International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys.14, No.1 (Jul-23)

http://dx.doi.org/10.12785/ijcds/140126

A Systematic Study of Clustering Techniques for Energy Efficiency in Wireless Sensor Networks

Mohammed Saleh Mutar*[1], Dalal Abdulmohsin Hammood[1] and Seham Ahmed hashem[2]

[1]*Department of Computer Technical Engineering, Technical College of Electrical Engineering, Middle Technical University, Al Doura 10022, Baghdad, Iraq*
[2]*Technical Instructors Training Institute, Middle Technical University, Baghdad, Iraq*

Received 16 Dec. 2022, Revised 30 Apr. 2023, Accepted 2 May. 2023, Published 1 Jul. 2023

Abstract: Recent advances in wireless sensor networks (WSNs) may be attributed to their increased accuracy and speed while gathering data, wireless communication, and data computation. Small, low-power sensor nodes present in these networks organize and set themselves up to do the activities that they are designed for. WSNs benefits are economical, simple to set up, adaptable, and efficient. However, there are some issues with longevity of networks and low energy consumption. By grouping nodes into a small number of clusters and choosing a cluster head (CH) to oversee data aggregation and transmission to the base station (BS), clustering has shown to be the most effective method for dealing with the difficulties of WSNs. Nevertheless, the insufficient CH selection and cluster construction methods, there are still a lot of challenges, including energy hole and isolated node difficulties. To learn more about this topic of how certain authors approach the aforementioned issues, we conducted an in-depth study of several meta-heuristic and non-heuristic approaches used in networks in a wide range of environments to choose CH and cluster creation, which are discussed in this paper.

Keywords: WSNs, Energy Consumption, Energy-Efficiency, Clustering Techniques, IoT

1. Introduction and Overview

Powerful, inexpensive multifunction sensors that can sense the environment, analyze data, and link with one another have been made possible by recent developments in communications, mechanical, and electrical systems. The efficiency of data collection and communication by sensors is constrained by their compute, memory, networking, battery, and sensing range capabilities. Therefore, a single sensor could only be able to acquire a very tiny area. They are all connected by the wireless network known as the wireless sensor network (WSN) [1], [2]. The prevalence of WSNs is rising quickly, and new applications are always being formed. Due to the wide range of functions that WSNs may perform, including military surveillance, data collection, industrial monitoring, disaster management, emergency relief, health monitoring, habitat monitoring, and environmental monitoring, they are now widely employed.

WSNs are often widely dispersed in an attempt to cover more land or interesting geographic region. The main goals of WSNs are to monitor and collect environmental and physical data for a specific region, such as traffic flow, pollution, humidity, light, temperature, and motion. After then, the information is sent to a manufacturing plant (sink or base-station), where it performs additional processing to provide the data needed for various applications [3], [4]. It's feasible that additional nodes will record and transmit the same data because of how widely and densely sensor nodes have been deployed in WSN. In order to handle the hundreds of sensors, the WSN must be scalable. In order to facilitate scalability and lessen the load on the sensor nodes' energy resources, a clustering method is utilized. In the next part of the study, we will provide a comprehensive explanation of clustering.

Here are the papers' subsequent chapters: The context of the work that is related is presented in Section 2. In Section 3, we go through the many different clustering strategies which can be applied to WSNs. The classification of clustering protocols is then presented in Section 4. However, in Chapter 5, we present a technique that doesn't rely on metaheuristics. The Metaheuristic Procedure is described in Section 6. Section 7 provides the last instructions for wrapping things up.

E-mail address: bbc0073@mtu.edu.iq, dalal.hammood@mtu.edu.iq, dr.seham.ahmed@mtu.edu.iq

2. Related Works

In [5] proposed two approaches to reducing the distance of data transmission. First, a clustering strategy dependent on the FCM algorithm decreases the distance of intra-cluster. Second, CR chooses the adjacent uncrowded sink based on FLIS. The authors in 2016, proposed the Vertex Cover Algorithm (VCA) to find the CHs. To improve the CHs even more, a heuristics algorithm was created. We use Prim's approach to determine the least spanning tree after we have located the cluster heads. Finally, we use the Depth First Search method to determine the traversal order for these CHs that the mobile sink should follow [6]. The study in [7], suggested a novel firefly optimization method based on hierarchical clustering. This method is employed in wireless sensor networks (WSNs) to create cluster structures that minimize transmission distance and maximize energy usage. To improve rule-based fuzzy clustering methods more energy efficient, they suggest a modified clonal election technique (CLONALG-M). The fundamental concepts of an adaptive immune system are explained using the clonal selection principle. We use this idea to identify how output-based membership functions should be roughly distributed in an effort to boost the efficiency of fuzzier algorithms [8].

The particle swarm optimization (PSO) method is discussed in this study. Uses a clustering algorithm with various settings to decrease energy usage amongst various MCHs. When MCH abruptly failed If it's essential to shorten the routing distance, in this case, the packets will be routed via intermediaries instead of the selected CH using the multidirectional routing approach [9]. The (FL-IZBCA) Algorithm proposed by the authors [10] since human interaction or reachability is often not allowed in WSNs, BSs are typically positioned a distance from the target network region. So, if the WSN is to function for a long time, it is essential that its energy efficiency be increased. The proposed algorithm has successfully balanced the network's load by decreasing the overall rate of energy consumption and increasing the network's lifetime in comparison to existing approaches. In 2021, a new hybrid algorithm named "CI-ROA" is proposed. An Algorithm The specified non-linear objective function achieves lifespan extension through the choice of the best CH [11].To improve the lustering FLC, this study provides a better (SSA) approach. The multi-sink heterogeneous WSNs are grouped into various multi-level clusters using a distributed and optimized fuzzy clustering technique in order to improve the FLC integrated for fuzzy clustering and protect the fuzzy rules and membership function functions of the fuzzy sets benefited in this FLC. For WSNs, a number of fuzzy clustering strategies are suggested [12]. For instance, in [13] Lata A suggestion has been made for LEACHFC, the LEACH protocol-based fuzzy clustering method that aims to maximize WSN lifetime. The CHs and vice CHs are chosen using a centralized methodology under this method. Regarding to energy usage and WSN longevity, it can beat other clustering techniques. In addition, it can ensure that all nodes in a WSN are using the same amount of energy. Aniji and Vinoth propose a dynamic CH selection method (DCHSM). This technique enhances energy efficiency on a wide scale, making it suitable for Internet of Things applications. CH elections are conducted twice. First-class CH candidates are chosen based on perceived likelihood, while second-class candidates are chosen based on estimated survival times [13].

In this paper, they provide a cutting-edge method for managing data exchange without sacrificing the integrity of data. The approach they advocated, known as EK-, is a two-solution. It then eliminates similar data generated at the sensor level using a Euclidean distance-dependent data aggregation approach. Moreover, it uses an enhanced K-clustering technique to merge identical neighbouring node-data sets for clusters, meaning that the sink will get less information from its neighbours [14]. In this study, clustering scalability techniques are planned to increase the applicability of IoT applications. An extensive explanation of the use of mathematical techniques and their impact on WSN may be found in the examination of radical algorithms. This study looked at scalable clustering procedures. The single hop solution and multiple hop clustering are used to group the protocols. Multiple hops are ideal for both homogeneous and heterogeneous networking, whereas single hop clustering is energy-efficient for homogeneous networking [15]. WSN is utilized for many applications, but energy consumption is a constant problem. So as to improve the lifetime of the network and energy efficiency enhancement. Proposed (MWCSGA) algorithm [16].

The authors of [17] offered a strategy for selecting CH using a modified threshold equation with fuzzy logic, taking into account distance to BS, energy remaining and node centrality. The suggested protocol utilizes rounds, much as the LEACH protocol does. There is a beginning and an end to each cycle. Selecting and forming CHs in the setup step results in each CH providing its members with a unique TDMA schedule cluster. To boost the energy efficiency of WSNs, the Chicken Swarm Optimization Based Clustering Algorithm (CSOCA) is presented. Using GA, this method modifies the CSO algorithm to maximize energy use in WSNs while utilizing crossover and mutation processes to promote population diversity. Specifically, the fitness function is built to reduce the sum of energy used and amount of times a subset of nodes has executed the CH [18]. Take use of the spatial correlations between sensor nodes with EDC in energy-harvesting WSNs for more efficient communication. Where should the data from which nodes be sent to the BS? This is determined by using a distortion theory framework constructed for both one- and two-hop commutation models. According to the data, a model with two hops of communication is more robust than one with just one. More distortion is seen in the two-hop model than in the one-hop model because there are two connections (two channels between the CMs and BS). It is also shown that the network's longevity rises in proportion to the source's (cell tower's) strength, thanks to the EDC algorithm's skillful use of energy harvesting [19].

The authors in 2020, proposed the (SBCH) Simple Balanced CH election Method. In the SBCH selection process, four factors were taken into account. It consists of leftover energy, neighbor sensor nodes, and information from one neighbor sensor hop, in addition to the distance between BS and CHs. Additionally, each round's energetically adjusted distance value is altered by a new factor, which aids in lowering energy usage and extending the duration of the WSN [20]. In this study, we suggested a clustering strategy that satisfies both energy and time limitations while managing critical and delay-sensitive workloads alongside other best-effort applications. In order to serve use in mission-critical and time-sensitive applications without sacrificing substantial energy savings, they developed a new CH selection algorithm that takes into account the distance between sensors and sink as well as any remaining energy in the sensors. Compared to the current strategy [21]. In this research, a clustered routing protocol named CRCGA, which combines these three aspects, is presented to increase network load balancing and energy efficiency. To efficiently code the optimal CHs and routing paths into a single chromosome, CRCGA makes use of the chaotic genetic algorithm. The method quickly converges due to the use of chaotic genetic operators depending on a novel fitness function that considers load balancing, the lowest energy consumption, and new determination criteria. For the clusters to be sustained, an adaptive round time that takes energy and load balance into consideration is provided as an additional means of lowering the clusters' overall energy footprint [22].

Hierarchical routing is a method used in WSN in an attempt to lower energy use. Using the LEACH and Q-LEACH protocols as inspiration, the suggested technique develops a novel threshold formula for selecting CH dependent on the energy remaining and distance needs of the node. More importantly, the CHs couns in each region was determined by the active nodes count in each round, leading to an unpredictable CH count. Network zoning and cluster development within the region improved coverage throughout the network's many locations. In addition, the BS selects the CHs and notifies the nodes, reducing the workload on the nodes and the sensor's power needs [23]. This research presents a static clustering method that employs predator-prey optimization (PPO) to locate the cluster leaders and the best paths for sending data to the sink. The PPO algorithm selects the optimal pair of cluster leaders for each cluster and figures out the most efficient communication path between them, which may include many relay nodes. The optimization technique seeks to minimize data collecting and transmission costs while maintaining a constant energy budget for all wireless sensor nodes [24]m. We employed energy data, neighbor CH, neighbor info, neighbor status, and base station distance in this work. When BS distance and one-hop neighbor information are taken into account, back transmission is typically reduced, saving a large amount of energy. To dynamically modify distance, we have employed a distance factor. It decreased energy use and significantly extended the network's life. To power the whole network, we utilized a total of 35 nJ. We compared our study with recently established methods using clustering and data transfer similar to LEACH and found a considerable improvement [25].

One of the key criteria for every wireless sensor network application is lifetime improvement. The sensor nodes' dispersed placement makes them difficult for a power supply to reach, which reduces their lifespan. As a means of increasing WSNs' durability, the suggested work uses the neural network method and is built with the intention of forming clusters. The study uses a simulated network model to provide a dataset for training a CNN to choose the ideal node to serve as a CH. The effectiveness of suggested model's is tested using the conventional LEACH and FPSO algorithms, and the outcomes of the CNN model in terms of final node death time are determined to be satisfactory [26]. The sustainability and stability of WSN are improved in this study work by the clustering process based on fuzzy approaches. To account for the uncertainties included in wsns, fuzzy approaches are used. Clusters are created with the utilize of the Fuzzy-c-means method. Grouping the nodes in the right way will reduce the amount of time spent waiting for messages sent inside the cluster. Following that, the Fuzzy Logic System is implemented to pick the CHs [27].

One unique approach, the diversity-driven multi-parent evolutionary algorithm with adaptive non-uniform mutation, presented for CH election in heterogeneous WSNs. To reduce the total fitness function, two goal functions—residual energy and distance traveled—must be maximized concurrently. The membership function for both optimal solutions, namely residual energy and distance traveled, is evaluated using fuzzy set theory. To calculate how far away the sensor nodes are from the BS and what percentage of power they have left, fuzzy theory is used to group them into clusters. When choosing a cluster leader, it's recommended to utilize the membership function's best value if you want to get a high cardinal ranking. The suggested method has proven advantageous since, when compared to other optimization-based approaches, it demonstrates an enhancement in the network lifetime, alive nodes, and stability period [28]. In this study, we investigated the conventional hierarchical routing method and presented an improved approach based on K-means++ to address its shortcomings. The suggested solution employed the K-means++ algorithm to cluster data and enhanced network capabilities by selecting CHs more efficiently and using the shortest channel possible for data transfer between CHs. According to the simulation findings, the suggested approach has a clear advantage over the LEACH and KUCR algorithms for clustering results and prolonging network life cycles [29]. In this study, a CH election strategy presented for energy-efficient PSNs that includes power control. We use fuzzy C-means, a well-known clustering method, to divide the network into several groups. After that, a procedure for choosing a suitable CH for each cluster is established. In order to restrict the transmission power, a power control process is ultimately used. Because of this, the network consumes less power overall. Through a thorough analysis of system performance, we have shown that our proposed method outperforms both conventional methods that do not rely on clustering and clustering-based methods. The purpose of this work is to boost PSN's functionality even more [30]. This study proposes a density-based fuzzy C-means clustering algorithm for WSNs, which may be employed in smart grid NAN networks while using little energy. In this setup, the base station initiates data gathering at any time and place by broadcasting a BEACON message to the NAN network. Upon receiving the BEACON signal, a node that wishes to follow it instantly begins making plans for its own wake-sleep cycle. Leaders are chosen using network density because of the unique nature of NAN traffic in smart grids. The DFCM is preferred for clustering, and the desired function is defined by the membership values' weights and the extent to which they are communicated between the leader and the followers [31]. As illustrated in Table I.

3. Classification of Clustering Protocols

In this part, we'll go through the several ways that clustering methods might be classed according to the approach and structure of the networks they use. As shown in Fig. 1, the protocols are classified into four groups depending on the networks they are designed to interact with: homogeneous, heterogeneous, fuzzy, and heuristic.

A. Homogeneous Network-based Clustering Protocols

Methods utilized to complete this kind of clustering in a controlled, consistent setting are exclusive to this procedure. In this class of protocols, nodes share common resources, including processing speed, energy, hardware, bandwidth, etc. The homogeneous approach executes clustering-related tasks on the nodes uniformly across all nodes, treating them as identical [32].

B. Heterogeneous Network-based Clustering Protocols

In this type of cluster, the methods utilized to carry out the clustering operations take into account the diverse environment. In heterogeneous ecosystems, the various nodes are given access to some additional capability, including but not limited to computing power, hardware, memory, bandwidth, and energy, so on. The nodes may be divided into many types depending on their abilities (memory, battery power, etc.). Powerful nodes may help keep the network running for longer by using less of the total available network energy. Homogeneous and heterogeneous networks are shown in Fig. 2.

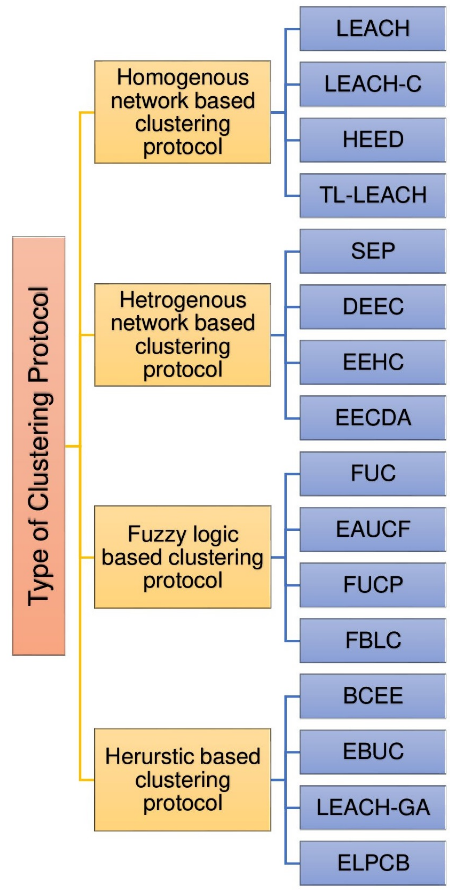

Figure 1. Types of clustering in WSN.

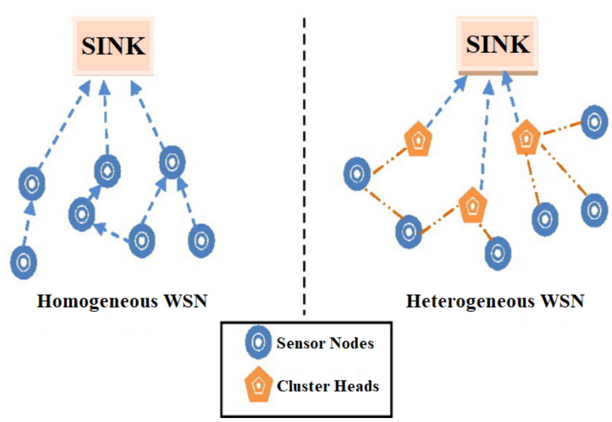

Figure 2. The homogeneous and heterogeneous network.

TABLE I. State of Art cluster head selection techniques.

REF/YEARS	ALGORITHM	OBJECTIVES	ADVANTAGES	SIMULATOR USED
[5] 2020	(FLIS, FCM). Fuzzy-c-means algorithm	enhancing the network lifetime, reduces the propagation delay and the deployment cost	Minimize the deployment cost and maximize the network lifetime.	-
[6] 2016	Vertex Cover Algorithm (VCA)	Resulted optimum number of CHs, throughput, network lifetime, and energy remaining.	Find the CHs, find minimum spanning tree	NS-2
[7] 2021	firefly optimization based Hierarchical Clustering Algorithm (FOHCA)	Enhancing the lifetime of the network.	Reduces the energy utilization, minimize the power consumption in WSN.	MATLAB
[8] 2021	(CLONALG-M), CLONALG algorithm	To prolong the lifespan	Improve the energy efficiency	-
[9] 2021	PSO method	Longevity enhancement in networks.	The capacity of the network to continue functioning in the event of a node failure is dependent on the energy consumption of the remaining MCHs.	MATLAB
[10] 2020	Fuzzy-Logic-Inspired Zone	Lengthening the life span of a network	Address the network's imbalanced energy dissipation issue among the CHs, enhanced for prolonged survival of the WSN.	MATLAB
[11] 2021	Cuckoo Insisted-Rider Optimization (CI-ROA) Algorithm	The lifetime prolonging through selecting the optimal CH	Like energy stabilization, minimization of delay during data transmission, minimization of distance among nodes, the limitations of increased routing overhead.	MATLAB
[12] 2021	Squirrel search algorithm(SSA)	Reduce the energy consumptions, enhance their lifespan	Boost their reliability by facilitating effective routing between source and destination nodes (CHs)	OMNET++
[33] 2020	LEACH-Fuzzy Clustering (LEACH-FC)	Lengthening the WSN's operational stability	Effective in reducing energy usage by equalizing loads across nodes and boosting dependability.	MATLAB
[13] 2017	Dynamic CH selection method (DCHSM)	boosts the longevity of the network.	Enhanced sensor node energy efficiency yields higher levels of spare power.	MATLAB 2016
[15] 2018	single hop and multiple hop clustering approach	Improve energy efficiency	To save energy, to reduce transmission distance, timely cluster construction and latency-free data routing in a large sensor network.	
[16] 2021	Using a genetic algorithm based on the behavior of a "multi-weight chicken swarm"	Reduce the energy consumption, maximize the network's productivity and extend its useful life.	Improved performance across the board regarding to energy consumption, packet loss, end-to-end latency, network throughput, and packet delivery ratio	NS-2
[17] 2021	Improved LEACH using a Fuzzy Logic Controller (E-FLEACH).	Improve network longevity, stability, and energy usage.	Determine the optimal number of CHs, decrease the energy used by each node and improves the network lifespan.	OMNET++
[18] 2020	Chicken Swarm Optimization (CSOCA) based Clustering Algorithm.	For a longer lifespan of the network.	The optimal collection of nodes to work as heads will be found, extending the network longevity and reducing energy usage.	MATLAB R2016b
[19] 2021	Event distortion-(EDC) based clustering algorithm.	To increase energy efficiency while preserving distortion at a manageable level.	Increases the power of the source.	MATLAB

TABLE I – *Continued on next page*

TABLE I – Continued from previous page

[34] 2020	Simple Balanced Cluster Head (SBCH) selection	To decrease back transmission difficulties and save a significant amount of sensor node energy.	Reducing the energy utilization and network life time increased, Reduce back transmission issues and sensor network sensing at every point in a reliable way, saving significant energy.	NS 3.23
[21] 2018	Priority Management with Clustering Approach (PMCA)	Better network lifespan, to manage different QoS applications.	Scaling up and power saving in WSNs, maintaining high energy saving.	MATLAB
[22] 2020	clustering routing with chaotic genetic algorithm (CRCGA)	Improve convergence speed, lifetime, energy efficiency, network throughput, and load balancing.	Minimal energy use, load balancing, and fresh resolve all contribute to lower energy usage.	MATLAB
[23] 2020	Quadrant Cluster (Q-LEACH) based LEACH protocols.	Enhancing network lifetime, both the first and final times a node died.	The energy usage is decreased, the coverage is improved, and the burden is decreased.	MATLAB
[24] 2021	predator prey optimization (PPO)	Reduce the energy consumed, to prolong lifetime.	Equalization in energy utilization, avoiding the expenses of cluster	
[25] 2019	Simple balanced CH selection	Increase network lifetime and minimize the energy consumption	Reduces back transmission, saves significant amount of energy	OMNET++
[26] 2022	Convolutional Neural Network (CNN) Algorithm	Increased lifespan of WSNs	Shows improved survival mode duration and energy usage, choosing a best node to act as CH.	NS2
[27] 2020	Fuzzy-c-means (FCM) algorithm	Energy conservation and network lifetime	Reduce intra-cluster communication distances, improve the stability, improve sustainability of WSN, increase in the coverage area, increase node density	MATLAB R2017b
[28] 2021	Diversity-Driven Multi-Parent Evolutionary (DDMPEA) Algorithm	Enhance the life of the network.	Improvement in the stability period, network lifetime and alive nodes.	MATLAB-2015b
[29] 2017	K-means++ algorithm	Prolonging life cycle of nodes, improving the life cycle of the network.	Improved CH election, improved capability of the network, improved mechanism of CH election, improved he shortest path between CHs	MATLAB
[30] 2018	CH election Scheme (CHESS-PC) with Power Control	Reduces the power consumption, improvement an efficiency.	Find an appropriate CH for each cluster, limit the transmission power, improve the performance of PSN	
[31] 2021	Density based Fuzzy C means clustering (DFCM)	Enhancing the network life span.	Improving the efficiency of the grid, low cost monitoring, operational power and memory	MATLAB

C. Fuzzy Logic Based Clustering Protocols

This group of protocols uses fuzzy approaches to do clustering. The clustering procedures use the fuzzy system to eliminate uncertainty in the clustering operations. In order to take in information and translate it into linguistic variables, the fuzzy system employs a fuzzifire [35]. The inference process in the fuzzy model applies the rules to generate the fuzzy output. By employing defuzzification techniques, the result can be made more precise. The fuzzy model employed by the clustering methods is depicted in Fig. 3.

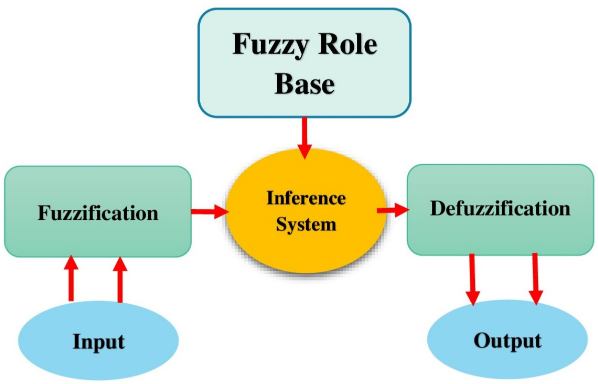

Figure 3. Fuzzy clustering model.

D. Heuristic Based Clustering Protocols

Heuristic techniques are used in this class of protocols to manage the clustering operations. The heuristic-based clustering algorithms combine several optimization techniques and carry them out repeatedly to arrive at an ideal outcome [36]. These methods don't always ensure the best outcomes, but they get you to the best answer faster. It keeps the processing time and the caliber of the solutions it produces in balance. The methods used in heuristic-based clustering draw their inspiration from how natural processes for optimization function in order to increase the efficacy of clustering protocols.

E. Non-Metaheuristic Method

In WSNs, clustering can be broken down into two broad classes: non-metaheuristic techniques and metaheuristic techniques. Cluster creation and CH election are carried out via these techniques. Here, we'll go through the many methods used to choose CHs and build clusters under different conditions. Clustering in WSNs can be categorized as illustrated in Figure 4.

1) Cluster Formation

When we discuss CH selection, we are immediately brought to the cluster creation stage of hierarchical clustering. The study of CH selection techniques and cluster building methods is being fueled by the expanding usage of sensors in numerous applications. Whether clusters are created before or after CHs are chosen depends on the network's purpose and context of use. WSN deployments with fewer hotspots are possible thanks to cluster building techniques. Several methods for forming clusters will be discussed below utilizing non-metaheuristic methodologies that have recently been developed by certain researchers, as outlined in Figure 5.

The hotspot and blind spot issues are directly addressed by the clustering process known as unequal clustering (UC), as described in [37] in unequal clustering, Clusters near the BS do have not many nodes and are typically lower in size. Similar to what is shown in Figure 6.

In 2020, researchers from [38] have presented strategies to improve the lifespan of cooperative data collecting and relaying networks (LCDGRA). The suggested LCDGRA routing method comprises just three elementary procedures. First, the nodes are partitioned into K clusters, and then the CHs are distributed throughout the clusters using a hybrid K-means clustering technique that makes use of both the K-means clustering and Huffman coding algorithms. In step 2, the non-CH nodes, not the CH nodes, are tasked with performing the data delivery duties, and the relay nodes are selected from among them. The CHs rely on groups of cooperating relay nodes to collect data and send it on to the final destination. Based on research into residual energy and communication distances between nodes, the relay node election is formulated as an NP-hard problem. It is also proposed that an efficient gradient descent heuristic-based approach be used to solve the NP-hard issue. Finally, the aggregated packets are randomly linearly coded and cooperatively routed through multiple hops to the central BS. According to the simulation findings, the proposed LCDGRA performs noticeably better than the CERP and TEEN routing protocols regarding to lower energy consumption with longer lifetime and greater data delivery rates with lower latency.

The study contrasted the Chemical Reaction Optimization Approach with a new approach for cluster formation, Hybrid Optimal Cluster-Based Formation (HOBCF) [39]. Integer linear programming and the optimization of chemical processes are used in this technique. The performance of integer linear programming improves for the first few iterations but then declines as the count of iterations increases. This innovation supplied the first complete answer for a distributed system. But the difficulty of keeping it functioning is certain to be great. This model of a chemical process does not include a failure condition since it was fed data from an integer linear programming (ILP) model. They will fall short on their own, however. Total energy used, average remaining energy, packets received, average consumed energy, normalized routing overhead, packets received, throughput, jitter, delay, dropping ratio, goodput, and network lifespan were all used to evaluate performance. Simulation findings demonstrated that the suggested method, Hybrid Optimal Based Cluster Formation (HOBCF), the nodes' lifetimes might be greatly extended.

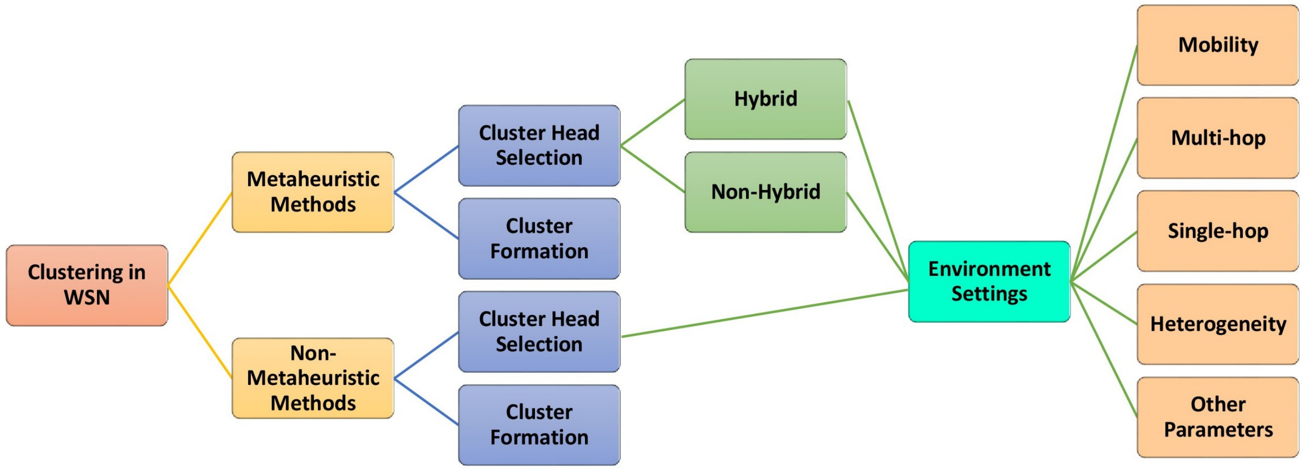

Figure 4. Taxonomy of clustering in WSNs.

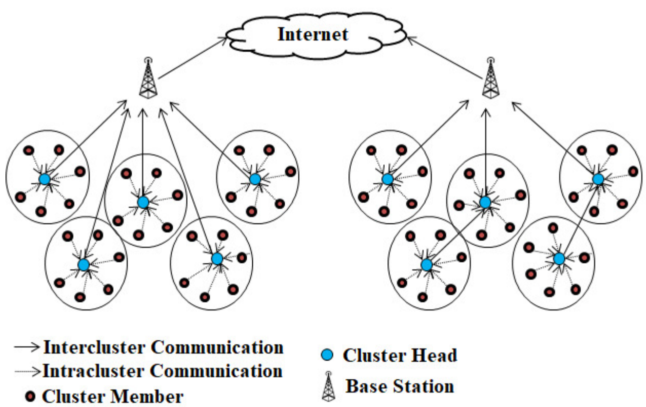

Figure 5. Cluster formation.

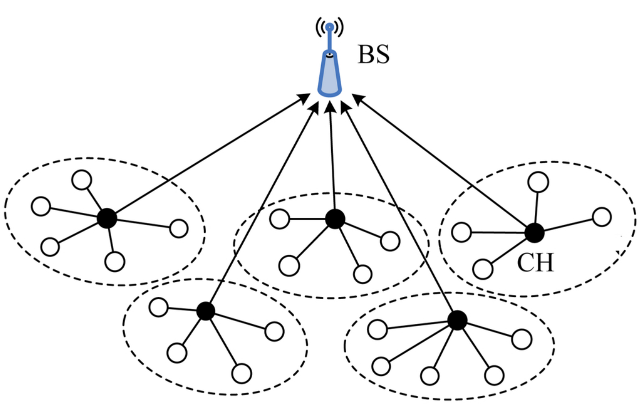

Figure 6. Unequal clustering.

The authors introduced in [38] a grid clustering algorithm based on the fuzzy rule system. In the beginning, clusters are made using a grid clustering technique, and CHs are chosen using that technique. The data aggregator node is further chosen based on criteria factors such as separation, overlap in the neighborhood, and algebraic connectivity using a fuzzy rule system-based reinforcement learning method. Finally, a fruit fly optimization technique is used to dynamically relocate the mobile sink inside an area of a grid-based clustered network. The results of the experiments showed that, when compared to earlier systems, the suggested data aggregation strategy offers improved performance with regards to both energy consumption and network longevity. An uneven clustering procedure was presented by [37] authors for use in networks of energy-harvesting sensors (UCEH). The multihop routing approach is used in the energy harvesting application, which causes a hotspot issue. As a result, uneven clustering based on node position, field area, BS coordinates, and node to BS distance is applied. All of the uneven clustering techniques investigated by the aforementioned authors have shown advantages in simulations when balancing energy usage and enhanced network lifespan compared to certain current techniques.

A Reliable and Efficient Routing (RER) scheme was presented in a research ([40]) that considered the issue of uneven clustering. The RER employs a two-step process: first, an application-centric RER model for establishing QoS restrictions; and second, a network-centric RER model for determining optimal routes; and second, an efficient CH selection method to increase efficiency. The results of the experiments demonstrate that the proposed routing method prolongs the lifetime of the network while reducing communication overhead and latency.

The research in [41] provides a balanced energy approach (EEUCB) for uneven clustering, which makes use of minimum and maximum distance to cut down on energy loss. The suggested EEUCB additionally makes use of a double CH approach and the greatest amount of node energy. Additionally, EEUCB has developed a clustering rotation approach that takes into account based on two stages, inter- and intra-clustering processes, and BS layering node, average distance threshold, and the average energy threshold. The effectiveness of the new ECB protocol is then evaluated against a number of previous methods. In comparison to LEACH, FLEACH, EEFUC, and UDCH in the simulations, EEUCB protocol fares the best.

When it comes to clustering data, a method called Energy-Efficient Unequal Chain Length Clustering (EEUCLC) was suggested by the authors of [42] . In EEUCLC, choosing a CH, making a chain, and sharing information are the three most important phases. During the CH selection phase, for each node, a CH is chosen in accordance with its distance from the BS and its residual energy. Subsequently, clusters are created, and communication links within them are established, with the closer chains to the BS being shorter than the further chains. The purpose of an intra-cluster chain is to reduce the volume of communication at the CH. The simulation's results demonstrated that, in comparison to LEACH and the other two approaches, EEUCLC increased longevity and balanced energy use. As shown in Fig 7.

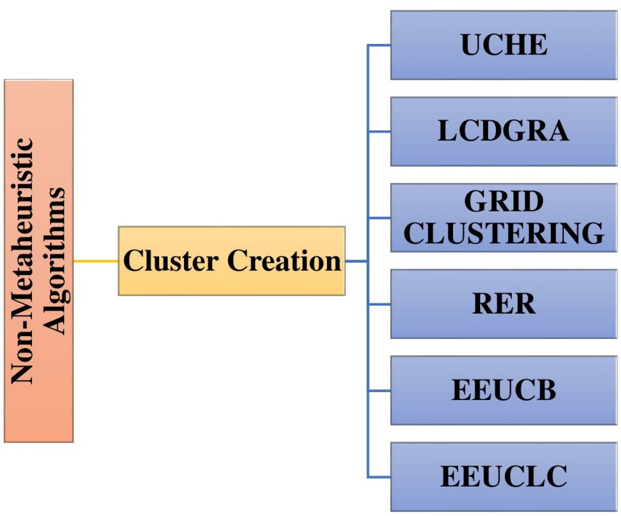

Figure 7. Classification of clustering techniques that do not rely on metaheuristics.

2) *Cluster Head Selection*

Clustering relies heavily on the CH selection process since it is crucial for effective data transmission and aggregation in WSNs. Since choosing the most accurate CH would extend the network's lifespan and dependability, the CH selection process has recently been concentrated on a number of literary works. When making a CH decision, nonmetaheuristic methods exclusively use application- and context-specific selection criteria. This section describes the different CH selection methods that are used in diverse environmental conditions. The settings for the environment and the associated CH selection techniques are shown in Figure 8.

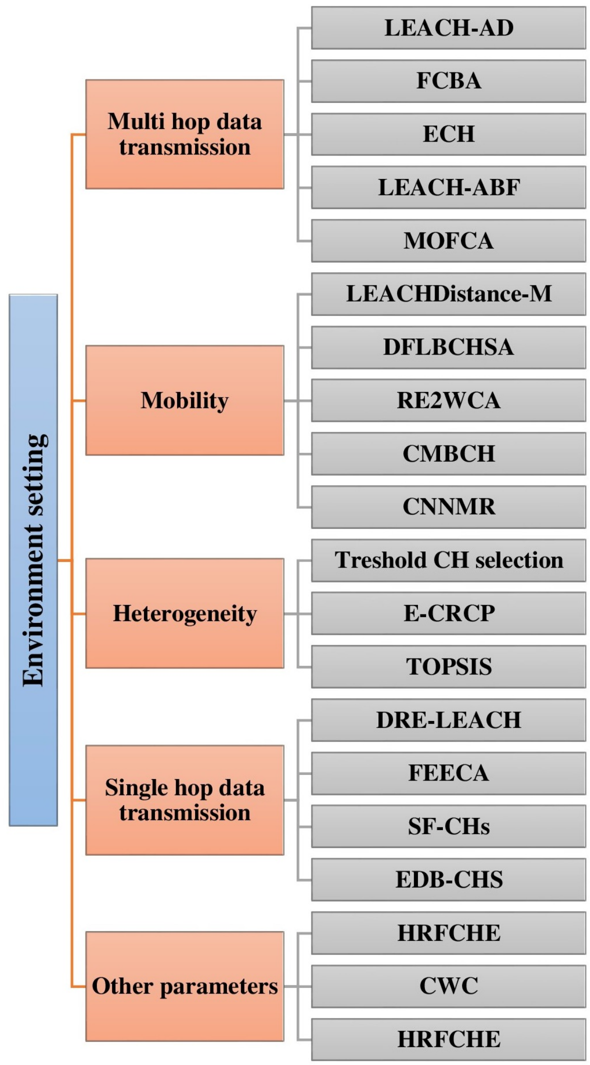

Figure 8. Taxonomy of CH selection using non-metaheuristic methods.

a) *Mobility*

When used in fields like medicine and drones, for example, the sensors are constantly moving, making clustering a considerably more challenging procedure. Frequent reclustering will also significantly degrade the network's overall energy level. Some studies that will be detailed below address this issue. To accommodate both mobile and non-mobile scenarios, Aseri and Khandnor introduced a threshold distance-based clustered routing approach [43]. Since the methodology is referred to as LEACH Distance in a stationary setting and LEACH Distance-M in a dynamic one, it is clear that LEACH is the foundation upon which this method is built. This procedure separates the criteria for choosing a CH into those that apply in a mobile setting and those that apply in a static one. In a static setup, the node's residual energy and its higher and lower threshold distances are taken into account. However, low node velocity is an extra criterion to consider in a mobile context (least mobile node) is taken into consideration in order to let the CH effectively communicate with its members. LEACH Distance-M outperformed LEACH Distance and other approaches in simulations regarding energy efficiency, data packets received by the BS, scalability, efficiency, correlation, network lifespan, and so on.

To improve network energy efficiency and decrease packet delivery latencies, the authors of [44] developed a fuzzy logic-based approach to selecting cluster leaders and disseminating it (DFLBCHSA). Three categories of network elements—static sensor nodes, mobile gateways, and static base stations—have been identified. The mobile gateway is made up of sensors that perform as a system of transportation, sending information from the CH to the BS. It is critical to have a precise CH selection procedure, as the authors demonstrate by presenting two varieties of selection criteria and using a fuzzy-based inference approach. The two methods are wireless sensor network general-node status (GSoSN) and sensor-node position in relation to mobile gateway nodes (LoSNRtMG). The GSoSN metrics include energy remaining, the number of neighbors, as well as the sensor's mean distance from its neighbor nodes; the transmission range of The mobile WSN environment still has an opportunity for study and development. Two approaches are introduced in this work. In the first, clustering is combined with mobile routing in a greedy fashion (CMR), while in the second, Using a greedy artificial neural network and mobile routing, lustering is coupled with both of these processes (CNNMR). A greedy technique is used in both models to determine the mobile sink's path. As opposed to CMR's use of a maximum energy remaining and distance from the cluster center to identify the CH, CNNMR feeds the CH's x, y locations and remaining energy data into a neural network to make a determination. Networks trained using CMR and CNNMR were shown to be more resilient in simulations than networks trained with other methods.

LoSNRtMG relies on four variables: the overall number of gates, distance between sensor nodes and gateways on average, the distance to the furthest gateway, and the distance to the next gateway. Results from the simulation show that DFLBCHSA did well in many important respects, including fewer dead sensor nodes, more energy on average, and faster packet transfers. The topology is always changing since the nodes are constantly changing. To address this problem. The authors in [45] used the weighted clustering method, which is both reliable and low-power, to organize data. Authors of this work stress the need of considering both remaining energy and group mobility when selecting a CH, since doing so greatly reduces clustering. In later rounds, we may base our selection of a CH on its mobility and energy efficiency by using a periodic defect detection methodology and spatial dependence with CH as CHSD hybridized with a weight model. The network's throughput, lifetime, and resilience were shown to be better than those of other protocols based on the simulation results.

For the CH's burden to be reduced, the authors of [46] recommended a cluster manager-based CH election (CMBCH) method. Two parts make up CMBCH: the CH and the cluster manager (CM). The CH is in charge of directing packet transfers between network nodes. The CM is in charge of overseeing and directing node activity. The CM selects a node with a high energy level when the current CH's energy is exhausted, and stores both the new and old CH activities at the same time. The elected cluster manager often retains the CHs' backup information, which lessens the issue with memory capacity limitations that CHs encounter in a mobile context. The cluster management selects the next CH during the reclustering phase based on the CH's remaining energy and proximity to the other nodes. It is stated by the authors that CMBCH offers a better ratio of packet delivery and lower power consumption than its rival technologies.

b) Multi-hop Data Transmission

Because long-distance transmission might reduce a sensor node's lifetime, multi-hop data transfer is often used in large and medium-sized WSNs. The data is sent to a CH closer to them until it reaches the BS after being aggregated by the CHs farthest from the BS. There are many different methods for choosing the right CHs based on the multi hop environment, as detailed below.

In [47], the authors suggest a fuzzy clustering technique called MOFCA specifically for WSN. Longevity improvement for WSNs is the target. MOFCA considers the node's density, residual energy, and sinking distance to determine the optimal CH. The absence of a centralized decision node for the CH selection process is also discussed as a means by which the energy hole issue might be mitigated, according to the author. Four scenarios with different sink locations and node distributions are the main focus of the simulation. To the sink, all four scenarios related to direct transmission or multi-section routing are evaluated. The simulation outcomes reveal that, relative to the overall amount of available power, the suggested method performs reasonably better than a number of already-in-use techniques.

To prevent gray- and black-hole attacks, the authors of [48] provided a method for choosing the most effective CHs in WSN. The LEACH-centric framework is called LEACH-Attack Defense (LEACH-AD). It provides a multi-hop inter-clustering protocol that not only outperforms LEACH, but also safeguards against a compromised node becoming the CH by selecting the candidate with the largest residual energy at each round of the CH selection process. The steps needed to put the proposed procedure into action have been broken down into three distinct stages. First, we analyze how efficiently WSNs consume energy while being subjected to two distinct kinds of attacks on some of its nodes. More digging is done in step two, and the affected node is isolated before it may develop CH. The third stage provides a comparison between the preceding two phases' efficacy and the presence of attacked nodes. The current system's efficiency is monitored in real-time by measuring parameters including end-to-end latency, throughput, and ratio of packet delivery (PDR).

The authors in [49] proposed a technique of Clustering Relies on Fixed Competition (FCBA). The distances between the CHs and the leftover energy are used to choose the CHs in the proposed FCBA. First, a starting group of CH candidates is formed by electing the highest-residual-energy-holding nodes that are closest to the nodes' density centers. The candidates then gather data from their participants and transmit it to the base station. Simulation findings demonstrate that our strategy is successful at reducing energy use and power consumption when compared to the most recent clustering techniques. The suggested method is successful in balancing energy usage and extending network lifetime, according to simulation results.

To extend the useful life of wireless sensor networks (WSNs), the authors of [50] suggested a new clustering hierarchy (ECH). After discovering which nodes are asleep and which are awake, the CH is arbitrarily selected from the latter group. For the CH, we employ characteristics like relative distance and residual energy. A multi hop network drastically reduces energy waste without transmission by using resting and waking nodes. However, it does not apply to other applications that require constant data transfer, such as environmental sensor nodes. By comparing the suggested technique to other existing protocols, the network's lifetime was increased while redundant data from overlapping nodes was reduced.

The authors in [51] proposed many-objective optimization algorithms to optimize the model (LEACH-ABF). Therefore, the CH election in LEACH is constructed using a multi-objective energy balance model. Taking into consideration four objectives. The cluster distance, the sink node distance, network energy consumption balance, the overall energy consumption. Which are used to investigate how to pick a CH node instance. The diversity function and convergence function are combined adaptively in ABF, and genetic processes are used to improve the solutions, making it easier to locate the best solution from the solution set. To evaluate the effectiveness of the algorithm, experiments from the DTLZ test suite and comparison tests are employed. It proves that LEACH-ABF is superior to competing methods regarding to convergence and distribution, which may extend the life of WSNs and improve their ability to save power.

c) Single-Hop Data Transmission

A weakness known as the hotspot issue exists in multi-hophop transmission, even though it may seem to be the greatest choice for sending data. In the hotspot issue, nodes near to the BS die off quickly because a large number of far-away CHs send data to the CH close to the BS, increasing the latter's traffic load and therefore its energy consumption. Due of this issue, several studies use CH selection in a one-hop environment.

Energy and Distance-based CH Selection (EDB-CHS) and Energy and Distance-based CH Selection with Balanced Objective Function (EDB-CHS-BOF) were suggested by the authors in [52]. According to the authors, a single-hop data transmission model's cluster region has a hexagonal form that is close to reality. By ensuring that the sensor node closest to the BS is elected, the node with the maximum residual energy is used, and energy consumption is minimized, a threshold probability is produced for the CH selection. One of their main focuses is making sure that all of the sensor nodes in the network are getting an equal amount of energy so that the network doesn't die out too soon. By introducing a new cluster shape, the EDB-CHS protocol generates a closed-form equation for the optimal number of CHs in the system. A useful CHS method is also described, which expresses threshold probability while accounting for the residual energy of sensor nodes, their distance from the base station (BS), and their ideal likelihood of becoming a CH. The EDB-CHS BOF protocol was created largely to deal with the problem of long-distance communications brought on by the acquisition of nearby CHs. Each sensor node's potential to act as a CH in any given round of the EDB-CHS-BOF protocol has been revised to include a new threshold probability. Furthermore, a balanced goal function is proposed to ensure that CHs are dispersed uniformly throughout the network. Results from computer simulations reveal that the proposed methods provide significant improvements over prior work of a similar kind with respect to both network lifetime and total data delivery.

As a technique for extending the useful life of the WSNS, the authors of [53] developed a fuzzy-based energy-efficientefficient clustering method (FEECA). Two scenarios are thought of in this literature. The BS is placed in the network's core in scenario 1 (S1), and at its edge in scenario 2 (S2). In FEECA, Consideration is given to three selection criteria which are average communication distance, residual energy, and communication quality. Next, a fuzzy inference technique is used to choose the best CHs based on these characteristics. In the network models, data routing takes into account single-hop data transfer for clusters that are close to the BS, Unlike nearby clusters, distant clusters must go via the master node before sending data to the BS. Based on the simulation results, it is clear that FEECA provides much higher throughput and longer network lifetimes than its predecessors.

The selectivity function-based CH selection (SF-CHs) approach was proposed by the authors in [54]. To better the clustering, it was suggested that CHs be selected. Specifically, a selectivity function that was developed dependent on energy remaining, motion velocity, neighbors number, and sensors transmitting environment was used to improve the selection of CHs. In the meantime, a clustering function was developed to optimize the grouping by removing excessively big or small clusters. In conclusion, the simulation proves that the DEAL protocol is superior in prolonging the lifetime of the sensor network. The SF-CHs method can increase the stability of the network and decrease energy loss by lowering the energy remaining variance of nodes and delaying the time before a network fails.

The authors of [55] suggested a novel energy-aware CH election approach for LEACH that may be used in WSNs to increase system lifespan while reducing energy consumption (DRE-LEACH). This method mandates four characteristics of a CH: residual energy, node distance from the sink, node centrality, and neighbor count. A threshold value is calculated by dividing the total number of CHs in the network by the total number of active nodes in the network. If the value of the threshold is less than 0.05, then the node is guaranteed to become a CH. In comparison to LEACH-based protocols, DRE-LEACH provides longer network uptime and higher dependability.

d) Heterogeneity

Wireless sensor networks that are heterogeneous include sensor nodes with a variety of varied capabilities, including computational power and sensing range. The author's in [56] proposed deployment and topology control method based on the irregular sensor model. Utilized to approximate the sensor nodes' behavior. Additionally, a cost model is suggested to evaluate the heterogeneity of WSN deployment costs. Results from the experiments show that the suggested strategy can deploy the same deployable sensor nodes more inexpensively and with greater coverage.

Clustering based on energy coverage ratio (E- CRCP) was suggested by authors in [57]. The problem of CH selection in WSNs is discussed, and a solution is proposed, which has proven effective in heterogeneous energy WSNs. The first step is to create a model of system-wide energy use. The ideal number of system clusters is established when energy usage is at its lowest. When the CH coverage is at its maximum, CH nodes are chosen, and those that use a lot of energy are replaced in the following communication iteration. The outcomes demonstrate that this strategy, for diverse power network applications, outperforms the LEACH, DDEEC, and SEP protocols in terms of network lifespan. E-CRCP balances the network load during CH selection, decreases total network energy consumption, and increases network lifespan.

To prolong network life and minimize power consumption, the authors of [58] suggested a clustering technique optimized for energy efficiency in heterogeneous WSNs. The proposed method provides an efficient mechanism for declaring CHs in order to lessen the need for re-clustering, hence decreasing the control packet cost and lengthening the CHs' useful lifetimes. The nodes use the TOPSIS multi-criteria decision-making approach to choose the optimal CH among a pool of probable CH candidates throughout the node association process. Additionally, the scheme provides tools like CH-Friendship and CH-Acquaintanceship to maximize workload optimization, reduce packet drop rate, and prolong CH lifespan. In addition to reducing the administrative and frequency burden of re-clustering, modeling results show that the suggested technique extends the lifespan of networks and reduces energy usage.

In [59] the authors proposed to use a new protocol in which the WSN is split in half and each half has its own SN. Nodes with a lot of energy are called ”advanced nodes,” whereas those with a regular amount of energy are called ”normal nodes.” The proposed procedure contains two distinct parts. In the first phase, the SN is dispersed and a new threshold value is established for choosing the heads of WSN clusters. During Stage Two. Using a trust function-based data fusion approach, precise information may be extracted without compromising the data's quality. Using the energy model, the WSN is able to reduce the amount of energy that is sent unnecessarily. The suggested protocol employs an innovative method for selecting CHs, eliminating the need for chance decisions. We choose the CH (s) with the highest RE of SN and the shortest BS distance. In contrast to previous attempts at fixing energy failure in the CH(s), the new T(H), which is made up of a distance ratio and weighted energy, is immune to concerns associated with low node energy. Using this strategy, the RE of the CH(s) nodes is enhanced. The CHs are patiently waiting for their data-transferring cluster nodes to finish their work. The proposed method improves system performance in WSNs while decreasing their overall energy consumption.

e) Other Parameters

Semi Markov was the inspiration for the work of Amuthan and Arulmurugan [60], who came up with the idea of a reliability factor that grows exponentially with each cluster's performance (HRFCHE). HRFCHE uses energy and trust aspects to decrease CHs while increasing implementation iterations. To choose a CH and create one that is more energy-balanced, one uses the hyper exponential dependability factor. According to the simulations, compared to LEACH, the proposed approach reduces energy consumption and improves network performance.

In this study, a novel energy-saving algorithm has been suggested, and its performance has been evaluated in comparison to the LEACH and HEED algorithms [61]. Improved network performance is a result of implementing the proposed technique, which prioritizes nodes based on their residual energy and their potential for becoming the cluster leader. This approach has been demonstrated to significantly affect energy savings and network longevity. However, it is demonstrated that when the residual energy parameter is set to its ideal value, the global performance in this condition is superior to that of the LEACH and HEED algorithms, and node death takes place more gradually.

According to [62], researchers have presented a technique called DCoCH, which stands for "dynamically changing coefficient-based adaptive CH election." Several factors, including intracluster communication cost, node residual energy, and the number of neighbors, are taken into account while choosing CHs. From the first round to FIND, then to HND, and lastly to LAND, the parameters are dynamically changed. In terms of extending network lifespan, DCoCH fared better than two other adaptive-based CH selection techniques.

Improved energy-efficient clustering procedure is a method developed by the authors in [63] needed to extend network lifetime (IEECP). An initial step in IEECP is to determine the optimal number of balanced clusters by using the modified fuzzy C-means approach (M-FCM), which accounts for the overlapping situation and multi -hop communications. The proposed IEECP consists of three stages that must be completed in order. In the first step, we decide on the best number of overlapping clusters that maintains a healthy equilibrium. Then, the balanced-static clusters are generated using a modified fuzzy C-means algorithm and a method to equalize the load and reduce the power consumption of the sensor nodes. Finally, an unique CH selection-rotation algorithm is used to pick CHs at the optimal locations and rotate the CH function across cluster members. This is accomplished by combining a back-off timing mechanism for CH selection with a rotation mechanism for CH rotation. And since it enhances clustering, this in turn decreases and evens out node energy usage, IEECP is well-suited to long-lived networks. The results of the assessment research demonstrated that the IEECP is superior to the standard approaches currently in use.

A non-threshold CH rotation strategy (NCHR) is proposed for IEEE 802.15.4 cluster tree networks in [64] research paper. Like LEACH, the CH is picked at random, however, the NCHR is then used to filter candidates for the next CH based on whether or not they would help prolong the cluster's longevity thanks to the hop count and remaining energy. The author also explores the application of NCHR in environments with dynamic topology and node heterogeneity, as well as how it manages CH failures. With regard to network longevity, the overall number of CH rotations, and the overhead of CH rotation, the suggested NCHR scheme's performance is evaluated. In comparison to previous analogous systems, it is demonstrated that the suggested technique increases network lifespan, costs less in rotational overhead and needs fewer changes to the CH's position.

3) *Analysis of Non-Metaheuristic Procedures' Parameters and Environments*

Non-metaheuristic clustering is evaluated and contrasted using the simulation settings and environment settings from all of the above techniques in Table II.

F. *Metaheuristic Method*

1) *Cluster Head Selection (Non-hybrid)*

By adhering to the right procedure and strategy, the optimization issue may be resolved. The words "meta" and "heuristic" were combined to create the term "metaheuristic." Meta is a high-level approach, and heuristics is the art of coming up with new ways to solve problems. A metaheuristic approach is a heuristic-based methodology that may be applied to any problem. Metaheuristic techniques may be broken down into two categories: those that rely on population data (random search) and those that rely on single-solution local searches [65]. The capacity of the metaheuristic algorithm to balance exploration and exploitation is crucial for achieving an optimal solution since this prevents the algorithm from becoming stuck at a local optimum or slowly converges [66]. A non-hybrid metaheuristic approach to optimization problems is an algorithm that doesn't use the algorithmic parts of other methods. This section explains how non-hybrid metaheuristic algorithms are used in CH selection using a variety of environmental contexts. The conditions and related CH selection methods are shown in Figure 9.

a) *Mobility*

In WSNs, a novel approach for CH election is presented. In 2018, the authors of [67] proposed the honey bee algorithm is used to choose the best CH in a mobile WSN (BeeWSN). In this case, the node's residual energy, velocity, angle, and direction serve as the selection criteria for CH selection. Two sorts of bees—the employed bee and the spectator bee—are distinguished in the honeybee algorithm. The employed bees are data packets, whilst the onlookers are control packets that seek the best CH using the selection criteria. We argue our approach provides both high-quality discovery (represented by "spectator bees") and high-quality utility (employed bees). According to the simulations, BreWS generates more balanced clusters than other available approaches.

This work suggests and evaluates the CH election and optimal multipath scheme. Proposed in Coral Reef Optimization (CRO) for the best multipath routing [68]. In MANET, each node's possible values, which are taken into account from that node's energy remaining, are utilized to determine the CHS. In the current phase, the mean energy of the whole network is determined using the total residual node energy. During multi-hop communication, the CH is chosen from the most likely nodes.

TABLE II. Non-metaheuristic clustering comparison examination of simulation parameters and environment conditions.

Ref.	**CH selection**	**Data trans-mission**	**Sensor type / Mobility**	**Selection criteria**	**Packet length**	**Network dimension**	**Location of BS / No. of nodes**	**Sensor initial energy**	**Outcomes**
[43] 2017	LEACH Distance-M	Multihop	Homogeneous / Mobile	Less mobility when the threshold is high in energy terms and vice versa when the upper limit is reached.		100 m x 100 m	(50, 50) / 10-100	0.5 J	This protocol prolong the network lifetime by 71.74% and 83.35% compared to LEACH-M and LEACH-M.
[42] 2017	EEUCLC	Multihop	Homogeneous / Static	distance to BS and Residual energy	250 bytes	(0m x 0m) (400 m x 400 m)	Outside the network / 150	1 J	In comparison to similar protocols, the EEUCLC mechanism improved energy efficiency and increased the lifetime of the network.
[49] 2017	FCBA	Multihop	Homogeneous / Mobile	degree, Energy, and distance		100 m x 100 m	(50, 50) / 50-200	15 J	FCBA simulations with 100 nodes and a sink location of (50, 50) are 30% more accurate than those with the sink at (95, 95).
[69] 2017	TTDFP	Multihop	Homogeneous / Static	Competition radius, Remaining energy, Distance to BS, and relative node connectivity.	500 bytes	1000 m x 1000 m	(1250, 1250), (500, 500) / 100	1 J	TTDFP outperforms LEACH by over 23.5%, CHEF by 47%, EEUC by 35.2%, and MOFCA by 17.5%.
[45] 2018	DFLBCHSA	N/S	Homogeneous / Mobile	Residual energy, most faraway gateway, distance, number of connecting nodes, and total number of neighbors.	500 bytes	350 m x 350 m	100	0.35 J	Simulation findings further show that the network's throughput, resilience, and lifespan are much higher than those of competing protocols.
[46] 2018	RE2WCA	Multihop	Homogeneous / Mobile	group mobility and Residual energy		100 m x 100 m	50	2 J	About 13% more energy is used to calculate EMDWCA than RE2WCA. When compared to DWCA, it's around 10% lower. It shows that the RE2WCA-selected CH residual energy is higher than the EMDWCA and DWCA residual energies.
[60] 2021	HRFCHE	N/S	Homogeneous / Static	parameter for trust and energy	500 bytes	100 m x 100 m	100	2 J	Compared to the CH election techniques, the network lifespan is increased by 28%, and the energy consumption is reduced by 34%.
[61] 2018	CWC	N/S	Homogeneous / Static	distance from the sink, The residual energy of each node by applying weighting coefficients	500 bytes	(50 m x 50 m), (100 m x 100 m)	(25, 87.5), (50, 175) / 20, 40	0.1 J	This protocol outperforms LEACH and HEED on a global scale, with slower node deaths as a side effect.
[50] 2019	ECH	Multihop	Both / Static	Power and close proximity	3000 bytes	100 m x 100 m	(50, 50) / 100	N/S	That DEEC-ECH shows 13.34% and 27.56% growth over DEEC-(ACH) 2 and DEEC, respectively, over the stability period. As compared to DEEC-(ACH) 2, DEEC-ECH increases network longevity by 12.60%, and DEEC by 28.36%.
[52] 2019	EDB-CHS	Single hop	Homogeneous / Static	Residual energy, node's optimal probability and distance.	625 bytes	(200 m x 200 m), (300 m x 300 m), (400 m x 400 m)	100, 300 / 100	0.5 J	Compared to LEACH-DT, the results show a massive increase of 302%, but the improvement from CEED over EDB-CHS is just 2%.

TABLE II – *Continued on next page*

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[54] 2019	SF-CHs	Single hop	Homogeneous / Mobile	Remaining energy, data transmission environment, number of neighbors, motion and velocity	500 bytes	100 m x 100 m	Center of the network / 200, 300	1 J	Network lifespan is increased by 16.5% due to a late failure node in the SF-CHs algorithm. By lowering the standard deviation of the nodes' remaining energies by 32%, the overall network stability is enhanced.
[57] 2019	E-CRCP	N/S	Heterogeneous / Static	Coverage ratio and Residual energy.	500 bytes	100 m x 100 m	(50, 50) / 100	0.5 J	The benefits of the suggested approach in a heterogeneous energy WSN are shown via simulation. These advantages include increased network lifetime, improved load balancing, and reduced total energy usage.
[44] 2020	CMBC	Multihop	Homogeneous / Mobile	The Relationship Between Energy and Distant	512 bytes	1200 m x 1200 m	20-100	5000	WSNs may benefit from a more precise cluster head selection, less wasted energy, and faster packet delivery.
[51] 2020	LEACH-ABF	Multihop	Homogeneous / Static	Cluster distance, network energy consumption balance, sink node distance, and overall energy consumption	500 bytes	100 m x 100 m	(50, 50) / 100	2J	reveals that, up to 1300 iterations, the residual energy produced by NSGAIII, KnEA, EFRRR, and LEACHABF is almost identical to that produced by the four algorithms (28.9534, 28.8228, 30.7334, and 33.5077).
[53] 2020	FEECA	Single hop	Homogeneous / Static	Residual energy, average distance of BS, communication quality.	375 bytes	100 m x 100 m	(50, 50), (150, 100) / 100, 200	0.5 J, 1 J	Compared to SCHFTL and DFCR, FEECA has showed a 592.36%, 87.23% improvement for the Stability period, 304.87%, 104.61% improvement for QND, and 36.9%, 83.26% improvement for all SN dead.
[58] 2020	TOPSIS	Single hop	Heterogeneous / Static	Residual energy, computational capability and available storage.	500 bytes	100 m x 100 m	100	6 J–10 J	compares well to the most up-to-date, relevantly suggested protocol for WSN in terms of lowering power consumption and increasing network lifespan.
[62] 2020	DCoCH	N/S	Homogeneous / Static	How much power is left, how many nodes are nearby, and how much it costs to communicate intra-cluster.		(100 m x 100 m), (300 m x 300 m)	Center, corner, outer 1, and 2 of network / 50, 100, 200, 300	0.5, 1, 2 J	DCoCH is favored because it outperforms PEECR and CATD when considering the network's lifespan over LND, by a margin of 2% to 14% and by 21% to 37%, respectively.
[63] 2020	IEECP	Multihop	Homogeneous / Static	The ratio from the initial energy and Energy consumed.	400 bytes	(100 m x 100 m), (1000 m x 1000 m)	(50, 125), (500, 1250) / 100, 1000	1J	Test findings show that the IEECP outperforms the competition.
[37] 2020	UCEH	Multihop	Homogeneous / Static	Residual energy	500 bytes	(0m x 0m)-(200 m x 200 m)	-100, 100 / 100-400	0.5J	Compared to UDCH, EEFUC, FLEACH, and LEACH, the EEUCB technique improves lifespan by 13.06%, 14.7%, 19.63%, and 57.75%, respectively.

TABLE II – *Continued on next page*

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[38] 2020	LCDGRA	Multihop	Homogeneous / Static	Residual energy metrics and Communication distances.	100 bytes	100 m x 100 m	(100, 50) / 100	5 J	With the suggested LCDGRA, power consumption is reduced by 37% compared to TEEN and 21% compared to the CERP protocol.
[39] 2020	HOBCF	Multihop	Homogeneous / Mobile	Distance and energy	512 bytes	1000 m x 1000 m	Center of the network	500 100 J	Using the suggested method, HOBCF, the nodes' lifespan increased significantly.
[70] 2020	Grid clustering	Multihop	Heterogeneous / Static	Residual energy, distance, algebraic connectivity and neighborhood overlap.	500 bytes	200 m x 200 m	(100, 100), (100, 50), (200, 200) / 20-500	0.5, 2, 200 J	Delivers better performance than previous systems with regard to of energy efficiency and network lifespan.
[55] 2021	DRE-LEACH	Single hop	Homogeneous / Static	Residual energy, centrality of nodes and the position.	500 bytes	70 m x 70 m	(35, 47.25) / 100	0.5 J	When compared to LEACH, the suggested method provides a 32% boost to the overall lifespan of the network.
[59] 2021	Threshold CH selection	Multihop	Heterogeneous / Static	Distance from BS and Residual energy.		150 m x 150 m	(150, 75) / 150	0.5 J	To lessen the network's reliance on external power sources, hence increasing its longevity (44%), steadiness (59%), and survivability (15%)
[64] 2021	NCHR	Multihop	Both / Static	Distance and energy remaining		1000 m x 1000 m	71	1J	The suggested technique reduces the amount of CH rotations required and the rotation overhead incurred by the network.
[71] 2021	CNNMR	N/S	Homogeneous / Mobile	Residual energy and Distance from the cluster center.	500 bytes	(90 m x 90 m), (120 m x 120 m)	100, 200	2J	The simulation findings showed that CMR and CNNMR were more effective than EESRA at extending the lifetime of The network.
[40] 2022	RER	Multihop	Heterogeneous / Mobile	Energy Efficiency, Reliability,	5000 bits	100m x 100m	Placed outside sensing region / 500 - 3000	0.1-0.2J	For devices of 500, 1000, 1500, 2000, 2500, and 3000 sizes, respectively, the RER model outperforms the UCT2TSK by 53.44%, 58.002%, 61.55%, 63.68%, 64.33%, 66.15%, and 61.18% during their lifetimes.
[72] 2022	OGWO	N/S	Both / Static	Energy, distance node centrality, and node degree.		200 m x 200 m	(0,0) (50,50), (100,100), (150,150) / 100 to 400	2J	When compared to GWO, ABC, and LEACH, the Network lifespan provided by the proposed OGWO approach is 20%, 30%, and 45% longer, respectively.
[73] 2022	EEUCWFL	multi-hop	heterogeneous / Static	receiving and energy consumption in transmitting,	4000 bits	(0, 0) m to (200, 200) m	(100,250) / 100	0.1 nJ	the three most well-known algorithms (LEACH, EEUC, and CHEF) with our new suggested method. Our suggested approach is shown to reduce energy usage and increase the lifespan of the network.
[74] 2022	HMABCFA	N/S	Both / Mobile	ensuring energy stabilization, inter-node distance and delay minimization	6400 bits	400 x 400m	(50,150) / 1000	1 J	Average improvements of 23.21% in network lifespan, 19.84% in energy stability, and 22.88% in network latency relative to the Benchmarked methods are validated for the HMABCFA.

The CH gathers data packets sent by nodes in the cluster. The essential concept is to split a top-secret communication into many parts and then send the parts to the target location through various channels. From the simulations, the Coral Reef Optimization outperformed a number of prior-approaches, including: the Butterfly Optimization Algorithm (BA), Butterfly Optimization Techniques (BAT), and Whale Optimization Algorithm (WOA).

Topology changes are one of the limitations of mobile WSNs, while scalability is another. Bio-inspired IoD clustering (BICIoD) was suggested by the authors of [75], who based their work on the dragonfly method (DA). Dragonflies exhibit two types of swarming behavior: static swarming (looking for food), which encourages exploitation; and dynamic activity (migration), which encourages the capacity for exploration. In the suggested technique, the drones' location, remaining energy, and connection to the BS are used to choose the CH. After the clusters have been produced, DA takes care of them, and cluster members must keep an eye on the CHs' motion and make adjustments accordingly. Compared to other algorithms, BICIoD does better in terms of how long a cluster lasts, how much energy it uses, and how fast it delivers.

b) Multi-hop Data Transmission

Because bioinspired algorithms offer faster convergence than nonmetaheuristic approaches, more research has been done on metaheuristic methods. Firefly CH selection algorithm (FFCHSA) was suggested by the authors of [76]. As the author explained in the introduction, FFCHSA selects the CH in a multihop WSN using a fitness function based on energy, end-to-end latency, and packet loss ratio. According to the simulations, the suggested method performs better overall than PSO and genetic algorithm (GA).

In addition to the higher computation required by this location-based method, the choose of duplicate nodes, and poor selection accuracy. To address these issues, the authors of [77] suggested an energy-efficient CH selection algorithm based on sampling from a spider monkey population (SSMOECHS). This strategy was suggested as a solution to the issues with the location-based CH selection methodology. The concept of spider monkey optimization (SMO) is based on how well-trained monkeys can explore while looking for food. The CH is chosen using the SMO sampling technique, where the notes' coverage and energy are seen as the main goals that must be achieved. By using multihop data transmission, the approach is simulated in both a homogeneous and heterogeneous environment, demonstrating how SSMOECHS increases network lifespan and energy efficiency.

Based on the technique used by artificial bee colonies, Aruna Pathak presented the Proficient Bee Colony-Clustering Protocol (PBC-CP) in [78]. The honey bees' sophisticated foraging behavior serves as the inspiration for the bee colony algorithm. Bee colonies consist of three different bee species: worker bees, observers, and scout bees. The position of a food supply represents the optimization issue's probable solution, and the quantity of nectar refers to how well the solution fits the problem. The colony size in this instance is equal to both the number of worker bees and the number of spectator bees. Each worker bee is assigned to a food source at random locations chosen for the food sources first. After that, in each iteration, a worker bee finds a different food source and rates how good it is. If the new food source's nectar yield is greater than the previous one, the worker bee will go to it; otherwise, it will stay at the current food source. According to the simulation findings, the PBC-CP algorithm performs better than HSA-PSO, PSO, and LEACH. Even though PBC-CP is a good protocol, it could be improved in some ways to make it more useful in more situations.

In order to address the energy hole issue that might arise in a multi-hop WSN environment, a load-balanced node clustering technique based on an enhanced memetic algorithm was suggested [79]. This system's CH is selected using a memetic algorithm with a fitness function that takes into account the amount of energy left over after processing, the distance of communications among clusters, and the number of nodes. In terms of energy efficiency and network longevity, the memetic algorithm ranked higher than state-of-the-art algorithms.

Chimp Optimization and Hunger Games Search (ChOA-HGS) methods are proposed in [80]. The ChOA is used first to choose capable cluster leaders and establish functional cluster structures. Then, the best routes in the network are found with the help of the HGS-based routing procedure. The proposed approach integrates clustering with routing for maximum network resilience and low power consumption. After simulating the proposed ChOA-HGS in three distinct scenarios, it is validated using a variety of metrics. The simulation results are compared to those of LEACH, TEEN, IPSO-GWO, MPSO, and PSO to provide insight into ChOA-performance. HGS's The results showed that the ChOA-HGS had the longest lifetime and lowest energy usage compared to the other standards.

c) Single-hop Data Transmission

This work talked about how the FCR approach, which was an extension of the traditional firefly algorithm, can be used to choose the head of a cluster in WSNs. In fact, the main problem with WSN is how to send data with the least amount of latency and the least amount of wasted energy. The present experiment has been the focus of these issues, and its main contribution has been to encourage efficient CH election by taking into account the latency of sensor nodes inside the network, energy and distance. Further, the effectiveness of the FCR-based CH election was evaluated and contrasted with that of more traditional protocols such as GSO, GA, FABC, and ABC algorithms [81]. This comparison was made using a statistical analysis

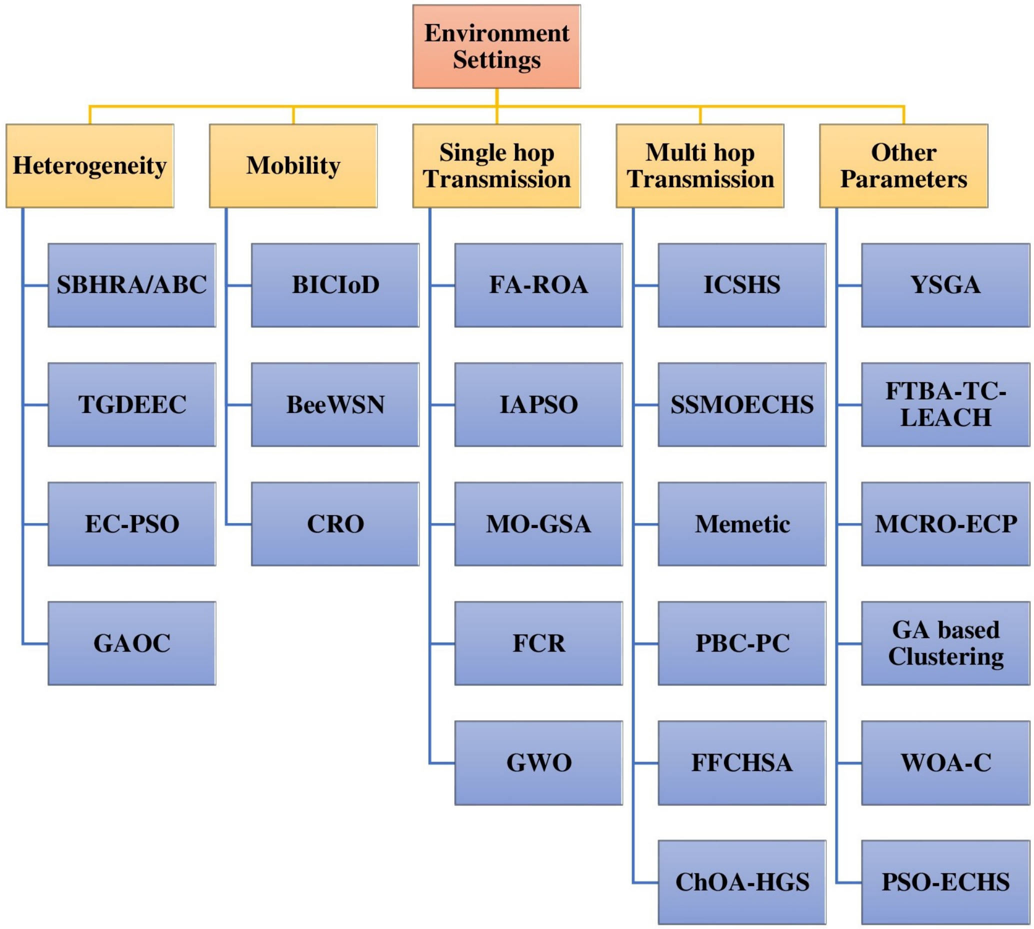

Figure 9. The contexts and the techniques for selecting CHs in certain contexts are described.

that was checked and an analysis that looked at FCR's ability to handle several goals. As a result of the FCR protocol, there is now less separation between nodes and more active nodes, and so the network's energy has been preserved. The suggested FCR approach beat the standard CH election algorithms in aggregate.

A modified gravity search technique (GSA) is presented in [66]. A middle ground between exploration and exploitation must be found, the GSA has been changed to include a tournament selection method and a changing mass value over time. The best CH is chosen with modified GSA, whose fitness function is based on how far away the nodes are from the CH and how much energy is left. The Modified GSA fared well in terms of network lifespan and data packet delivery when the suggested technique was tested utilizing a variety of unimodal functions, fundamental multimodal functions, and composition functions.

An enhanced adaptive particle swarm optimization (IAPSO) was presented in [82]. To begin, we developed a multi-objective area coverage optimization model to improve coverage ratio and reduce redundancy ratio. Then, we made a CH election optimization model that uses less energy and suggested a weight-based cluster formation method. By detecting the direction of rotation, using IAPSO-MOACO, we were able to maximize coverage while minimizing duplication. In addition, we used IAPSO-CHSO to manage energy usage by prudent CH election. When compared to other methods for area coverage optimization, our suggested method successfully increased coverage ratio and decreased redundancy ratio for data transmission rounds of up to 700. Because the IAPSO could sometimes avoid local optima, the IAPSO-MOACO generally did a better job of optimizing. Compared to the previous method for optimizing energy consumption, IAPSO-CHSO was able to achieve energy consumption balance because it could make sure that BS received data packets from a greater number of active nodes.

The authors of [83] proposed a fitness averaged rider optimization algorithm (FA-ROA)-based multiobjective CH selection mechanism for a single-hop smart city application. The load, temperature, latency, and distance between nodes are among the several goals that are optimized in this method. The basis of ROA is the concept of a group of cyclists cycling to a destination that includes a bypass, overtaker, follower, and attacker riders. In order to boost performance, this work refines the ROA processing of the group update phase. The simulation findings demonstrate that FAROA outperforms certain existing metaheuristic algorithms in terms of latency, normalized energy, and the percentage of nodes that are still operational.

In this study, we came up with a new way to choose the CHs in a wireless sensor network based on clusters. In our method, the significant routing overhead is offloaded by using the optimum selection CH. Moreover, we suggested a fine-tuned GWO method to choose the best CH so that transmission distances would be shorter and the network would use the least amount of energy [84]. Beyond that, in order to strike a middle ground between exploration and exploitation, customized parameters help, which finally chooses the best method to extend the network lifespan. Several tests have shown that the network could improve energy efficiency by lowering the total amount of energy used and making sure that each node uses the same amount of energy over the life of the network. According to our experimental results, the suggested algorithm performs better than other comparable algorithms. Additionally, it has been shown that the algorithm's effectiveness lowers the amount of energy needed for both packet transmission and data aggregation.

d) Heterogeneity

The purpose of this research was to find a way to eliminate the issue of hot spots in wireless sensor networks. For multi-objective optimization, the developers of [85] developed a better non-dominated sorting particle swarm optimizer (INSPSO). When we mention multiple goals, we imply that there are both minimizing and maximizing objectives. In this study, for example, to choose the best CH, energy consumption should be minimized while maximum residual energy is produced. When figuring out how well a network works, many different situations are taken into account in which sensors and gates come in a wide range of quantities. INSPSO performed effectively in choosing the CH based on multiobjective variables, boosting network lifespan and lowering energy consumption.

If you want your WSN to use as little energy as possible, you need to choose your CH wisely. This goal may be accomplished with the help of two novel reactive routing techniques for heterogeneous WSNs: GAOC, or the Genetic Algorithm-based Optimized Clustering protocol, and MS-GAOC, or the Genetic Algorithm-based Optimized Clustering protocol with Multiple Data Sinks, are two such examples. The fitness function for either strategy may be calculated with the help of the parameters residual energy, distance to the sink, and node density. It has been possible to reduce the amount of power needed for intra-cluster transmission thanks to the high density of nodes. The chromosomes' role in the human body and how they shape the fitness function are both well discussed. Multiple data sinks are used in MS-GAOC to reduce the hot-spot problem, which is the premature demise of the network's lifetime in a large network area due to the need of multi-hop communication. Furthermore, MS-GAOC has a substantially greater throughput than GAOC, MS-GADA, MS-TEDRP, and MS-DCHGA. This enhancement is accomplished by using CHs that are efficient in terms of both energy consumption and their ability to reduce the effective communication distance between nodes and the appropriate sink. This enhancement is accomplished by using CHs that are efficient in terms of both energy consumption and their ability to reduce the effective communication distance between nodes and the appropriate sink.

An example of this is the "Energy Centers Searching via Particle Swarm Optimization (EC-PSO)" method presented in [86]. In order to pick CHs with the highest probability of being stable, it is important to avoid these energy gaps. The network occurs in two phases, and two distinct clustering strategies are used. During the first phase, when the CHs were chosen using the geometric technique, the topology was kept for many rounds. After the energy in the network became uneven, PSO was used to do a specific clustering to find energy centers for the election of CHs. EC-PSO prevents the energy holes that are often caused by clustered routing protocols. To further prevent CHs from being too near to one other, random reinitialization was implemented, and a threshold-based protection mechanism prevented low-energy nodes from forwarding. A mobile data collector was used to gather the sensor data, and it was attracted to the energy hub with the highest mean energy level. Several simulations show that the suggested EC-PSO achieves better results regarding to both network lifespan and energy usage.

Maintaining energy balance is one efficient technique to prolong network life. the authors in [87] proposed The threshold game theory (TGDEEC) approach was used to improve the distributed energy-efficient clustering (DEEC) technique. Game theory is a kind of mathematical calculation that aids in decision-making settings. It is taken for granted in this literature that there are heterogeneous networks consisting of super nodes, normal nodes, and advanced nodes. To calculate a cutoff, TGDEEC considers the energy consumption of each cluster member and CH and assigns a relative weight to each. To choose the appropriate CH, the threshold is applied to the total distance traveled and the total energy used. In terms of performance and network lifespan, TGDEEC is known to outperform numerous other algorithms.

Section-based hybrid routing protocols (SBHRA) and the artificial bee colony (ABC) algorithm were presented in [88]. SBHRA creates a heterogeneous environment by segmenting the network into several subsets, each of which contains nodes of one of three types (1, 2, and 3). ABC uses a technique similar to [67]; however, its applications in this literature are more varied and specific. In ABC, node regions of types 2 and 3 employ the residual energy parameter as a fitness function to choose CH. The simulation of SBHRA with ABC for CH selection demonstrates improvements in throughput, period of stability, and lifetime of the network compared to other approaches currently in use.

e) Other Parameters

Although the aforementioned articles provide information about the network environment, it may not be necessary to make major adjustments to the environment in order to perform the research, or the work may not define the kind of data transfer. In a static and homogeneous network architecture, the following are some of the most up-to-date techniques that can be used.

Based on particle swarm optimization, the authors of [89] offer a method for selecting CHs that is both energy efficient and robust (PSO-ECHS). Energy-efficient CH selection is optimized by considering characteristics elements like energy remaining at sensor nodes, the distance between clusters, and the sink distance. The proposed technique is tested in a simulated environment with a dynamic number of nodes, central hubs (CHs), and base stations (BSs). In comparison to certain existing algorithms, PSO-ECHS has better results for network lifetime, data packet delivery, and total energy usage.

Based on the whale optimization technique, a new low-power routing strategy called (WOA-C) is presented in [90]. Using a fitness function that considers both the node's own remaining energy and the aggregated energies of its neighbors, energy-aware CHs may be selected to help keep the sensor network's overall power usage down. In addition, WOA-performance C's are compared to other popular modern routing protocols including LEACH, LEACH-C, and PSO-C. Different algorithms are assessed for their throughput, durability and low power consumption in networks. Consequently, Compared to older routing algorithms, the proposed technique excels in the following areas: residual energy, network lifespan, throughput, and extended stability period, according to thorough simulations. This study introduces a reliable whale optimization-based routing method that can choose CHs for optimum WSN energy utilization.

The authors propose a Bio-Inspired Algorithm based on genetic algorithms (GAs) in 2019. Using a genetic algorithm, wireless sensor networks may address their unique energy problems. As a result, we have chosen an energy-efficient CH, resulting in an environment that is optimized for energy and has a longer network lifespan [91]. The nodes' fitness function is calculated dependent upon their distance from the BS and the CH, both in the aggregate and separately for each sensor. Since the fitness function in this study does not prioritize energy metrics, it is possible that a CH with a low energy level will be chosen, which might cause problems down the line. Simulations showed that GA, unlike K-means and LEACH algorithms, was able to make the network last longer by spreading the load evenly across the nodes.

The TSBOA proposed in [92], is a hybrid of BOA and TSA, and it is utilized to determine an effective method for selecting the CH in a WSN setting. The proposed method selects the CH optimally within the constraints of fitness measures including expected energy, node energy consumption, LLT, latency, and inter- and intra-cluster distance. Prediction energy is calculated using the starting energy value and a Deep LSTM classifier. The energy of the receiver, the energy of transmission, and normalization factors are used to determine total node energy consumption. During route maintenance, connection failures are counted and analyzed to determine the routing path's reliability. Data packets are sent from their source to their destination after the connection reliability factor is evaluated to a threshold value. The proposed technique outperformed alternatives results in (0.1118J) and (82.101%) for the remaining energy and throughput, respectively.

Energy-efficient clustering is the basis of the mutation chemical reaction optimization methodology (MCRO-ECP) described by Daniel and Rao [93]. There are two main operators in MCRO-ECP, the turn operator and the mutation operator. The mutation operator broadens the search space and promotes solution convergence, while the rotating operator enhances the algorithm's best solution quality and consistency. The shortest path among sensor nodes, the shortest path to the BS, and the energy proportion are the three criteria considered in selecting the CH. From what we can see from the simulation, MCRO-ECP is a significant improvement over the state-of-the-art in terms of energy efficiency, network lifetime, data packets received by the BS, and convergence rate.

Improvement in LEACH's ability to pick CHs Considering that the node in the center of a cluster is picked at random, it is possible that it will be distant from the base station and that the system's distribution of the remaining energy will be inefficient, which will cause the node to die before its time. We altered the BA to optimize cluster-head node selection in order to address this issue, and we also put out a curve method using FTBA (FTBA-TC) [94]. Because the bat method could be used in more ways at first, the authors of this paper improved the algorithm by enhancing the efficacy of global searches using a hybrid of BA and LEACH that makes use of triangular flips and curves (FTBA-TC-LEACH). Initially, using the remaining energy, a temporary CH is chosen, and then a modified BA is used to figure out where the temporary CH should go. Using three distinct curve types and six distinct parameter permutations in simulations, FTBA-TC-LEACH outperformed the competition.

In this study, a new clustering routing technique named YSGAP was proposed [95]. The approach determines the best network design to reduce overall energy use and increase network longevity. In its operation, in each cycle, the YSGAP protocol automatically calculates the number of CHs and selects the sensor nodes that will serve as CHs. Some of the most popular clustered routing protocols, like DEER, LEACH, and SEP, were used to compare our method to them. The experimental results demonstrated that the suggested technique outperforms the methods under consideration. The suggested routing protocol was evaluated, revealing that our technique significantly increases network lifespan while also offering resilience in communications, fault tolerance, and time-bound response inquiries.

2) Cluster Head Selection (Hybrid)

The theory behind the hybrid metaheuristic method is that the optimal outcome may be achieved by integrating elements of several algorithms or search techniques [96]. While numerous new metaheuristic algorithms have been introduced in recent years, several of them still struggle to strike a decent balance between exploration and exploitation. Because of this, issues arise, such as sluggish convergence, becoming stuck in a rut with the same local best solution, etc. Many metaheuristic algorithms, as shown in the nonhybrid section, incorporate features or methods that enhance both global and local search (exploration and exploitation). Similarly, hybridization employs the same approach, but it combines features from many metaheuristic algorithms or the algorithm itself to keep the exploration and exploitation skills in check while still finding the optimal solution. Several cases are used to demonstrate the use of Hybrid metaheuristic algorithms for CH selection. Figure 10 Shows how hybrid metaheuristic algorithms are employed in CH selection, with examples from a variety of settings.

a) Mobility

As mobile device technology improves, it's influencing how the internet evolves. This new course of action reduces expenses and paves the way for the deployment of wireless networks that need no physical infrastructure at all [97]. In the year 2019, the authors attempted to increase the overall performance of MANET using a unique algorithm technique that combined the total of simulated annealing and GA features in MANET [98]. The SAGA protocol chooses the head of the cluster for better performance than other protocols. In this literature, the CH is chosen depending on the degree of CH and the energy value. Although the genetic algorithm has a better capacity for global search, it has drawbacks, issues include slow convergence and ineffective local search capabilities. According to the authors, SAGA may solve MANETs' significant combinatorial optimization issues and the limits of genetic algorithms. Simulations showed that the protocol selected CHs with better performance than those used by other procedures.

b) Multi-hop Data Transmission

In [99], authors present ECHSR, an energy-efficient method of selecting and routing CHs. An improved method for choosing CH is proposed in this study using a combi-

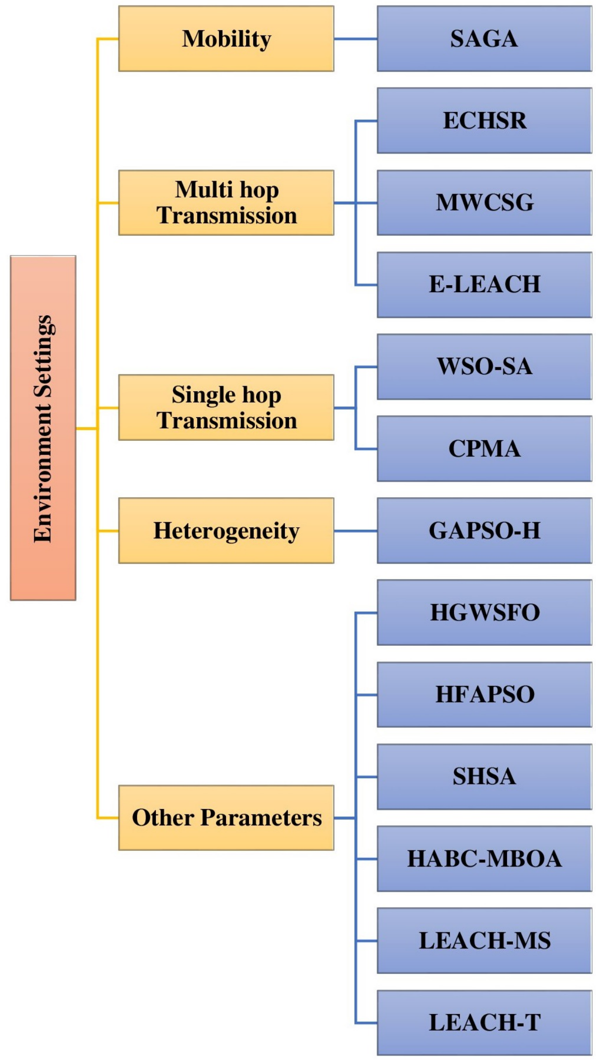

Figure 10. Classification of hybrid metaheuristic approaches for choosing cluster heads.

nation of particle swarm optimization and the previously established Harmony Search Algorithm. After that time period, data is sent through a PSO-based multihop routing system that employs enhanced tree encoding. An energy-efficiency criteria, proximity to clusters, and network coverage are utilized to rank candidates for CHs in the proposed strategy. An AWS approach is used to analyze the fitness function in order to determine the optimal solutions to the MOOP. When compared to previous systems of its kind, ECHSR performed better in a simulation of a forest fire with several sink sites.

E-LEACH, energy-aware TDMA scheduling, and dynamic fuzzy-based optimal channel selection all come together to provide a superior WSN system model for network lifetime in the recommended research [100]. At first, E-LEACH forms clusters using the optimal selection of heads as its guiding principle. To speed up the process of electing the head, this research uses a combination of two optimization strategies—GWO and D-PSO—in a parallel fashion. A CH and an HCH are selected using these techniques in order to minimize the network's overall energy footprint while maintaining adequate data collection rates. Reducing unnecessary energy consumption in bigger cluster sizes, E-LEACH is also connected with cluster size management by splitting or merging. The leader then schedules members' times using energy-conscious TDMA by slicing the available communication space into 24 equal halves. In their designated time periods, members perceive and report their findings to the cluster's central node. The information is obtained by the CH and then sent to the sink. Head transmission use dynamic fuzzy to choose the most efficient channel for data transfer. When channels are chosen and timeslots are scheduled, throughput, packet loss, and latency all get better. On the whole, increasing the network lifespan of the planned WSN results in achieving the aim of decreasing energy usage.

A novel approach to clustering is introduced in this research; the multi-weight chicken swarm-inspired genetic algorithm for energy-efficient clustering (MWCSGA) [16]. The chicken swarm optimization approach uses the GA's crossover and mutation operators to ensure that the optimal answer is generated by a wide variety of sources. The best CH is elected dependent on the fitness function, which considers the CH's energy usage, its distance from the BS, and its proximity to the node. Multiweights for node localisation and energy remaining are also used prior to electing the CH to ensure optimal energy efficiency. The ratio of delivered packet, throughput, end-to-end latency, and energy efficiency were all improved upon in simulations using MWCSGA in contrast to other cutting-edge approaches.

c) Single-hop Data Transmission

The research paper [98] suggested a metaheuristic-based clustering hybrid methodology (CPMA). Combining the artificial bee colony (ABC) approach with the harmony search algorithm (HSA) for a topology with a single hop. The expected energy distribution ratio and the overall energy cost are two criteria that are taken into account while choosing the CH based on HSA. This metaheuristic-clustering hybrid approach was proposed in this research article.

d) Heterogeneity

Two methods are provided in [98] to help find the best candidate for CH in WSN. One is a genetic algorithm, and the other is a particle swarm optimization, together known as (GAPSO-H). In a heterogeneous network, the GA selects the best candidate hub (CH), while the PSO selects the optimal path for the mobile sink. Supernodes, advanced nodes, and standard nodes are the three forms of energy heterogeneity that have been put into use. The optimum CH is determined by a fitness function which considers five fitness metrics: average energy, number of neighbors, energy remaining, and energy consumption rate. Several existing algorithms were beat by the GAPSO-H because it was more stable.

e) Other Parameters

Since most published works only briefly touch on context outside of the CH selection process, we focused here on describing a few hybrid metaheuristic methods to CH selection. A uniform network topology with fixed nodes is used throughout the following literature; this is often called the "default" topology.

Determine the best candidates for CHs in each cycle to maximize energy efficiency and service life. To choose CHs in WSNs, the authors of [101] offer a teaching-based learning-optimization (TLBO) approach using a variant of the LEACH protocol (LEACH-T). The TLBO algorithm is based on a teacher-and-student paradigm of learning. In the CH selection phase, TLBO is enhanced with genetic crossover and mutation operators to speed up convergence. When determining the CH, we look at the fitness function, which is a measure of how much power is used during data transmission. Compared to classic LEACH, LEACH-T has better throughput and a higher number of active nodes.

Clustering algorithms have been extensively used in WSNs to achieve high energy savings and extend the network lifespan. In [102] the authors suggested hybrid method combines Low-Energy Adaptive Clustering Hierarchy (LEACH) with the Monkey Search (MS) algorithm, called as LEACH-MS. The suggested strategy is based on the traits that both the LEACH and MS algorithms share. According to the simulation findings, the LEACH algorithm works better early on because it has a greater value for the first node death, but the MS approach performs better overall because it gives optimum CH election. Hence, in the hybrid method, the LEACH algorithm runs first for a short period of time before being followed by the MS algorithm for the remaining period, increasing the lifespan of the network. This method's benefit is that it uses the LEACH algorithm's delayed First Node Death capability together with the MS algorithm's optimum CH selection to extend the lifespan and enhance throughput. This method thus produces good results regarding to lifespan, residual energy, and throughput.

In [103], two methods are shown for choosing the best possible CHs. In the first case, we have the Monarch Butterfly Optimization Algorithm, while in the second, we have the Artificial Bee Colony (HABC-MBOA). According to the suggested HABC-MBOA, the worker bee stage of ABC is swapped out for a modified butterfly adjusting operator of MBOA, which maintains a healthy equilibrium between exploitation and exploration. The suggested HABC-MBOA is a starting point for fixing the ABC algorithm's shortcomings in terms of its ability to conduct a worldwide search. The proposed HABC-MBOA further protects CHs from being overwhelmed by an excessive count of sensor nodes. When the ineffective CH election mechanism is put into place, sensor nodes die off rapidly. The active nodes count in the network beat reference CH election methods in simulations.

In specifically, the Hybrid Squirrel Harmony Search (SHSA) method was presented by Lavanya and Shanker in a homogeneous WSN [104]. The SSA learns its natural behavior by keeping track of where squirrels are and how likely it is that a predator is nearby. Utilizing the gliding constant allows one to strike the right mix between exploitation and exploration. Seasonal monitoring means that the solution of the suggested method is not limited to the solutions of regional optimums. As a result of these advantages, the suggested optimization approach achieves better results than the PSO regarding to throughput and residual energy. Results from simulations reveal that the proposed HSHSA is more efficient at conserving energy than the most popular existing CH election methods (PSO, HSA, SSA, LEACH and Direct Transmission).

Data transmissions that minimize power consumption and increase the network's longevity are common applications of the clustering methodology. The authors suggested combining the firefly technique with particle swarm optimization for a more effective result [105]. The hybrid method finds the CHs best and improves the firefly's search behavior as a whole by using PSO. Utilizing the number of living nodes, throughput, and residual energy, the suggested methodology's performance is assessed. The findings point to a longer network lifespan, which boosts the total count of active nodes and decreases overall energy usage. Throughput and residual energy are both improved over the firefly algorithm in this case.

In [106], maximum network lifetime for optimal CH selection (CHS) was sought by proposing Hybrid Grey Wolf Sunflower Optimization (HGWSFO) subject to constraints such as energy consumption and physical distance between nodes. The grey wolf optimization (GWO) method may readily enter a local optimum, and the sunflower optimization (SFO) strategy might have a slower convergence rate. Because of the need to strike a balance between exploitation and exploration, this method is also provided. Sunflower optimization (SFO) is used to search (explore) more thoroughly. When the step-size parameter is changed, the plant moves closer to the sun in search of a more thorough refinement, which makes exploration more efficient. When using grey wolf optimization (GWO) for a limited search (exploitation), the parameter coefficient vectors are needed on purpose to put the focus on exploitation. This strikes a good middle ground between discovery and utilization, boosts energy efficiency, prolongs the lifespan of the network, and improves its performance regarding to throughput, failure rate, network survivability index, energy remaining, and convergence speed. In order to identify the optimal CH, the HGWSFO's objective function makes advantage of energy and distance limitations. In terms of stability and network longevity, HGWSFO outperformed certain current cutting-edge algorithms.

3) Cluster Formation

The metaheuristic methodology employs two well-known cluster generation techniques: CH election through a metaheuristic approach, after employing K-means and uneven clustering, much like nonmetaheuristic algorithms. This part will go into more detail about the cluster creation phase so that you can understand how these common strategies work, which will make network deployment better.

The study in [107][108] published two papers K-means clustering (KC) and unequal clustering (UC) with metaheuristic methods. In these works of literature, it is suggested that decreasing mobile WSN energy usage will increase network lifespan. K-means clustering (KC-PSO) and uneven clustering (UC-PSO) (in the first article) are shown as examples of applications of PSO. The distance between CH and BS, energy remaining, connectivity of neighbors, and mobility measures are considered thoroughly while selecting the CH in UC-PSO. Then, the nodes that make up the cluster form asymmetrical groups such that the CH in the cluster nearest the BS doesn't die quickly. Meanwhile, PSO is utilized to choose the optimal CH after the clusters are initially divided into size-balanced subsets. As shown by the results of the comparison between the two suggested approaches, KC-PSO outperformed LEACH regarding to decreased energy usage and increased network lifespan. The second study suggested using a Genetic Algorithm (GA) for both uneven clustering (UC-GA)and K-means clustering (KC-GA). Both the (KC-GA) and the (UC-GA) use a procedure that is similar to that of the (KC-PSO) and the (UC-PSO). Uneven clusters are first produced in UC-GA before picking the CH; in KC-GA, clusters are divided first before selecting the CH for each division. Both methods use the same parameters to determine the CH. In dynamic clustering situations, the network might be more stable when GA is used. The simulation outcomes demonstrate that KC-GA is outperform to LEACH and UC-GA in regard to reduced energy usage and longer network lifetime. The K-means clustering method outperforms its uneven counterpart in almost every metric we looked at. Although K- means outperforms uneven clustering in terms of performance, implementing K-means may be time consuming, and picking the incorrect k number might have network-wide consequences. Clustering of nodes has evolved as a highly useful strategy for mitigating the primary problem of constructing an energy-efficient network. When clustering is done right, it can make the network last longer, make it easier to grow, and spread the load evenly across the network nodes. The authors presented Metaheuristic Load-Balancing Based on Clustering Technique (MLBCT) [109]. A fitness function has been developed to meet the primary goal of load-balanced clusters by creating clusters that are evenly distributed regarding to energy and size, and in which all members are within a comfortable distance to one another. Cutting down on the price of intracluster communication. Tests and simulations show that the suggested technique MLBCT performs better than existing methods DEBCRP and DE-LEACH regarding to enhanced the lifespan of network and network stability, data packet delivery, and residual energy. In addition, The approach has also been shown to be flexible and scalable by changing the design of the network by changing the nodes number and where the base stations are placed.

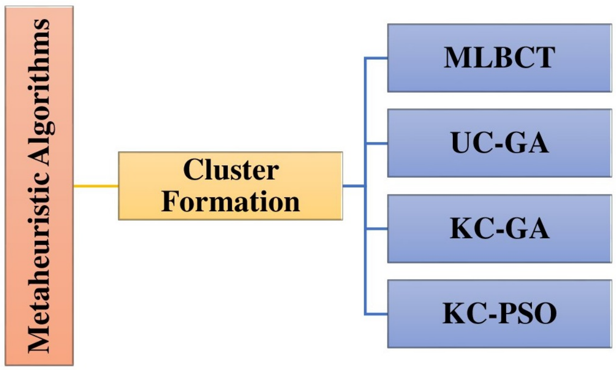

Figure 11. Clustering techniques using metaheuristics: a taxonomy.

4. The Objectives of Clustering Algorithms

Different objectives were explored in the this research based on the desired application, QoS, load balancing, encompassing network Lifetime extension, network connection, data aggregation/fusion, scalability, fault tolerance, etc. Based on the node grouping goal, clustering techniques in WSNs may be divided into several categories. ”Network lifetime extension” is the clustering method’s most common goal. After that, we’ll go through some of the most crucial goals of clustering.

- **Scalability:** Thousands, or even millions, of SNs might be set up in the sensing area, depending on the use case. Scalability in networks may be ensured using techniques like network clustering, which can localize message transmission, reduce the total number of messages sent through the network, etc [110].
- **Fault tolerance:** Hardware failure, latency, interference, and depleted energy are just some of the factors that might affect sensor nodes. There are times when cluster-based protocols are appropriate, such as when nodes in a network are in a hostile environment and cannot be replaced. WSNs must thus be capable of reconfiguring themselves without the aid of humans, notably in hostile environments and inhospitable locales. To protect aggregated data, fault tolerance mechanisms must be taken into consideration at the protocol design phase. Cluster upkeep and CH backup are more practical methods for assuring the whole network rebuilds when CH fails [110].
- **Lifetime:** Growing network lifetime is crucial since nodes have limited bandwidth, energy, and computational capabilities. Optimization of many WSN difficulties, including intracluster communication costs, duplicate data collecting, and constant cluster loads, is typically an essential undertaking. By considering these parameters while selecting CHs, will increase the network lifespan. Also, larger energy routes are preferred for sending data when doing so requires a constant drain on energy across the network and makes the network last longer [110].
- **Data aggregation/fusion:** In data aggregation/fusion, CHs gather information from several nodes and transmit it to the BS. In order to reduce the burden of data transmission on the sensor nodes, redundant information is removed at the CH level by the use of data fusion and/or data aggregation. As a consequence, data fusion and aggregation prolong the lifespan of the whole network while preserving all network energy [110].
- **Robustness:** After the cluster-based WSN has been formed, the cluster maintenance phase begins. It is advantageous to preserve a cluster’s integrity. Network expansion, node relocation, and unanticipated operational faults are just some of the many scenarios it can adapt to. All that is required of clustering methods is to take into consideration the differences between individual clusters. Therefore, cluster upkeep strengthens the network and facilitates topological changes [110].
- **Latency Reduction:** What we mean by ”latency” is the entire length of time requires for a message to transit from its origin node to its final destination node. A routing table is maintained at the CH level in a WSN based on clustering, which speeds up the sending of data packets. The connected dominant set (CDS) provides a predetermined communication route, or ”backbone tree,” which facilitates fast and simple multihop routing in cluster-based networks [110].
- **Secure Data Communication:** Since CH handles data aggregation, malicious nodes could attempt to alter or manipulate data. To stop hostile nodes from joining a clustered WSN, reliable authentication methods must be created. These methods enhance the data’s secrecy and integrity [110].
- **Collision Avoidance:** In a sensor network, each sensor node shares a single channel when it is seen. Because of this, when several nodes transmit data at once, the network’s performance declines, leading to a collision. This is easy to handle in cluster-based WSNs because the CH sets a specific time for each member node [110].

TABLE III. Metaheuristic clustering's comparative examination of simulation settings and environments.

Ref.	CH selection	Data transmission	Sensor type / Mobility	Selection criteria	Packet length	Network dimension / Location of BS	No. of nodes / Initial energy	Hybrid/ nonhybrid	Outcomes
[76] 2017	FFCHSA	Multihop	Homogeneous / Static	The amount of energy used, the percentage of successfully delivered packets, and the latency from beginning to finish.		1250 m x 1250 m	100 / 40J	Nonhybrid	Comparing the suggested algorithm's energy use to those of PSO and GA, the former is shown to be 20% more efficient.
[85] 2017	INSPSO	Multihop	Heterogeneous / Static	Distance and energy remaining	4000 bits	500 m x 500 m / (500,250)	300, 400, 500/Gateway=10J Nodes=2J	Nonhybrid	Comparing the suggested algorithm's energy use to those of PSO and GA, the former is shown to be 20% more efficient.
[90] 2017	WOA-C	N/S	Homogeneous / Static	The total energy of neighboring nodes, and the node's remaining energy.	500 bytes	100m x 100m / (50×50), (100×100), (50×200)	100, 300, 500 / 0.5J	Nonhybrid	Energy efficiency drops for LEACH, LEACH-C, and PSO-C
[101] 2017	LEACH-T	N/S	Homogeneous / Static	Residual energy	4000 bits	100 m x 100 m /inside the sensor field	100 / 0.5J	Hybrid	By decreasing the amount of energy needed to send each packet, the method extends the lifespan of the network.
[102] 2017	LEACH-MS	N/S	Homogeneous / Static	Distance and energy remaining	256 bytes	100 m x 100 m / (-50,150)	150 / 0.5J	Hybrid	LEACH, Monkey Search, and Hybrid achieved improvements of 0.0408, 2.194, and 5.8551 in residual energy, respectively.
[81] 2017	FCR	Single hop	Homogeneous / Static	Energy, distance, and delay		100 m x 100 m / (50,50)	N node / 0.5J	Nonhybrid	FCR algorithm for maximizing energy production in every single round
[67] 2018	BeeWSN	N/S	Homogeneous / Mobile	Degree, velocity, direction, and node's energy that remains.	175 bytes	3000 m x 3000 m x 3000 m / (100,100), (150,50), (200,200)	¡200 / N/S	Nonhybrid	Compared to New LEACH and ANP, the suggested BeeWSN performs better.
[108] 2018	KC-GA UC-GA	Multihop	Homogeneous / Static	Distance from sensor node to BS, connectivity degree, mobility factor, and Node residual energy.	512 bytes	100 m x 100 m / (50,175)	200 / 2J	-	Based on the simulation findings, KC-GA used less energy than UC-GA (1.65 J) and LEACH (1.71 J) when starting with 200 nodes and 2 J.
[107] 2018	KC-PSO UC-PSO	Multihop	Homogeneous / Static	Mobility measure, energy remaining, the connectedness of neighboring nodes, and the separation between the CH and the BS.	512 bytes	100 m x 100 m / (50,175)	200 / 2J	-	When compared to UC-PSO and LEACH, KC-PSO has superior performance in terms of lowering energy usage and increasing the lifespan of the network.
[75] 2019	BICIoD	Multihop	Homogeneous / Mobile	Position of the drones and Residual energy level.		1000 m x 1000 m, 2000 m x 2000 m, 3000 m x 3000 m	15, 20, 25, 30, 35 / 80Wh	Nonhybrid	By comparing the results of their latest optimization to those of ant colonies and grey wolves, they find that they have reduced energy use by 23% and 33%, respectively.
[77] 2019	SSMOECHS	Multihop	Both / Static	Node distribution, distance, node energy	800 bytes	100 m x 100 m / (-50, 150)	100 / 1J, (0.5-1 J)	Nonhybrid	Using SSMOECHS often results in a 1.8%, 34.6%, 7.1%, and 13.4%, increase in Network lifespan and stability periods.
[66] 2019	MO-GSA	Single hop	Homogeneous / Static	Remaining energy and Distance of nodes to their corresponding CH.	800 bytes	100 m x 100 m / (50, 175)	100 / 0.5J	Nonhybrid	There would be an 18% improvement in network lifespan compared to LEACH-C, LEACH, and PSO-C.
[82] 2019	IAPSO	Single hop	Homogeneous / Static	energy consumption balance degree and Residual energy ratio	500 bytes	500 m x 500 m / (-250,250)	100- 200 / 2J	Nonhybrid	When we tested the IAPSO-CHSO on networks of varying sizes, we found that 70% of the sensor nodes survived the first 700 rounds.
[111] 2019	GAOC	Single hop	Heterogeneous / Static	Densities of nodes, residual energies, and distances to sinks.	2000 bits	100 m x 100 m, 500 m x 500 m	100, 200 / 0.5J	Nonhybrid	With GAOC, network lifespan is improved by 33.48% and 6.22% compared to DCH-GA, and TEDRP, respectively.

TABLE III – *Continued on next page*

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[86] 2019	EC-PSO	Multihop	Heterogeneous / Static	Network nodes located near power plants	125 bytes	1000 m x 1000 m /(500,500)	400 / 0.5J	Nonhybrid	on comparison to other PSO algorithms, EC-PSO uses less power and lasts longer on the network.
[91] 2019	GA based clustering	N/S	Homogeneous / Static	Lowest distance to BS Highest and residual energy.	4 bytes	100 m x 100 m /(50,50)	40 / 1000J	Nonhybrid	Results from computer simulations show that GA-Clustering is superior than LEACH and K-Means.
[93] 2019	MCRO-ECP	N/S	Homogeneous / Static	Intra-cluster distance, CH node degree, base station distance, Neighbor node distance and ratio of energy.	512 bytes	400 m x 400 m /(50,50)	200, 400, 600, 800 / 2J	Nonhybrid	MCRO-ECP performs better than CRO-ECA, DECA, GALBCA, GLBCA, LDC, and PSO-C, by a combined margin of 17%, 11.8%, 6.20%, 20.6%, 23.5%, and 27.1%, respectively.
[98] 2019	SAGA	Single hop	Homogeneous / Mobile	Residual energy and distance	780 bytes	1000 m x 1000 m	150 / 10J	Hybrid	In comparison to the MEGA protocol, the suggested SAGA protocol reduces energy usage by 0.851%
[103] 2019	HABC-MBOA	N/S	Homogeneous / Static	Network-extracted distances between clusters, distances to cluster centers, and energy left behind after clusters have been broken apart.	512 bytes	400 m x 400 m /(200,200)	1000 / 0.5J	Hybrid	It was found that the network's total number of living nodes was 18.92% higher than using the reference cluster head selection methods.
[104] 2019	SHSA	N/S	Homogeneous / Static	Separation energy And Energy.	512 bytes	100 m x 100 m	100 / 0.5J	Hybrid	With HSHSA, the WSN's residual energy and throughput have improved by 85.69% and 31.02%, respectively..
[78] 2020	PBC-CP	Multihop	Homogeneous / Static	Node degree, node energy, and distance from the base station are all considered.	512 bytes	100 m x 200 m /(50,150)	100 / 0.5J	Nonhybrid	4r in LEACH loses 52.27% of its value after 380 rounds when compared to the other methods.
[79] 2020	Memetic algorithm	Multihop	Homogeneous / Static	Residual energy, Node degree and intracluster communication cost.	500 bytes	400 m x 400 m /(0,0)	200 / 2J	Nonhybrid	When compared to already existing schemes, the suggested scheme's average energy usage grows more slowly as the number of cycles rises from 500 to 3000 in increments of 500.
[87] 2020	TGDEEC	Multihop	Heterogeneous / Static	distance and Residual energy		100 m x 100 m /(50,50)	50 / 0.5J	Nonhybrid	In practical applications, TGDEEC outperforms DDEEC and TDEEC.
[88] 2020	SBHRA/ ABC	Single hop	Heterogeneous / Static	Residual energy and distance	500 bytes	400 m x 400 m	400 / 0.5J	Nonhybrid	When compared to the improved Stable Election Protocol (E-SEP), the stability period provided by SBHRA is 55.88% longer, and the typical node's lifespan is extended by 64.04%.
[95] 2020	YSGA	N/S	Homogeneous / Static	CH's leftover energy and the distance between CH and the BS.	500 bytes	100 m x 100 m /(50,50)	100 / 0.07J	Nonhybrid	When reporting residual energy, 100% of the value is used for round 0 and 0% for the last round.
[99] 2020	ECHSR	Multihop	Homogeneous / Static	network coverage (NC), the residual energy of CH and cluster closeness (CC)	512 bytes	100 m x 200 m /(50,150), (100,100), (0,100), (50,200)	100 / 0.5J	Hybrid	Relative to LEACH, TPSO-CR, and PSO-HSA, the improvement in residual energy is on the order of 1.70–1.77, 1.24–1.46, and 1.04-1.42 times.
[100] 2020	E-LEACH	Multihop	Homogeneous / Static	centrality as input and D-PSO takes distance	512 kilobytes	1000 m x 1000 m /(500,500)	50 / 100J	Hybrid	Decreased efficiency is a direct outcome of the rise in packet loss. When compared to the LEACH protocol, E-LEACH reduces packet loss by around 12%.
[112] 2020	CPMA	Single hop	Homogeneous / Static	energy distribution ratio and Total energy cost	500 bytes	200 m x 200 m /(100,100),	100 / 1J	Hybrid	In case 1, CPMA is superior than HSACP, PSO-C, and Leach-C by 11%, 8%, and 6%; in case 2, by 43%, 42%, and 51%; and in case 3, by 38%, 37%, and 72%, respectively.

TABLE III – *Continued on next page*

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[106] 2020	HGWSFO	N/S	Homogeneous / Static	Distance and energy		200 m x 200 m	100 / 0.5J	Hybrid	When compared to GWO, SFO, and PSO, the proposed HGWSFO achieves higher overall performance of 28.58 percent, 31.53 percent, 48.8 percent, 49.67 percent, 54.95 percent, 70.7 percent, and 87.10 percent, respectively.
[105] 2020	HFAPSO	N/S	Homogeneous / Static	average distance and Energy	500 bytes	100 m x 100 m /(50,175)	100 / 1–5J	Hybrid	With residual energy values of 158.32, 32.97, and 144.89, respectively, the HFAPSO outperforms the LEACH-C and Firefly algorithms.
[113] 2021	GAPSO-H	Multihop	Heterogeneous / Static	Mean energy, node degree, distance, energy, and rate of energy consumption.	250 bytes	100 m x 100 m, 500 m x 500 m	100, 200 / 0.5J	Hybrid	GAPSO-H has been shown to extend the stability of a system by 5.5%, 14.9%, 44.3%, 39.5%, 44.8%, and 72.6% when compared to PSOECSM, PSO-UFC, GADA-LEACH, GADA-LEACH, PSOBS, GABEEC, and DCH-GA.
[83] 2021	FA-ROA	Single hop	Homogeneous / Static	Temperature, Energy, delay, distance and load.		100 m x 100 m /(50,50)	100 / 0.5J	Nonhybrid	At the 500th iteration, the network's energy performance was 66.66% better than ABC-GSA, GSA, PSO, GA, and ABC, and 1.02% better than ROA, respectively.
[92] 2021	TSBOA	multi-hop	Heterogeneous / Mobile	Throughput and residual energy		X and Y coordinates of sink 0.5	50,100 / 0.6J	Nonhybrid	Measures of performance showed that TSBOA was superior, including residual energy of 0.1118J and throughput of 82.101%.
[84] 2021	GWO	Single hop	Heterogeneous	Dead node count, living node count, and remaining energy.	4,000 bytes	100 x 100 m /(100,100)	100 / 0.55J	Nonhybrid	As a result of its superiority in cluster head selection, this GWO algorithm also contributes to extending the life of the underlying network.
[80] 2022	ChOA-HGS	multi-hop	homogeneous / Mobile	Energy efficiency	4 Kbits	200m x 200m	300 / 0.5J	Nonhybrid	The ChOA-HGS model outperforms the alternatives. When compared to the ChOA-HGS, which occurs at 2144 rounds, the FND in the LEACH occurs at 799 rounds.
[68] 2022	CRO	multi-hop	homogeneous / Mobile	threshold RSSI and reduce the number of beacon transmission,	256 bytes	1000 m x 1000 m /random locations in MANET	100–150 / 180J	Nonhybrid	At a node distance of 150 meters, the suggested CRO saved 2.9J of energy, 98 PDR, 0.6 average packet delay, 22 average path life time, and 1200 PDR in routing overhead.
[109] 2022	MLBCT		homogeneous / Static	Energy distribution, nodes' distribution, and nodes' proximity.	4000 bits	100m x 100 m /(50,50), (50,150)	50, 100, 150, 200 / 0.1J	Nonhybrid	In a perfect world, simulation findings show a 51.85% increase in network lifespan across all network topologies.

- **Data Communication Assurance:** The base station may receive aggregated data from CH through single-hop or multihop routing. Because of its high frequency, recent research has focused on data leakage in wireless systems. To avoid this, a mobile node will coordinate with its CH to issue a combined request before establishing a data connection. Sender nodes carry on data transmission if they get the acknowledgement message; otherwise, they presume they have been detached from the network and must reconnect. The network starts sending data to the parent node when a disconnected node is rejoined. So, for data transfer to work, it is important for member nodes and their CH to be able to talk to each other [110].
- **Efficient Quality of Services (QoS):** QoS is essential for network applications and WSN capabilities (QoS). Quality of service characteristics that matter include those that improve performance all the way through. It is challenging for cluster-based protocols to meet all of the QoS parameter requirements. Depending on the needs of the application, evaluating one or more QoS factors may necessitate making a trade-off. The quality of service (QoS) is less of a concern for modern cluster-based protocols. Healthcare, military, and event monitoring are just a few of the real-time application domains that take QoS considerations into account [110].

5. Conclusion

This article has been developed in an attempt to make it easier to examine clustering techniques that have been suggested for WSNs. This article discusses a number of meta-heuristic and non-heuristic methods used in networks across a variety of contexts to choose CH and form clusters, and provides a complete overview of the state-of-the-art methods. Energy-efficient clustering techniques and the elements that affect them have been highlighted. This may be used as a benchmark against which to measure the efficacy of current clustering methods and as a starting point for developing new, more power-efficient approaches. We've looked at several current clustering procedures and compared them based on the criteria we just specified. We found that meta-heuristic-based algorithms, in particular, help centralized protocols produce optimal clusters in terms of both number and size. They also contribute to picking the best cluster hubs (CHs) that include neighboring nodes. This allows for direct communication between nodes and their CHs, while a straightforward energy-aware technique is employed to transmit data from the CHs to the BS. The initialization message the nodes send to the BS with network information and the message the BS broadcasts to notify the established clusters are the two main contributors to the total cost of implementing such a centralized system.

As a future suggestion for this work is to compare and contrast the efficacy of various meta-heuristic algorithms (bats algorithms, SA, PSO, GA, etc.) and fuzzy-logic approaches to the clustering issue. By doing so, the most effective strategy for clustering in terms of energy efficiency may be determined.

Acknowledgment

My sincere appreciation goes out to Assist Professors Dr. DALAL and Dr. SEHAM, my research supervisors, for their kind advice, endless enthusiasm, and insightful criticisms.

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Mohammed Saleh Mutar received his B.Sc. in Computer Techniques Engineering in 2017 from Al-Mustaqbal University College. He is currently studying to complete his master's degree in computer techniques engineering from the College of Electrical Engineering Technical, Middle Technical University. His research interest include computer networks, wireless Sensor networks, and IoT.

Assist. Prof. Dr. Dalal Abdulmohsin Hammood. Received the B.Sc. degree in computer engineering and information technology from the University of technology Baghdad in 2003, and the M.Sc. degree in computers engineering techniques from the college of electrical engineering technical, Middle Technical University, in 2011. Shewas the Ph.D, with the faculty of electronic engineering & technology (FKTEN) Universiti Malaysia Perlis (UniMAP). She graduated on Nov. 2020 to get Ph.D. She is IEEE member Malaysia section. Her research interest include computer networks security, wireless body area networks, and image processing.

Seham Ahmed Hashem. Doctor of Engineering Ph.D. (Assistant Professor) received her BSc, MSc, and Ph.D. from the University of Technology-Baghdad in 1996, 2000, and 2005, respectively. She is a full-time lecturer at Middle Technical University, Technical Instructors Training Institute, and Technical Electronic Department, Iraq, Ministry of Higher Education and Scientific Research. She has been a senior researcher at the Center for Iraqi Development since 1986. She has good skills in designing and modeling soft computing systems, image processing, and communication. She has published more than 20 research papers and attended many international conferences.