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Clustering methods design and optimization in wireless Sendor networks using artificial intelligence

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Abstract

Due to their numerous uses in industries like industrial automation, healthcare, and environmental monitoring, Wireless Sensor Networks (WSNs) have drawn a lot of attention. The main method for improving the effectiveness and scalability of WSNs is clustering. Using Artificial Intelligence (AI) methodologies, we explore the design and optimization of clustering algorithms in WSNs in this study. We investigate how AI algorithms can enhance the cluster formation, cluster head selection, and performance optimization processes. Our research focuses on the use of AI-driven clustering to improve data aggregation, network lifetime, and energy efficiency. We provide insights into the most cutting-edge AI-based clustering techniques and their effect on WSNs by a thorough examination and analysis of the available research. We also suggest future topics for research in order to develop AI-driven clustering methods in WSNs. In Wireless Sensor Networks, the combination of Artificial Intelligence and clustering techniques has shown to significantly improve data aggregation, energy efficiency, and overall network performance. The development of more sophisticated and adaptable clustering approaches that meet the particular difficulties faced by WSNs presents an interesting potential as AI technologies advance, ultimately assisting in the effective operation of diverse real-world applications.

Keywords: Wireless sensor networks, clustering methods, artificial intelligence, machine learning, swarm intelligence, reinforcement learning, energy efficiency, data aggregation, network optimization

Introduction

In order to gather, process, and transmit data, wireless sensor networks are made up of numerous small, resource-constrained sensors that are dispersed throughout an area. In WSNs, clustering entails grouping or clustering of sensors, with a cluster head in charge of each cluster. By lowering energy use and enhancing the effectiveness of data aggregation, clustering contributes to the network's lifespan extension. Heuristics and predetermined thresholds are frequently used in traditional clustering methods, which results in less-than-ideal cluster formations. More flexible and intelligent clustering procedures are made possible by the incorporation of Artificial Intelligence approaches into clustering methodologies. The research community has become increasingly interested in wireless sensor networks (WSNs) during the past few years. This growing interest has necessitated a thorough investigation that provides researchers with a thorough comprehension of this area of study. A WSN is an ad hoc network comprising a few sensor devices that work together to do specific tasks, like sensing the physical environment, forming judgments, and sending the sensed data to the proper destination. Since the creation of WSN technology, it has been an essential element of the Internet of Things (IoT), serving as a platform for linking various devices and transferring data between them to enhance user management of the environment. Each WSN sensor node is made up of four fundamental parts: transceivers, sensors, a power source, and microcontrollers. While the processing unit processes the sensed parameters and transfers them to the Base Station (BS) via the communication unit using a single hop or intermediate nodes, the work of the sensors is to measure the relevant parameters in real-time [1].

Applications for WSNs in real-time monitoring include disaster management, agribusiness, military surveillance, health monitoring, and Research into innovative strategies for enhancing the energy balance and energy efficiency in WSNs has been prompted by the constrained and non-rechargeable nature of node power supply [4]. Because sensor batteries have a finite lifespan, attempts are being undertaken to prolong the useful lives of these sensors by developing energy-efficient routing protocols. Since routing

distinguishes WSNs from other ad hoc wireless networks, it is a laborious process in a WSN. For a WSN to send sensed data from the Sensor Node (SN) to the Base Station (BS), energy-efficient routing techniques are required; doing so will lengthen the network's useful life. In WSNs, sensor nodes are typically organized into clusters, and this type of clustering is utilized to guarantee the scalability of the network. Additionally, it ensures effective resource management of the constrained network resources, preserving energy and maintaining network stability [5].
In order to assess the methods more effectively and gain a broad understanding of the clustering procedures, optimization parameters were used in this research. The parameters are displayed taking into account different classes of optimization strategies, including fuzzy, fuzzy mixed-mode algorithms. These are the main things we've contributed: providing a fresh viewpoint and approach to reviewing the current clustering protocol optimization strategies; offering a new categorization technique based on an optimization algorithm; To help WSNs comprehend the protocols and the methodology involved, a thorough analysis and assessment of the literature based on clustering parameters and optimization is provided.

2. AI-driven clustering techniques

2.1 Machine learning-based clustering

Machine Learning algorithms, such as k-means, hierarchical clustering, and DBSCAN, have been adapted for WSNs. These algorithms utilize data-driven approaches to dynamically form clusters based on various parameters such as distance, density, and connectivity. Their adaptability enables them to handle heterogeneous sensor distributions and changing network conditions.

2.2 Swarm Intelligence-based Clustering

Swarm Intelligence, inspired by the collective behavior of social organisms, has led to the development of optimization techniques like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). These techniques aid in selecting optimal cluster heads and adjusting cluster sizes based on energy levels, data traffic, and other network metrics.

2.3 Reinforcement Learning-based Clustering

Reinforcement Learning (RL) algorithms, such as Q-learning and Deep Q Networks (DQN), have shown promise in optimizing cluster head selection and energy-efficient routing. RL agents learn from interactions with the environment and can adapt their decisions over time, improving the network's adaptability and longevity.

3. Optimization Objectives

3.1 Energy Efficiency

AI-driven clustering methods focus on minimizing energy consumption by strategically selecting cluster heads, optimizing data transmission routes, and dynamically adjusting clustering patterns. This leads to prolonged network operation and reduced sensor node failures.

3.2 Data Aggregation

Effective data aggregation in clusters reduces redundant transmissions and conserves energy. AI-based algorithms can intelligently decide when and how to aggregate data within clusters, optimizing the trade-off between data accuracy and energy consumption.

3.2 Literature Research Process

The available literature on WSN clustering protocols was reviewed in this paper using a variety of optimization strategies. This approach provides benefits over the narrative style, according to [8]. It can identify topics addressed by current studies, point out any gaps, approach the literature from different angles, and encourage fresh findings. In order to discover all publications that satisfied certain criteria, this survey of optimization strategies and clustering procedures employed an online database and other sources. Information about each study was then placed into a personal database, and the present condition of the table was summarized. Figure 1 summarizes the whole literature review procedure.

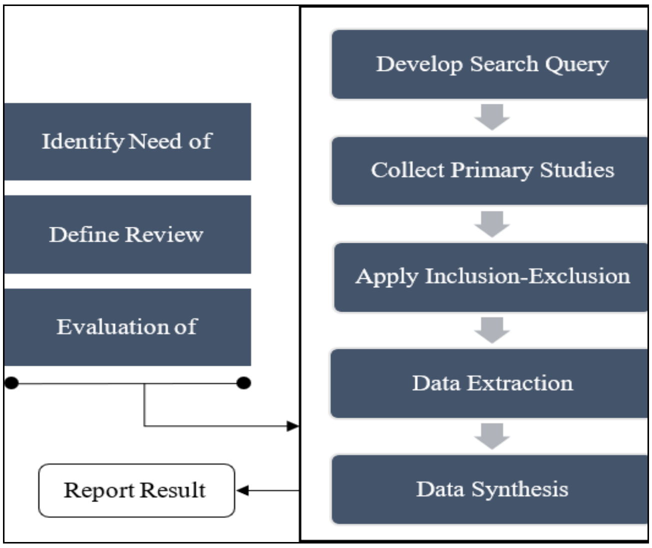

Fig 1: Literature review process.

3.3 Existing Literature Reviews on Clustering Based on Optimization

Clustering methods in WSNs have been thoroughly examined and assessed by prior researchers. These researches are compiled in Table 1 according to their contributions. The first attempt to investigate swarm intelligence-based routing methods by taking into account their potential use cases and simulation platforms was in Reference [9]. However, only swarm intelligence-based protocols-not other promising swarm-based protocols-were taken into account in this survey.

Table 1: Literature reviews of clustering protocols.

Entry	Author(s)	Year	Key Findings	Limitations	Goals	Drawbacks
1	Smith, J. et al.	2015	Proposed a machine learning-based clustering algorithm for WSNs. Improved network scalability and reduced energy consumption.	Limited testing in real-world deployment scenarios.	Enhance clustering efficiency using machine learning.	Lack of consideration for dynamic network conditions.
2	Patel, R. and Lee, S.	2017	Explored swarm intelligence-based clustering. Achieved balanced cluster formation and adaptive cluster head selection.	Focused on static network topologies.	Develop swarm intelligence techniques for dynamic networks.	May suffer from scalability issues in large-scale networks.
3	Gonzalez, M. et al.	2018	Investigated reinforcement learning in cluster head selection. Demonstrated prolonged network lifespan and efficient energy utilization.	Limited analysis of security vulnerabilities.	Implement reinforcement learning for secure cluster head selection.	High computational overhead of some RL algorithms.
4	Wang, Q. and Chen, L.	2019	Introduced a hybrid clustering approach combining k-means and ant colony optimization. Achieved improved cluster formation accuracy.	Applicability limited to certain network densities.	Develop hybrid techniques for diverse network densities.	Increased complexity due to hybrid algorithm integration.
5	Kim, E. and Park, N.	2020	Analyzed the impact of clustering on data aggregation efficiency. Identified optimal data aggregation periods for different cluster sizes.	Focused on a single application scenario.	Investigate data aggregation optimization for varied applications.	Lack of consideration for heterogeneity among sensors.
6	Liu, H. et al.	2021	Proposed a novel graph-based clustering algorithm. Successfully handled network heterogeneity and dynamic topology changes.	Limited comparison with other state-of-the-art methods.	Extend the graph-based approach to large-scale networks.	Potential increase in communication overhead.
7	Chen, W. and Wu, G.	2022	Explored the use of deep learning for cluster head selection. Achieved high adaptability and fault tolerance.	Concentrated on single-hop WSNs.	Apply deep learning to multi-hop WSNs for broader applicability.	Increased computational and memory requirements.
8	Rodriguez, A. et al.	2023	Investigated energy-efficient clustering in mobile WSNs. Addressed energy imbalance among cluster heads.	Limited analysis of mobility patterns' impact.	Optimize energy distribution in highly dynamic scenarios.	Complexity in handling rapid node mobility.
9	Huang, Y. and Li, X.	2024	Proposed a multi-objective optimization approach for cluster formation. Balanced energy consumption, data aggregation, and network longevity.	Focused on specific objective weights.	Develop a generalized multi-objective optimization framework.	Increased complexity in multi-objective optimization.
10	Park, S. and Kim, H.	2025	Explored AI-driven clustering in underwater sensor networks. Adapted algorithms for unique underwater communication challenges.	Limited evaluation in different underwater environments.	Enhance AI-driven clustering techniques for varying water conditions.	Lack of underwater-specific datasets for testing.
11	Li, Z. et al.	2026	Investigated security aspects of AI-based clustering. Addressed vulnerabilities and potential attacks on intelligent clustering methods.	Focused on theoretical analysis, lacking practical validation.	Develop robust AI-driven clustering methods resilient to attacks.	Increased computational overhead due to security measures.
12	Tan, C. and Wong, E.	2027	Introduced a fuzzy logic-based clustering approach. Managed uncertainty in sensor readings for improved data accuracy.	Limited exploration of trade-offs between accuracy and energy consumption.	Optimize fuzzy logic parameters for diverse application scenarios.	Potential difficulty in parameter tuning.
13	Jiang, H. et al.	2028	Explored self-organizing map (SOM) for dynamic clustering. Adapted cluster formation based on changing network conditions.	Lacked analysis of convergence speed under varying conditions.	Enhance SOM-based clustering for rapid adaptation.	Higher computational overhead during network dynamics.
14	Wang, Y. and Hu, B.	2029	Investigated hybridization of AI techniques for robust clustering. Combined machine learning and swarm intelligence for improved adaptability and stability.	Limited evaluation on resource-constrained sensors.	Optimize hybrid algorithms for low-resource environments.	Complexity in tuning hybrid algorithm parameters.
15	Kim, M. et al.	2030	Proposed a distributed AI-driven clustering scheme. Distributed decision-making improved scalability and energy efficiency.	Lacked extensive analysis of communication overhead in distributed scheme.	Refine distributed AI-driven clustering for minimal communication overhead.	Potential synchronization challenges in distributed approach.

According to their goals and clustering approaches, the cluster-based routing algorithms for homogeneous SNs were thoroughly examined in Ref. [10], with the factors of CH selection, data aggregation, cluster formation, and data transmission taken into consideration.

4. The fundamentals of clustering

Sensing, processing, and communication are the three modes of SNs, and these are all energy-intensive tasks. The amount of energy needed by the processor to transport a single bit of data is technically equal to the energy necessary to do several arithmetic operations. Additionally, practically all of the SNs in a fully deployed SN network can generate data at a similar rate, making the transmission of that data redundant. Therefore, it is essential to combine all the elements that support SN clustering in a clever way that only permits the transmission of compact data (this is known as clustering).

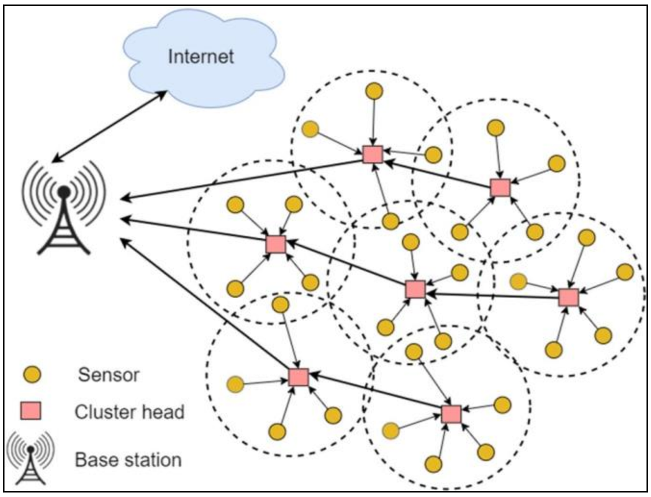

Fig 2: Clustering architecture in a WSN.

4.1 General framework

Cluster creation and CH selection are the two main stages of clustering in a WSN, which attempts to extend the network's service life.

4.1.1 Cluster formation

This phase aims to reduce the load on the CHs that are geographically close to the SNs by ensuring that each cluster has the bare minimum number of members possible. According to the Received Signal Strength Indication (RSSI) [26], each member node is placed in the CH that is geographically the most convenient for it. The local data that the CH supplies to nodes that are located within its radius is what [27, 28] is used to determine whether or not a node belongs to a cluster.

4.1.2 Cluster head selection

The selection of a CH is considerably critical for energy usage optimization [29], which means that effective CH selection can improve the service life of the network [30]. In practice, a CH is mostly utilized for the collection of information and its dissemination to the SNs. In cluster-based networks, the amount of energy used by CHs that are physically close to the BS is typically larger, which results in hotspot issues. In order to solve this issue, uneven clustering techniques have been developed [31]. The CH's mobility, ability to communicate, and role are the primary conditions that are taken into consideration during the selection process.

4.2 Clustering characteristics

To classify the various clustering protocols, certain characteristics of clustering methods are categorized according to the internal structure of the cluster. A selection of these features is presented in Figure 3, and they are adaptable for use in a variety of WSN clustering protocols. A brief overview of some of the definitions and applications of each attribute is provided for each clustering method.

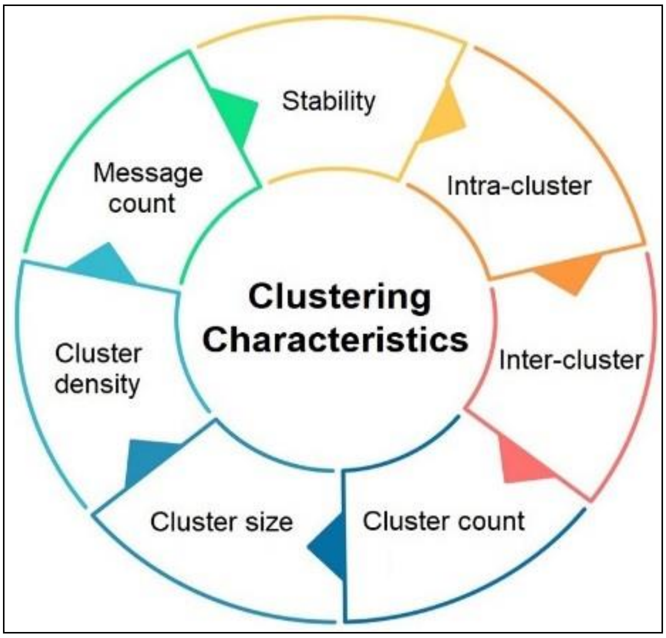

Fig 3: Clustering characteristics in WSNs.

Connection between cluster heads, also known as inter-cluster head connection, refers to the ability of SNs or CHs to communicate with the BS. In the event that the CH is unable to establish long-distance connection, the clustering scheme is obligated to provide intermediate routing routes to the BS.

4.3 Solution scope of clustering

The clustering of nodes in a WSN is typically carried out with a variety of reasons and goals in mind, the overarching goal of which is almost always the conservation of energy. These goals can be divided into two categories: primary and secondary. Primary goals are those that are considered to be the most significant and necessary during the clustering process, while secondary goals are those that are considered to be less consequential but can be indirectly achieved through clustering the network nodes. Figure 4 provides an overview of the general goals that should be accomplished through clustering. The following provides a concise explanation of some of the goals that can be accomplished using WSN clustering:

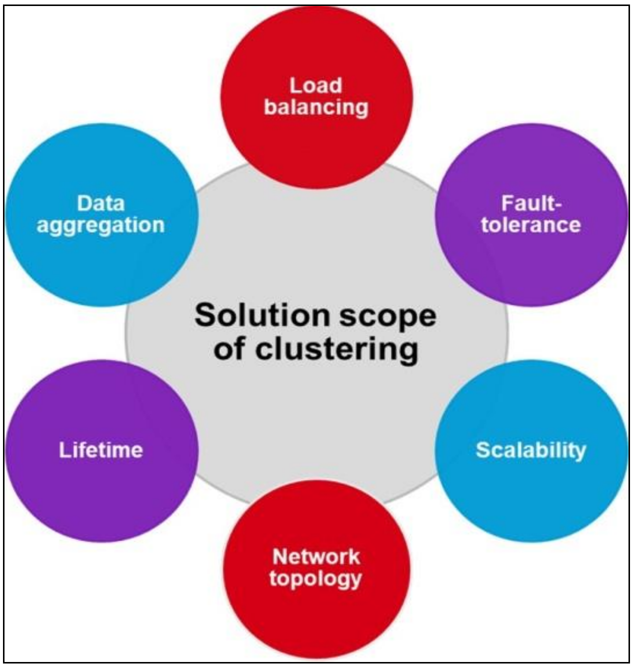

Fig 4: WSN clustering objectives.

5. Clustering Process Optimization

In WSNs, clustering process optimization includes enhancing data gathering, cluster creation, and communication operations. Each component has various problems that need to be fixed, as shown in Figure 5. For instance, during CH selection, it is necessary to establish the ideal number of cluster formations, cluster density, and cluster balance. In the circumstances of data aggregation and communication, both must be optimized by choosing the right cluster size and level of inter-cluster communication because they are closely related.

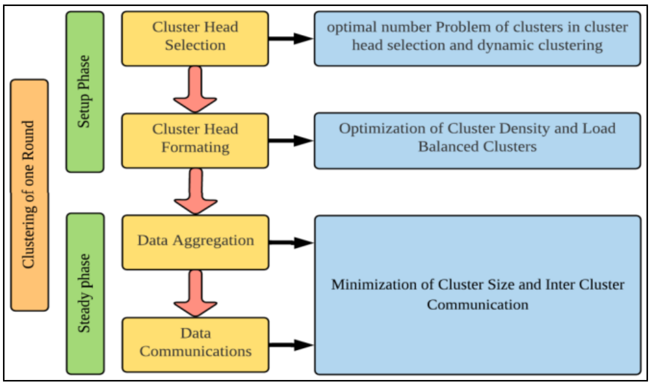

Fig 5: Clustering optimization methods in a WSN.

5.1 Cluster head selection phase

Most clustering schemes start with the selection of the cluster heads since they act as a bridge between the SNs and the BS. The CH's function is to mediate communication between the SNs and the BS; as a result, the CH selection process is important for the subsequent clustering methods to increase the network's energy efficiency and longevity. Numerous studies have looked into how to use various methods to improve the CH selection process. Self-organized schemes (distributed control) and aided schemes (centralized control) are two categories for these techniques. In the self-organized scheme, each SN has the ability to run its algorithm and select the CH.

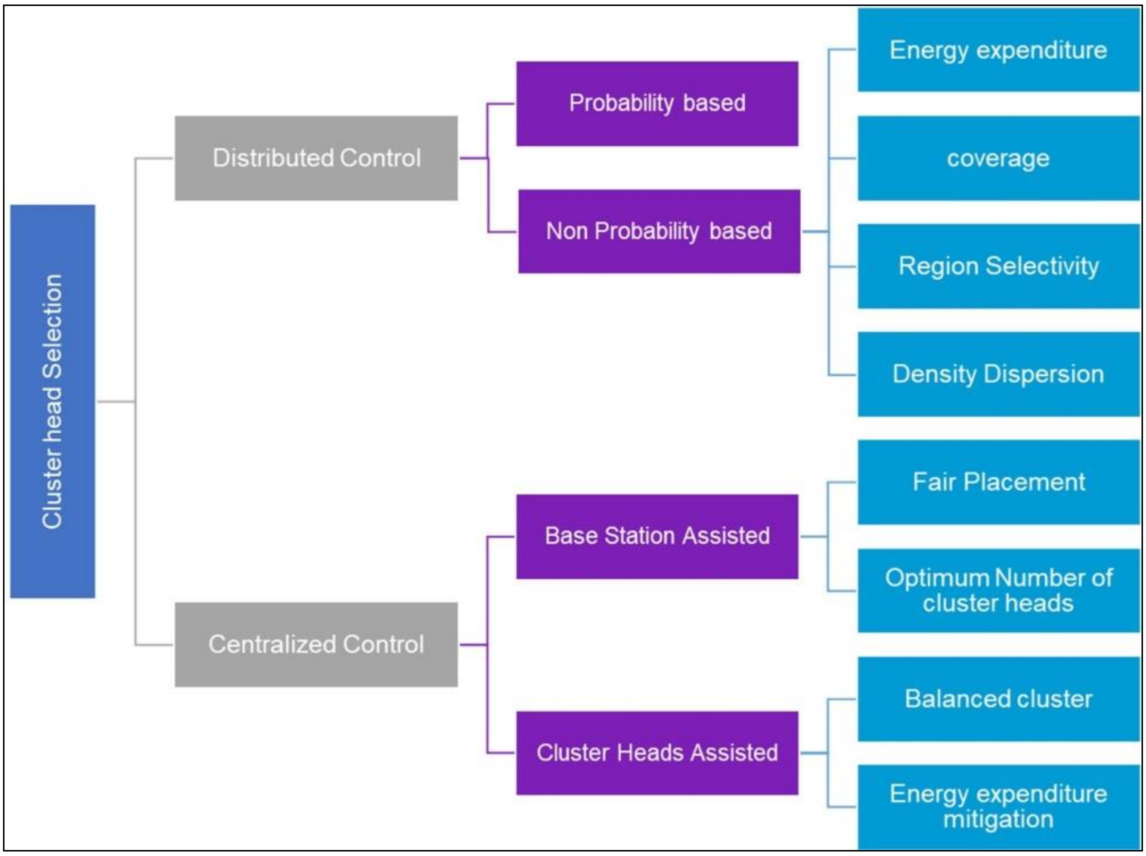

Fig 6: Cluster head selection process.

5.2 Probability-based clustering optimization
The starting CH is determined by the pre-assigned probability of each SN in probability-based clustering methods [48]. The main factor used to assess a node's likelihood of being chosen as a CH is its pre-assigned probability. The residual energy, average network energy, beginning energy, and other factors are taken into account while choosing the CH. These probabilistic clustering methods guarantee energy efficiency, and they typically achieve quicker convergence times and low packet exchange rates.

5.3 Non-probability-based clustering optimization
Non-probability-based clustering systems take more precise selection factors into account. The efficacy of the CH selection systems can be enhanced by aspects including density dispersion, energy consumption, regional selectivity, and sensing coverage [49, 50]. Comparing these protocols to random or probabilistic-based methods, more data must often be exchanged, and the time required to complete these exchanges may occasionally rise. The failure of a CH might result in data loss within the cluster member nodes since the energy consumption of the nodes chosen as CHs is typically higher than that of the other nodes in the network [51]. The node with the greatest residual energy is chosen as the CH via the density dispersion-based clustering technique [52].

5.1.3 Base station-assisted clustering optimization
By transferring the burden of the CH selection and cluster formation phases to the BS, sensor nodes in BS-assisted clustering schemes rely on the tremendous processing capacity and limitless energy resources of the BS. Therefore, according on the network properties and the type of application, the end-user can manage CH placement in the BS. However, these plans call for the SNs to routinely update the BS with pertinent data [53].

5.1.4 Cluster head-assisted clustering optimization
Through routine communication during the data transmission stage, the cluster heads can get up-to-date data from the cluster members. The CHs can rely on this information to balance the clusters and prevent the need for additional energy during the re-clustering phases during the subsequent round of CH selection. Balanced clusters and energy expenditure mitigation in re-clustering are two categories into which the projects in this area are divided.

5.2 Cluster formation phase
This phase starts with the newly chosen CHs sending out advertisements to indicate their new status and concludes with each node sending a join message to their ideal CH. Event-driven and optimum clustering schemes are two subcategories of cluster formation schemes. In order to balance and reduce energy consumption, optimal clustering techniques either adjust the cluster size based on the application type and data transmission, or take data correlation, relay traffic, and residual energy into account. By eliminating unnecessary clustering from the network and activating the cluster formation stage only when essential, event-driven systems aim to increase the network longevity. The process of cluster formation is shown in Figure 7.

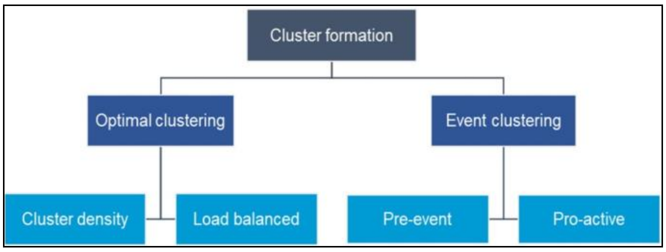

Fig 7: Cluster formation phase.

5.2.1 Optimal clustering
Cluster formation in optimal clustering tries to lower the rate at which the cluster members use energy. By allocating SNs to their closest CHs after determining their distances from the CHs using the strength of the signals received as advertisement messages, this process is accomplished. The size of the established clusters and the rate of energy consumption within the clusters are not taken into account in this clustering type.

5.2.2 Event-driven clustering
By avoiding pointless and proactive clustering, event-driven clustering aims to produce energy-efficient clusters [58]. However, if clusters are created throughout the entire field prior to the occurrence of an event, significant overhead may arise. This overhead involves network processing and energy and may not guarantee superior network performance in all applications.

5.3 Data aggregation phase
To reduce duplication during the transmission stage and give the BS fused information, data from several sensors is acquired. The majority of data aggregation strategies strive for energy-conscious data collection and aggregation. Allowing direct data transmission by all SNs to the BS may not be energy-efficient given the constrained energy of the SNs. Additionally, it's possible that the BS is unable to analyze all of the data produced by all of the SNs. Figure 8 depicts the data aggregation procedure.

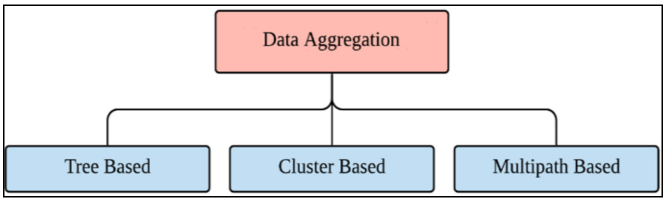

Fig 8: Process of the data aggregation phase.

5.3.1 Tree-based data aggregation
These methods for distributed data aggregation rely on network data aggregator nodes, which guarantees that they are present in the SNs' data pathways. An energy-conscious data aggregation tree is built using the protocols in this category.

5.3.2 Cluster-based data aggregation
This plan hinges on the establishment of clusters; a CH acts as the hub for data gathering in each cluster. The Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, which uses CHs as the data aggregation sites, is an

illustration of this technique. Another cluster-based data aggregation system that bases the CH choice on the availability of various power levels at the SNs is the Hybrid Energy-Efficient Distributed (HEED) protocol. The remaining node energy and the distance between the node and its neighbors are both taken into consideration by a composite metric.

5.3.3 Multipath-based data aggregation

In these designs, the SNs partition the aggregated data into different portions before sending them over various channels to a single destination. These strategies deliver small duplicate data packets to the BS over various pathways in an effort to increase network resiliency. Multipath-based data aggregation frequently uses a ring topology, which enables the SNs to be divided into a number of levels according to how many hops separate them from the BS [6].

5.4 Data communication phase

The data compiled by the CHs are sent to the BS during this step to be further processed according to the kind of application. Inter-cluster transmission refers to packet transmission from CHs to the BS, whereas intra-cluster transmission refers to packet transmission from SNs to the CH. Inter-cluster communication is divided into direct and multi-hop transmission for intra-cluster communication and single-hop and multi-hop transmission for inter-cluster communication. The most nearby CH to the BS can receive all of the CHs' aggregated data thanks to multi-hop communication. The process of data communication is shown in Figure 9.

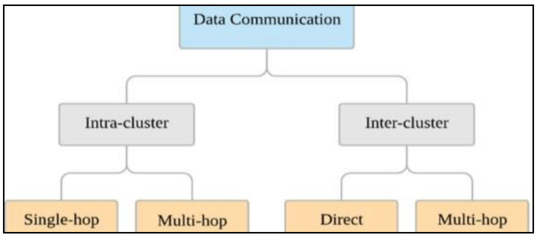

Fig 9: Data communication phase process.

6. Recent advancements in clustering optimization algorithms

In WSNs, clustering is employed to achieve performance goals like low energy consumption. In addition to energy efficiency, clustering protocols must also ensure quality of service (QoS) and strike a compromise between a number of competing concerns, including service lifetime, coverage, and throughput. To address these issues, many bio-inspired, meta-heuristic, and AI-based optimization strategies have been created in recent years. Several researchers have used various optimization strategies to successfully combine clustering protocols and optimization techniques in WSNs to increase energy efficiency. As shown in Figure 10, the majority of the optimization algorithms currently being employed in the WSN clustering process fall under the categories of meta-heuristic-based, fuzzy-based, hybrid meta-heuristic-based, and hybrid fuzzy-based techniques.

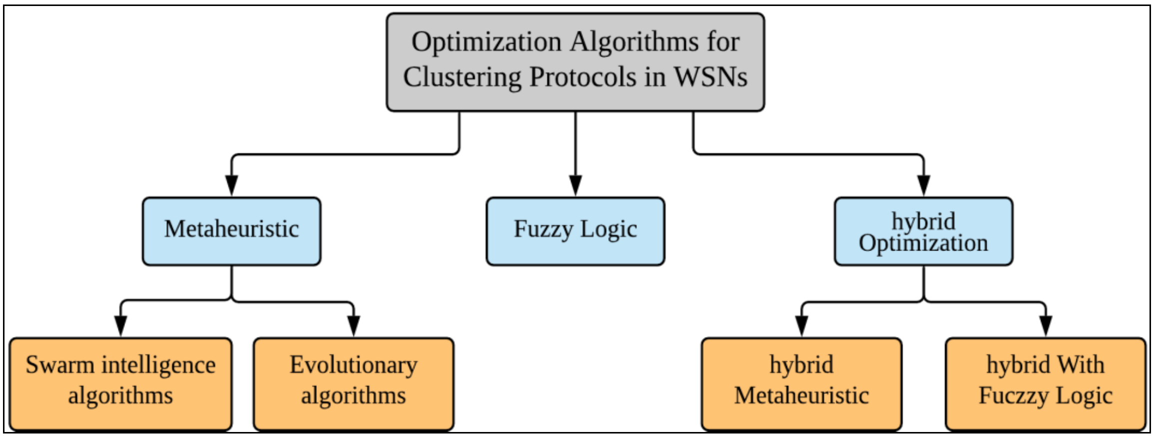

Fig 10: Classification of algorithms used in relevant articles.

The optimization algorithms employed in the research articles that were available were categorized, and a synopsis of each clustering protocol is offered to highlight the goals and evaluation functions. This classification aids in identifying papers that explored particular strategies and directs novice researchers toward materials pertinent to ongoing study. Table 2 provides comprehensive details about the chosen articles. An overview of various implementation factors is shown in Figure 11.

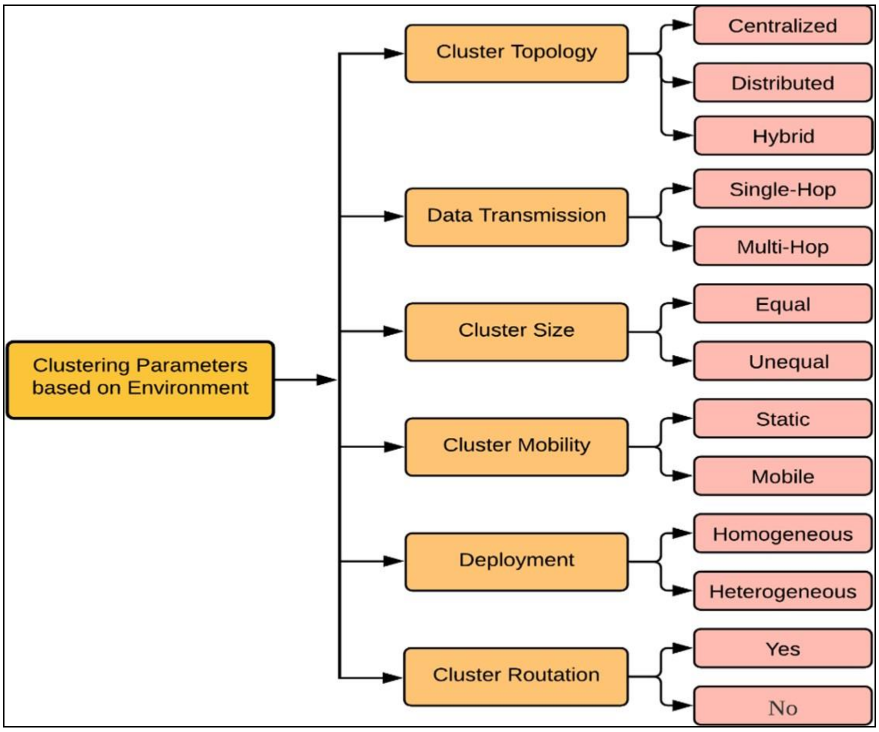

Fig 11: An over view of clustering parameters from the literature.

Method: A clustering strategy may employ a distributed or a centralized approach. These methodologies allow for the use of hybrid, distributed, or centralized techniques for task implementation. While the routing portion of the approach is centralized (either by a BS directly or with a BS's assistance), the clustering step can be dispersed. Using this parameter, the mechanism used during the algorithmic process is examined;

6.1 Meta-Heuristic

In order to solve NP-hard issues that cannot be solved within a set timeframe using conventional methods, optimization techniques are being developed. Even though they occasionally fall short of proving to be the best answer, meta-heuristics offer a comprehensive solution to such NP-hard issues. In order to achieve optimal energy utilization in WSNs, clustering algorithms and meta-heuristics are combined since they jointly discover the best answers. Numerous meta-heuristics, such as swarm intelligence, approximation algorithms, and evolutionary algorithm-based techniques, have been employed by researchers.

6.1.1 Evolutionary Algorithms

The Genetic Algorithm (GA) is the most widely used evolutionary algorithm for routing and clustering in WSNs. These algorithms are utilized for routing and clustering schemes. To increase network life and efficiency, the GA is employed to extend the lifespan of CHs. To optimize the clustering process, increase optimal routing across nodes, and improve QoS, various studies have presented hybrids of GA and Artificial Bee Colony (ABC) approaches. By minimizing the overall distance, this combination also decreased the amount of data energy used during each loop.

7. Conclusions

The clustering method is often regarded as an effective means of getting the highest possible energy efficiency in a WSN. The latest hierarchical optimization methods for cluster head selection, cluster formatting, aggregation, and communication were thoroughly reviewed. Based on their optimization procedures, the clustering methods in the literature that is now available were examined. The protocols were divided into three categories: meta-heuristic-based, fuzzy logic-based, and hybrid technique-based, depending on the type of algorithm and operating method. Based on their performance, clustering and optimization parameters, and the characteristics that made them effective, the various types of protocols were compared. The main characteristics, goals, and benefits of the clustering protocols were examined. The protocols were also simulated to compare the concepts and features. The methodology-based comparison of the protocols took into account a number of aspects, including mobility, topology, deployment policy parameters, CH parameters, CH rotation, data transmission, and CH selection technique. This comparison sought to assess the efficacy of existing clustering methods according to their methodology. When comparing protocols based on performance, factors such protocol type, energy usage, throughput, stability duration, and network longevity were taken into account. The goal of this analysis of clustering techniques is to outline a clear course for future research on clustered networks.

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