability, making them suitable for addressing complex optimization challenges in WSNs. However, they often require substantial computational resources and may not guarantee optimal solutions due to their stochastic nature[13].

3.2. Non-Metaheuristic Methods

In contrast, Non-Metaheuristic Methods rely on deterministic algorithms and mathematical models to optimize CH selection and cluster formation in WSNs. These methods leverage mathematical formulations, graph theory, and optimization techniques such as Integer Linear Programming (ILP), Mixed Integer Programming (MIP), and Dynamic Programming (DP) to find optimal or near-optimal solutions. Non-metaheuristic methods provide a systematic approach to problem-solving, offering deterministic solutions that are often easier to analyze and implement. However, they may struggle with scalability and complexity when applied to large-scale WSNs or dynamic environments[14].

Understanding the characteristics, strengths, and limitations of both Metaheuristic and Non-Metaheuristic Methods is crucial for researchers and practitioners aiming to design efficient clustering algorithms for WSNs. By exploring and comparing these methodologies, we can gain valuable insights into their applicability, performance, and suitability for different WSN scenarios, ultimately advancing the state-of-the-art in WSN clustering[15].

The following section offers a comprehensive review of related work, encompassing recent studies and existing literature in the WSN field. This review aims to provide insight into the current state of research and identify trends, methodologies, and findings relevant to the optimization of cluster formation and CH selection in WSNs.

Selecting the optimal cluster head in WSNs is critical for network efficiency and performance. It ensures balanced energy consumption, prolongs network lifetime, and minimizes transmission delays by distributing computational tasks effectively. Optimal cluster head selection promotes load balancing among nodes, prevents network congestion, and facilitates efficient data aggregation, conserving bandwidth and enhancing scalability. The efficacy of node energy is crucial in maximizing energy efficiency, optimizing network performance, and ensuring the reliability of WSNs across various application deployment scenarios.

4. Related Work

Over the past few years or so, various research proposals were emerged, each suggesting enhancements for cluster head selection. Additionally, numerous surveys have been conducted on the theme of clustering, leading to the identification of several advantages and limitations. However, there are still gaps in the existing literature that need to be addressed to provide an optimal solution.

The authors [16] proposed Energy Optimization Routing using Improved Artificial Bee Colony (EOR-iABC) aims to enhancement of energy adequacy and extend the the lifetime of network of cluster-based WSN. It utilizes an improved artificial bee colony algorithm to select energy-efficient CHs at regular intervals, integrating crossover and mutation to enhance search policies. By incorporating employee and onlooker-bee stages, eliminates delay convergence and improves local search strategies. Additionally, it discovers optimal paths from CH to the BS to enhance data collection efficiency. The EOR-iABC employs the Grenade Explosion Method (GEM) and Cauchy operator to dynamically extend search policies across regions for large-scale WSNs. Simulation results demonstrate that EOR-iABC outperforms existing schemes in terms of energy efficiency, showing a 27% improvement compared to the OCABC scheme and a 16% improvement compared to the IABCOCT scheme. The integration of GEM and the Cauchy operator enhances exploration and exploitation for CH selection methods. The scheme also reduces convergence delay through self-adapting update strategies.

Experimental results confirm significant improvements in packet delivery, increased node longevity, lower energy consumption, and reduced delay. Future work may involve formulating hybrid energy-saving algorithms to optimize CH selection with a mobile sink, aiming to balance energy usage further.

The authors [17] proposed Meta-heuristic Optimized CH selection-based Routing algorithm for WSNs (MOCRAW) aims to minimize energy consumption and facilitate rapid data transmission. By integrating the Dragonfly Algorithm (DA) and employing both Local Search Optimization (LSO) and Global Search Optimization (GSO), MOCRAW ensures loop-free routing while addressing isolated nodes and hot-spot issues. It comprises two subprocesses: the Cluster Head Selection Algorithm (CHSA) and the Route Search Algorithm (RSA). CHSA utilizes an Energy Level Matrix (ELM) considering factors like node density, distance to the BS, and inter-cluster formation. RSA employs levy distribution to find optimal paths between source and destination nodes. The results demonstrate that MOCRAW outperforms other protocols in terms of energy efficiency, PDR, delay, and the number of alive nodes. It achieves this by optimizing routing decisions, leveraging metaheuristic approaches, facilitating optimal path selection, and aggregating traffic to minimize information exchange and communication overhead. MOCRAW focuses on loop-free routing to mitigate concerns related to greedy forwarding and dynamic routing, offering improved performance across various evaluation parameters.

The authors [18] introduced a novel approach aimed at simultaneously addressing the selection of CHs and optimizing multi-hop routing in cluster-based WSNs to enhance network lifetime. Unlike previous studies that tackled these issues separately, this approach integrates them to improve overall network performance. The proposed scheme considers the role of cluster heads in transmitting inter-cluster traffic during the selection process, with a focus on reducing energy consumption. It employs a genetic algorithm at two levels: the first level selects cluster heads, while the second level determines optimal multi-hop routing among them. Simulation results comparing this approach with three existing schemes, which handle cluster head selection and routing separately, demonstrate the superiority of the proposed optimization scheme in prolonging network lifetime. By concurrently addressing cluster head selection and multi-hop routing, the two-level genetic algorithm enhances network efficiency and extends its operational lifespan.

The author [19] introduces a routing protocol based on genetic algorithms designed for a middle layer-oriented network structure, wherein multiple stations receive and forward data to a sink. The optimal number of stations is crucial to balance construction costs and transmission energy consumption. Five methods are implemented and compared to assess performance and stability. Experimental results reveal that the proposed scheme reduces the number of stations by 36.8% and 20% compared to FF and HL methods, respectively, in a 100-node network. The protocol incorporates two key phases: selecting candidate middle layer nodes and applying a genetic algorithm to construct an energy-aware middle layer-oriented routing network. This approach strategically determines station locations by considering factors such as the distance between common nodes and stations, aiming to minimize the number of stations while ensuring full network coverage.

The author [20] introduces the Binary Multi-Objective Adaptive Fish Migration Optimization (BMAFMO) algorithm, which enhances the global search capability of optimization algorithms by implementing a Pareto optimal solution storage strategy. It addresses the cluster head node selection problem by transforming continuous solutions into binary ones using a sigmoid transformation function. Comprehensive testing on eight test problems using four metrics, along with reliability assessment via rank sum test, demonstrates the algorithm's superior performance compared to other methods, achieving the best results in 78.13% of test problems. Moreover, the BMAFMO algorithm proves effective in solving the cluster head selection problem in WSN, outperforming other heuristic algorithms in terms of consumption of energy, number of CHs, and coverage of nodes. The algorithm exhibits competitive performance in convergence, distribution, and scalability across various test scenarios, showcasing its potential for practical optimization problems.

The author[21] introduces an enhanced algorithm named ESO-LEACH, which utilizes meta-heuristic PSO optimization for initial sensor node clustering. ESO-LEACH addresses the random nature of the algorithm by introducing advanced nodes and an enhanced set of rules for CH election. Python-based simulations demonstrate that ESO-LEACH surpasses conventional LEACH, significantly extending the network's lifespan. Comparative analysis between ESO-LEACH and LEACH reveals that the former nearly doubles the network's lifespan, indicating its effectiveness in prolonging network longevity. ESO-LEACH mitigates shortcomings of conventional protocols by considering node vitality, maintaining optimal CH count, and reducing random dependence. Simulation results illustrate a gradual decline in node vitality with ESO-LEACH, leading to a longer network lifespan compared to LEACH, which experiences sudden node depletion. This demonstrates ESO-LEACH's superior vitality efficiency and longevity compared to traditional LEACH protocols.

The author [22] introduces a novel CH selection model aimed at maximizing lifetime and energy efficiency in WSNs. Additionally, it proposes a hybrid algorithm called Fitness-based Glowworm Swarm with Fruitfly Algorithm (FGF), which combines Glowworm Siwarm Optimization (GSO) and Fruitfly Optimization Algorithm (FFOA) to select the best CH. The performance of FGF is compared against various existing methods, including PSO, Genetic Algorithm (GA), Artificial Bee Colony (ABC), Ant Lion Optimization (ALO), Cuckoo Search (CS), Group Search Ant Lion with Levy Flight (GAL-LF), FFOA, and Grasshopper Optimization Algorithm (GOA), in terms of alive node analysis, energy analysis, and cost function. The results demonstrate the effectiveness of the proposed approach in improving network lifetime, reducing energy consumption, and optimizing cost functions. This paper contributes by introducing a novel cluster head selection approach and evaluating the performance of FGF against traditional methods, highlighting its superiority in achieving network optimization objectives.

The author [23] introduces a novel method for cluster-based routing aimed at enhancing routing efficiency and maximizing network lifetime. The approach consists of two phases: firstly, selecting the optimal cluster head using the Moth Levy-adopted Artificial Electric Field Algorithm (ML-AEFA), and secondly, data transmission facilitated by the Customized Grey Wolf Optimization (CGWO) algorithm. The selection of the optimal CH is based on considerations such as energy levels, node degree, distances between sensor nodes, distances between CHs and the BS, and the time of death for nodes. The performance of the novel method is evaluated against existing schemes using various metrics, including alive nodes, residual energy, network lifetime, packet loss ratio, throughput, and total packets delivered to the BS. This paper contributes by introducing a new cluster-based routing model that integrates advanced algorithms to optimize routing decisions and enhance network longevity, as demonstrated through comparative analysis with current models.

The author [24] introduces a novel cluster scheduling technique for WSNs utilizing a local gravitational method to dynamically determine the number of time-varying clusters based on a sequence of vectors. Inspired by the physical properties of gravity force among mass units, the method treats nodes in vector space as units of mass. Clustering occurs where gravitational force is highest, corresponding to high-density feature vectors. Through cooperative and distributed clustering, the number of clusters is determined via a distribution-optimization scheme. Results obtained through Matlab programming demonstrate the effectiveness of the proposed algorithm, particularly in dense networks, where it increases the number of clusters while maintaining clustering balance. The method reduces energy consumption, thereby enhancing network lifetime. Inspired by gravitational force between sensor nodes' mass units, the local gravity clustering method effectively clusters nodes based on high-density feature vectors, facilitating balanced energy consumption within clusters and extending network lifespan while reducing overall energy consumption.

The author [25] introduces a novel clustering technique for WSN called Hybridization of Pigeon Inspired with Glowworm Swarm Optimization (HPIGSO) algorithm. This technique integrates features from Pigeon Inspired Optimization (PIO) and Glowworm Swarm Optimization (GSO) algorithms. The HPIGSO algorithm operates in three main stages: initialization, CH selection, and cluster construction. Initially, nodes are deployed, followed by the execution of the HPIGSO algorithm by the base station (BS) for efficient CH selection. Subsequently, nearby nodes join the CH and become cluster members (CMs), facilitating cluster construction. Data from CMs is then sent to CHs and forwarded to the BS via inter-cluster communication.

The proposed HPIGSO algorithm incorporates an objective function based on residual energy, distance, and energy. This method optimally selects CHs to maximize network lifetime. Extensive experimental validation demonstrates that the HPIGSO algorithm significantly prolongs the WSN lifetime compared to existing clustering techniques. Specifically, the HPIGSO model delays the first node death (HND) to 1421 rounds with an overall network lifetime of 2345 rounds.

The author [26] introduces the Quantum Tunicate Swarm Algorithm Based Energy Aware Clustering (QTSA-EAC) scheme for WSN. The focus is on effectively managing energy distribution among nodes in the network. QTSA-EAC incorporates quantum computing principles into the traditional TSA and employs a fitness function aimed at minimizing total energy consumption. By integrating multiple parameters into the CH selection process, the scheme achieves energy efficiency and extends the WSN's lifetime. Performance evaluation indicates that QTSA-EAC outperforms other methods, enhancing lifetime, reducing energy consumption, and minimizing delays. The proposed scheme offers an effective energy management solution for WSNs, with potential future enhancements including the incorporation of multi-hop routing to further extend network lifetime.

The author [27] introduces a hybrid approach combining the Sparrow Search Algorithm (SSA) with Differential Evolution (DE) to address energy efficiency concerns in WSNs. By leveraging SSA's efficient search capabilities and DE's ability to enhance node lifetime, the proposed algorithm aims to improve cluster head selection. Performance evaluation considers metrics such as alive and dead node counts, throughput, and residual energy. The Improved Sparrow Search Algorithm with Differential Evolution (ISSADE) is proposed to enhance exploitation capabilities and prevent local optima traps. ISSADE simplifies the process by utilizing existing SSA and DE operators without introducing additional complexity. The algorithm efficiently selects cluster heads based on estimated residual energy, promoting non-uniform distribution and high stability. Experimental results demonstrate ISSADE's superior performance in global optimization compared to other methods. While DE is effective for exploration and exploitation, it can be time-consuming for large-scale data due to mutation, crossover, and selection processes. Adjusting parameters dynamically may enhance robustness for larger problems, thereby improving network performance.

The author [28] introduces a distributed multi-level clustering scheme for WSNs employing Sugeno-based Fuzzy Logic Controller (FLC). The scheme organizes the network into multi-level clusters, with cluster heads (CHs) collecting and forwarding data to sinks through multi-hop routing. An enhanced Sparrow Search Algorithm (SSA) is proposed to optimize the clustering FLC, aiming to minimize the rule-base and enhance its effectiveness. Extensive simulations in OMNET++ evaluate the scheme across various metrics including First Node Dead (FND), Half Nodes Dead (HND), Last Node Dead (LND), average node energy, data packet loss, and retransmission ratio. Results indicate superiority over existing clustering and multi-hop routing methods. The paper underscores the significance of addressing energy consumption in power-limited sensor nodes, highlighting clustering as an effective strategy. It also discusses the use of mobile sink nodes for energy reduction and improved reliability. However, optimizing clusters and establishing efficient routing between CHs and sink nodes remain challenging tasks in WSN literature.

The author [29] introduces a novel clustering-based dragonfly optimization (CDFO) algorithm designed for decentralized forwarding in wireless networks, particularly focusing on Underwater Wireless Sensor Networks (UWSNs). CDFO-UWSN determines the optimal number of clusters for routing, outperforming analogous algorithms such as Ant Colony Optimizer (ACO), Adaptive Node Clustering for UWSN (ANC-UWSN), Grey Wolf Optimizer (GWO), and Moth Flame Optimizer (MFO). Through simulations accounting for various parameters like grid size, transmission range, and node density, CDFO-UWSN demonstrates superior performance, enhancing overall routing and extending network lifetime by establishing more efficient clusters. Specifically, CDFO-UWSN surpasses GWO, ACO, MFO, and DFO algorithms in terms of the number of nodes and transmission range, with substantial percentage improvements for a 1500*1500 m grid size. The protocol utilizes a dragonfly optimizer for adaptive clustering, employing an evolutionary-based approach for packet routing to iteratively explore and optimize node clustering. Simulation results affirm CDFO-UWSNs as an efficient routing solution, particularly when compared to other evolutionary algorithms, indicating significant performance advantages in terms of network scalability and transmission range optimization.

The author [30]proposes a novel energy-efficient clustering scheme named PSO-EECS, integrating Particle Swarm Optimization (PSO) for WSNs. The focus is on selecting CH to handle data aggregation and forwarding in a cluster-based routing paradigm. PSO-EECS optimizes fitness parameters for CH selection, considering factors like energy ratio, distance, node density, load balancing, and average network energy. Simulation results demonstrate significant improvements in network stability and operation time compared to existing approaches such as PSOGSA, GAPSO-H, and ABE-DE protocols, with stability enhancements of 95.4%, 34.8%, and 29.2% respectively. PSO-EECS enhances network lifetime through stages of cluster formation and data collection, employing an innovative waiting time strategy for CH selection based on various parameters. It addresses the challenge of limited battery life in sensor nodes and proposes the inclusion of sensor nodes in cluster networks to mitigate hotspot issues and improve load distribution.

The author [31]introduces a routing algorithm that leverages a Reposition Particle Swarm Optimization (RPSO) algorithm along with a novel fitness function. RPSO serves to rescue particles trapped in local minima, enhancing convergence speed and global optimum identification compared to standard Particle Swarm Optimization (PSO) and PSO with Levy Flight. The routing algorithm, utilizing RPSO, is evaluated against various performance metrics including network lifetime, dead sensor nodes, energy consumption, and packet delivery to base station, against four competitive Meta-Heuristic algorithms. Results indicate the superiority of the routing algorithm across all metrics, with notable improvements in network lifetime, dead sensor nodes, energy consumption, and throughput. Additionally, two algorithms, RPSO and RA-RPSO, are introduced to address local minima and premature convergence issues while enhancing WSN lifetime and throughput. RPSO modifies particle update equations and employs a Repositioning Module (RM) to overcome local minima, while RA-RPSO selects optimal Cluster Heads (CHs) to extend network lifetime and throughput.

The author [32] study introduces an energy-aware farmland fertility optimization-based clustering scheme (EAFFO–CS) for WSN. The EAFFO–CS aims to determine optimal Cluster Heads (CHs) and improve overall network efficiency by leveraging concepts from farmland fertility. It utilizes a fitness function incorporating input variables such as distance to neighbours, distance to the BS, and energy levels to select CHs with maximum fitness. Nodes closer to CHs are then grouped to form clusters. Through extensive simulations, the EAFFO–CS is demonstrated to outperform other systems, achieving a maximum residual energy of 11% with 1000 sensor nodes, surpassing systems like HABC-MBOA, FFCGWO, FFOCR, and HASPSO which resulted in lower residual energy levels. The novel EAFFO–CS technique enhances WSN energy efficiency and lifespan, validated through comprehensive simulation analyses.

The author [33] presents a PSO algorithm integrated with an Energy Efficient Clustering and Sink Mobility (PSO-ECSM) approach to tackle cluster head selection and sink mobility issues in WSN. Through extensive computer simulations, the PSO-ECSM algorithm optimizes five factors including residual energy, distance, node degree, average energy, and Energy Consumption Rate (ECR) for CH selection. Additionally, it introduces sink mobility to address data traffic relaying in multi-hop networks. Performance evaluation against state-of-the-art algorithms is conducted using five metrics: stability period, network longevity, number of dead nodes, throughput, and remaining energy. Statistical tests validate the significance of performance improvements. Results indicate that PSO-ECSM enhances stability period, half node dead, network lifetime, and throughput compared to existing methods, achieving improvements of 24.8%, 31.7%, 9.8%, and 12.2% respectively. The proposed PSO-ECSM method effectively addresses sustainability challenges in WSNs and outperforms existing schemes, demonstrating its efficacy in addressing real-time network stability, lifetime, and throughput issues. The integration of multi-objective PSO and sink mobility factors ensures optimized performance in optimizing multi-hop hot-spot problems. Experimental results underscore the superior performance of PSO-ECSM compared to existing schemes.

The author [34] introduces a Deep Learning-based Grouping Model Approach (DL-GMA) to optimize energy utilization in WSNs. DL-GMA utilizes advanced deep learning techniques, specifically Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM), to enhance energy efficiency by facilitating effective cluster formation, Cluster Head (CH) selection, and CH maintenance. Evaluation based on key metrics—Energy Efficiency (88.7%), Network Stability (90.8%), Network Scalability (87.1%), Congestion Level (18.3%), and Quality of Service (QoS) (93.4%)—demonstrates DL-GMA's effectiveness in optimizing energy utilization and overall network performance. By incorporating deep learning and intelligent grouping, DL-GMA extends WSN lifespan and improves data transmission efficiency. It represents a significant advancement in addressing the challenges of limited energy resources in WSNs, maximizing network potential, and enhancing data transmission efficiency. The proposed DL-GMA offers promising methodologies for enhancing energy efficiency in WSNs through advanced grouping and clustering techniques, resulting in optimized energy consumption, improved network stability and scalability, mitigated congestion, and enhanced quality of service. While the evaluation highlights significant accomplishments, future work could explore constraints related to heterogeneous networks, mobile nodes, communication overhead, and scalability. Additionally, integrating DL-GMA with emerging technologies such as edge computing and IoT frameworks, along with addressing challenges associated with cluster head selection and individual sensor node energy efficiency, would further enhance its practical implementation.

The author [35] introduces the Golden Eagle Optimization Algorithm (GEOA) and an improved Grasshopper Optimization Algorithm (IGHOA) within an energy-efficient cluster-based routing protocol (GEIGOA) to enhance energy stability and prolong network lifetime in WSNs. GEOA optimizes node centrality, degree, distance to the base station, neighbor distance, and residual energy to select an optimal CH. IGHOA is then employed to establish an efficient route between CH and BS considering node degree, residual energy, and distance. GEIGOA demonstrates significant improvements in preventing the selection of suboptimal CHs compared to other schemes, with enhancements ranging from 12.64% to 20.98%. Additionally, it minimizes computational costs by 14.98% to 21.62%. The proposed hybrid routing protocol effectively addresses CH selection challenges, optimizing network energy and lifetime. Extensive simulations validate GEIGOA's superior performance in energy consumption, data packets transmission, node longevity, and network robustness compared to alternative CH selection methods.

The author [36] paper proposes a novel approach, the Ant Colony Optimization integrated Glowworm Swarm Optimization (ACI-GSO), to optimize the selection of CHs in wireless sensor networks (WSNs) for energy-efficient routing. The CH selection process aims to minimize distance among selected CH nodes, utilizing a fitness function based on multiple objectives including distance, delay, and energy. The performance of ACI-GSO is evaluated and compared to conventional methods, demonstrating its efficiency. Specifically, for a network with 50 nodes, ACI-GSO outperforms GSO, ACO, and PSO algorithms by 11.11%, 7.14%, and 15.38% respectively in terms of alive nodes at the 40th round. Moreover, at the 60th round, ACI-GSO surpasses GSO, ACO, and PSO algorithms by 21.05%, 35.29%, and 76.92% respectively. Additionally, in terms of network energy, ACI-GSO performs 4.37%, 2.26%, and 2.42% better than GSO, ACO, and PSO algorithms respectively at the 20th round. This highlights the effectiveness of ACI-GSO in optimizing CH selection for energy-efficient WSN routing.

The [37]author introduces an enhanced PSO algorithm called Culled Fuzzy Adaptive Particle Swarm Optimization (CFAPSO), specifically tailored for Cognitive Beamforming (CBF) applications. This algorithm incorporates a novel fuzzy logic-based scheme to adapt confidence and inertia weight parameters, thereby improving exploration and exploitation capabilities. By utilizing normalized particle quality and iteration count as inputs to a fuzzy logic inference system, computational complexity is minimized through a lookup table implementation. Additionally, a particle culling/re-initialization procedure is employed to enhance swarm diversity. Statistical analysis shows that CFAPSO outperforms other metaheuristic algorithms when applied to standard unimodal and multimodal functions. Specifically in CBF scenarios with a planar random arrangement of sensor nodes and an elevated sink, CFAPSO demonstrates superior performance compared to adaptive PSO variants, basic PSO, MPA, CMA-ES, and GA algorithms. Moreover, CFAPSO produces beamsteering outcomes comparable to conventional methods, making it suitable for beamsteering and beam-pattern optimization tasks in CBF applications.

The author [38] investigates the impact of reducing CH load on enhancing the energy efficiency of clustering algorithms within WSNs. It proposes a model that optimally distributes the CH load among cluster member nodes using Wireless Power Transfer (WPT) strategy. Each node transfers a specific amount of energy to the CH node, thereby sharing the load and extending the WSN lifetime. Simulation results demonstrate significant lifetime improvements compared to conventional clustering algorithms like Leach and K-means. By practically proving the effectiveness of CH-load reduction, the paper highlights its importance in enhancing WSN energy efficiency. The proposed model integrates WPT technology with multi-objective optimization techniques, such as quantum behaved particle swarm optimization and game theory, to determine optimal load distributions tailored to each node's status, thus mitigating the centralized overhead on CH nodes. This approach divides the CH load into smaller, node-specific portions, optimizing energy consumption and prolonging WSN lifespan.

The author [39] introduces a novel energy-efficient clustering methodology for WSNs utilizing a local gravitational optimization algorithm. Inspired by the physical concept of gravitational force among mass units, this method adaptively determines the number of clusters based on the density of feature vectors. The algorithm distributes gravitational force among neighboring nodes through a distribution-optimization scheme to form cooperative and distributed clusters. Simulation results, conducted using MATLAB programming, demonstrate the efficacy of the proposed approach, especially in dense networks. It increases the number of clusters while maintaining clustering balance, ultimately reducing energy consumption and enhancing lifetime of the network. By leveraging the local gravitational method, sensor nodes are clustered based on the highest gravitational force, ensuring efficient data gathering and balanced energy consumption within each cluster, thereby extending the network's lifespan.

The author [40] introduces a novel hybrid approach, GAPSO-H (Genetic Algorithm and Particle Swarm Optimization based Hybrid), to optimize CH selection and sink mobility for improved performance in WSNs. The robust behavior of GA optimizes CH selection by considering factors like remaining energy, node level, and energy consumption rate. Meanwhile, Particle Swarm Optimization (PSO) optimizes sink mobility based on factors such as proximity to CHs and cluster length. Extensive simulations demonstrate that GAPSO-H outperforms contemporary algorithms in terms of various performance metrics. By effectively combining GA and PSO, GAPSO-H achieves enhanced network performance in terms of energy efficiency, data transmission reliability, and overall network lifetime. The proposed approach offers a robust solution to the CH selection and sink mobility optimization challenges in WSNs, demonstrating superiority over existing methods such as DCH-GA, GABEEC, PSOBS, GADA-LEACH, PSO-UFC, and PSOECSM.

The author [41] introduces the Golden Eagle Optimization Algorithm (GEOA) and Improved Grasshopper Optimization Algorithm (IGHOA) within the context of an energy-efficient cluster-based routing protocol (GEIGOA) to enhance energy stability and prolong network lifetime in WSNs. GEOA optimizes CH selection by considering factors like node centrality, node degree, distance to base station, distance to neighbors, and residual node energy. Additionally, IGHOA is utilized to determine an optimal route between CH and base station by assessing node degree, residual energy, and distance parameters. GEIGOA improves CH selection, preventing the selection of suboptimal CHs and reducing computational costs compared to competitive schemes. Simulation results demonstrate the efficacy of GEIGOA in sustaining network stability, extending network lifetime, and enhancing energy efficiency, outperforming benchmarked protocols in terms of various performance metrics such as energy consumption, data packets received, and node longevity. This optimized hybrid routing protocol offers a promising solution for improving CH selection strategies and overall network efficiency in WSNs.

The author [42] introduces a novel clustering model called Duty Cycle-based Clustering Model (DCCM) aimed at reducing energy consumption in WSNs. DCCM employs a duty cycle method where nodes alternate between active and inactive states to conserve energy. This model incorporates a Coverage Relationship Matrix (CRM) and Cover Sets (CSs) to optimize node utilization. Additionally, an Improved Adaptive Clone Jellyfish Search (DCC-IACJS) algorithm is proposed to optimize DCCM further. DCC-IACJS introduces an adaptive parameter strategy and a new clone scheme to enhance clustering efficiency. Simulation experiments compare DCC-IACJS with other state-of-the-art clustering schemes, including GA-CSO-LBCM, FGF, and O-LEACH. Results demonstrate that DCC-IACJS prolongs network lifetime by 10.24%, 7.04%, and 8.54% compared to O-LEACH, FGF, and GA-CSO-LBCM, respectively. The proposed DCCM and DCC-IACJS offer improved energy efficiency and node utilization in WSNs, showcasing their superiority over existing approaches.

Table 1. Comparison summary of the related works

Proposed Methodology	Objective	Advantages	Challenges	Future Directions
EOR-iABC [16]	Enhance energy efficiency and extend lifetime of the cluster	Eliminates delay convergence and improves local search strategies	Remaining energy utilization	Optimize CH selection with a mobile sink.
MOCRAW [17]	Cluster head selection-based Routing algorithm	Facilitating optimal path selection	Only inter-cluster formation	Multihop cluster formation.
2-level GA [18]	Selection of CHs and optimizing multi-hop routing	Reducing energy consumption enhances prolonging network lifetime	Separate consideration of CH selection and routing	To improve the genetic algorithm.
Routing Protocol Based GA [19]	Middle layer-oriented network structure	Costs and transmission energy consumption reduces the number of stations	Incorporates two key phases	High network node density.
Fish Migration Optimization Algorithm [20]	Enhances the global search capability of optimization algorithms	Proves effective in solving the CH selection problem	Convergence, distribution, and scalability	Add some strategies to existing algorithm to improve the convergence speed of the algorithm.
ESO-LEACH [21]	Meta-heuristic PSO enhancement is utilized for initially clus-tering the sensor nodes	Extending network lifespan	Reducing random dependence and introducing advanced nodes in the network	To be position the rely node in the cluster.
FGF-GSO [22]	New cluster head selection method enhance the energy consumption	Acquire maximum network lifetime, minimum energy con-sumption	Number of iterations is limited.	To increase the maximum rounds for getting better results.
ML-AEFA [23]	Enhancing routing efficiency and maximizing network lifetime	Optimize routing decisions and enhance network longevity	The selection of CH and data transmission utilized two algorithms	Combined with single algorithm.
Local Gravitational Algorithm [24]	Energy efficient clustering methodology proposed based on local gravity optimization algorithm	The nodes in the each cluster formed in the network consume energy in a balanced technique	Cooperative and distributed clustering	An effective CH selection method within the clusters with more selection criteria.
HPIGSO [25]	Objective function based optimization	Maximize network lifetime and prolongs the WSN lifetime network	Minimum parameter	More Number of parameters .
QTSA-EAC [26]	Energy Aware Clustering	effectively managing energy distribution	Consideration of Energy	Incorporation of multi-hop routing.

	minimizing total	among nodes energy consumption		
ISSADE [27]	Hybrid approach	Efficient search capabilities enhance node lifetime	Promoting non-uniform distribution	Dynamic parameters.
Optimized fuzzy clustering [28]	Distributed multi-level clustering	Superiority over existing clustering and multi-hop routing methods	Efficient routing between CHs and sink nodes	Mobile sink nodes.
CDFO-UWSN [29]	Decentralized forwarding UWSNs	Enhancing routing and extending network lifetime	Considered in UWSNs	network scalability and transmission range.
PSO-EECS [30]	energy-efficient clustering scheme	Enhances network lifetime	Mitigate hotspot issues	To integrate PSO and other optimal solution.
RPSO and RA-RPSO [31]	Novel fitness function	Enhancing lifetime and local throughput	Local optimization Meta-Heuristic algorithms	Heuristic algorithms.
EAFFO–CS [32]	Optimal Cluster Heads selection	Minimizing residual energy	Fitness function incorporating input variables	WSN lifespan.
PSO-ECSM [33]	CH selection and sink mobility	Data traffic relaying in multi-hop networks	Five network parameters	Statistical test validation.
DL-GMA [34]	Deep-Learning based Grouping Model Approach	Energy Efficiency, Network Stability and Congestion Level	Deep Learning in WSN	Constraints relation and heterogeneous networks.
GEOA [35]	Energy-efficient cluster-based routing protocol	Stability and prolong network lifetime	Base station considering node degree	Enchantment IGHOA with more metrics.
ACI-GSO [36]	Optimalization selection of cluster heads	Minimize distance among selected CH nodes	Compared to conventional methods	High density WSN.
CFAPSO [37]	Novel fuzzy logic-based scheme	Superior performance compared to adaptive PSO	Specifically tailored for Cognitive Beamforming (CBF) applications	Non-metaheuristic algorithms.
CH using WPT [38]	Reducing Cluster Head (CH) load	Sharing the load and extending the WSN lifetime	Centralized overhead in CH	Mitigating the load to all the nodes.

Local gravitation [39]	Distribution-optimization scheme to form cooperative and distributed clusters	Cluster balancing	Local gravitational method	Real time applications.
GAPSO-H [40]	Hybrid approach for CH selection and sink mobility	Enhanced network performance with transmission reliability	Proximity to CHs and cluster length	PSO with other GA.
GEIGOA [41]	Optimal Cluster Head (CH) selection and route between CH and base	Improves CH selection, reducing computational costs	Preventing the selection of suboptimal CHs	More Hybrid approach.
DCCM [42]	Duty Cycle-based Model for energy consumption	Optimized node utilization, prolongs network lifetime.	Not consdiered the QoS parameters	Enchanted Cloning approach.

5. Conclusion

In recently, clustering technique in WSNs has garnered increased high attention due to its ability to optimize energy consumption and extend lifetime of the network. The pioneering LEACH protocol paved the way for various clustering techniques. CH selection is critical as its collection, aggregation, and transmition of data efficiently to the BS, impacting network efficiency and performance significantly. Proper cluster formation is also vital for enhancing energy efficiency and network lifespan. The conclusion of this review highlights the significance of clustering in WSNs for minimizing energy consumption and enhancement of network lifetime. The survey covers clustering techniques published between 2020 and 2023, categorizing methods into non-metaheuristic and metaheuristic algorithms across various environmental settings. Detailed descriptions of CH selection and cluster formation methods, along with their advantages, limitations, and future suggestions, are provided. The discussion emphasizes the importance of proper method of CH selection and cluster formation in addressing challenges such as network load balancing, stability, reliability, and scalability. Readers gain insights into differentiating methods, understanding their performance in diverse environmental settings, and identifying future research directions to enhance energy efficiency in WSN applications.

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