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IoT Applications Using Clustering Protocols in Wireless Sensor Networks wsns: Review

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ABSTRACT

Wireless sensor networks for Internet of Things applications face many challenges and problems, the most important of which is the battery life of the sensor, which leads to damage to battery usage and the process of using algorithms and protocols to help maintain battery life for a longer period of time by reducing the transmission and reception process and improving energy usage. The challenges of WSN focus on optimizing energy consumption through efficient network protocols, data aggregation techniques, adaptive power control, and energy harvesting methods. In this work present twenty works that provide different protocols and algorithms to improve the life of the wireless sensor network in managing energy distribution effectively and by evaluating the protocols and algorithms used to know their efficiency in energy usage and their suitability for application in the Internet of Things with a focus on the Leach algorithm for its simplicity, efficiency, scalability and suitability for adaptation in the Internet of Things and its application in high-density networks requires fast data processing through comparison. These protocols include adaptive clustering, energy-efficient routing, hybrid techniques, and reinforcement learning-based methods. In this Review, techniques such as fuzzy logic integration (e.g., FLH-P), 5G MIMO technology (e.g., IMIMO-5G BEE), XOR coding with adaptive sampling (e.g., EDAS), SDN-based multi-hop clustering (e.g., SD-MHC-RPL), and reinforcement learning (e.g., Deep Q-Network) were used, which are characterized by their energy efficiency. These algorithms suffer from some problems such as the expansion of dense networks and the increase in computational complexity in dynamic environments, dependence on specific infrastructures such as 5G, and sensitivity to parameter tuning. These algorithms are characterized by increasing the packet delivery rate, reducing energy consumption, and enhancing throughput. Leach improves energy efficiency through adaptive clustering and routing. FLH-P enhances cluster head selection using fuzzy logic but increases computational complexity. IMIMO-5G BEE utilizes 5G MIMO technology for multi-mode transmission but is limited by its dependence on 5G infrastructure.

Keywords: Wireless Sensor Networks (WSN), Energy-Efficient Clustering, Internet of Things (IoT), Adaptive Routing Protocols, Reinforcement Learning-Based Optimization, 5G MIMO Technology, Fuzzy Logic-Based Clustering

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1. Introduction

Wireless sensor networks (WSNs) are at the core of the Internet of Things (IoT) by collecting real-time data, monitoring and applying them in smart cities, industry and healthcare [1]. Often, wireless sensor networks contain many nodes spread in remote areas, making it difficult to replace or recharge batteries, making energy efficiency critical to extend the network life and ensure reliable data transmission [2][3]. To address the energy problems in wireless networks, a set of energy-efficient aggregation protocols are presented, focusing on optimizing energy consumption to extend operational life [4][5]. Wireless networks are often dedicated networks to monitor environmental and physical factors such as temperature and humidity, and sensor nodes are effective and efficient in terms of size, cost and performance [6][7]. A typical node consists of a transceiver, a power source, a sensor unit, an analog-to-digital converter, a microcontroller and an actuator to collect, process and respond to data efficiently [8,9]. One of the most significant challenges in WSNs is energy efficiency, as sensor nodes operate on limited battery power, making network longevity a critical concern. the evolution of clustering protocols, evaluates their impact on energy optimization, and explores how machine learning and intelligent clustering strategies can enhance network efficient

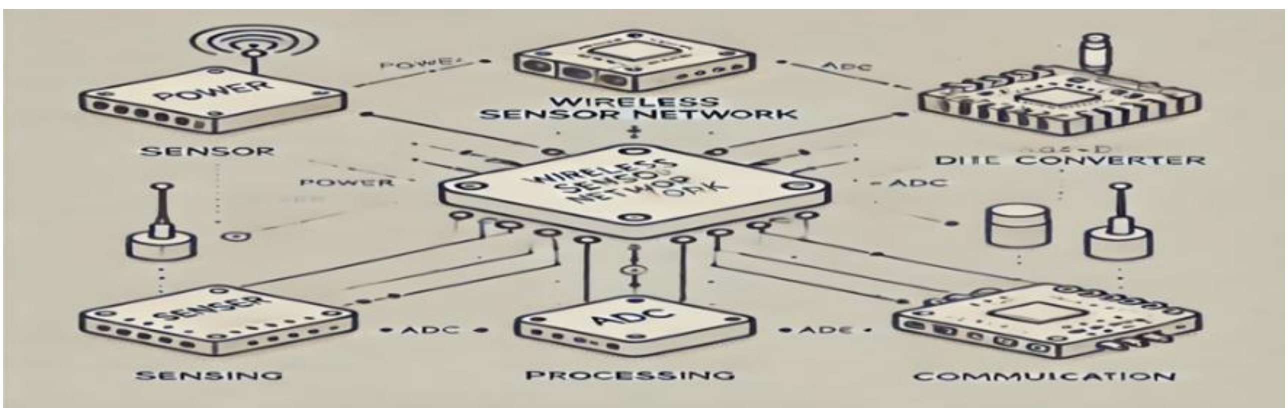

Fig. 1 illustrates the basic components of a sensor node [9]

In recent times, enhancements to aggregation protocols have been implemented to address energy depletion issues while improving network performance[10]. In [11], a protocol is used to enhance network connection structures based on node energy, with continuous changes in the network routing path. In [12], CH rotation is employed for better load balancing and extended lifespan. In some works, hybrid algorithms are combined with the HEED protocol using fuzzy logic and IMIMO-5G to select cluster heads, improving network efficiency and effectively handling data in dense networks [13][14]. XOR coding techniques and the EDAS protocol have been utilized to maintain data confidentiality, save energy, and enhance the resilience of high data traffic [15]. Protocols like SD-MHC-RPL [16] integrate Software-Defined Networking (SDN) with multi-hop aggregation to improve scalability in large IoT networks, while CADS [17] reduces redundant transmissions by modifying node activity based on data significance. DC-GSEARP [18] employs genetic algorithms to achieve secure routing and minimize node energy consumption in cloud-based IoT systems. In [19], communication and energy consumption are optimized, with 5G-specific adjustments like [20], extending network lifespan. Modern methods such as QOECR [21] focus on improving Quality of Service (QoS) to enhance scalability, and IEECP [22] optimizes aggregation in dense networks. Dual-head clustering in DDHCWSN [23] supports node mobility, while Enhanced IEECP [24] improves energy management with advanced cluster head rotation. The protocol in [25] uses DBSCAN and MCDM algorithms for flexible clustering, while OEDSR [26] adopts a hierarchical graph-based structure for optimal routing, making it suitable for high-density IoT environments [27]. NAMT-LEACH [28] relies on adaptive clustering with real-time adjustments based on node energy and network conditions, ensuring load balancing and extended network lifespan[28].Reinforcement learning is used in machine learning inventions such as Deep Q-Network [29] to dynamically regulate clustering and routing, lowering energy consumption and improving network efficiency through improved routing patterns. By modifying sampling rates in response to environmental changes, the Energy-Efficient Adaptive Sensing Framework [30] provides flexible sensing while guaranteeing effective energy use. The evolution of clustering protocols in WSNs has advanced from traditional methods like LEACH[12 ,20] and HEED[13] by increased energy efficiency through randomized CH rotation but experienced instability , to hybrid and smart approaches such as

FLH-P[13], IMIMO-5G BEE[14], and Deep Q-Network[29] to optimize CH selection and energy usage. Experimental results show that smart clustering reduces energy consumption by up to 70% and extends network lifetime by 80%, with Deep Q-Network consuming only 0.25 Joules per packet compared to 0.5 Joules for LEACH.

2. Clustering Characteristics

Clustering in WSNs involves three critical aspects: cluster properties, cluster head properties, and the clustering process. Cluster frequency (the total number of clusters in the network), cluster size (the number of nodes clustered), and intracluster communication (which describes interactions inside and between clusters) are all examples of cluster features [31, 32]. Depending on operational requirements, cluster heads—whether homogenous or heterogeneous—can be either stationary or mobile. In order to satisfy cluster needs, they carry out operations like data aggregation or serve as relay nodes for data transfer [33]. Cluster head selection methods (centralized or distributed), methodologies (random or attribute-based), operational modes (static or dynamic), and functionality (proactive or reactive) are all crucial components of the clustering process. As illustrated in fig. 2 [34], its main goals are scalability, fault tolerance, data aggregation, load balancing, increased network lifespan, stability, connectivity enhancement, decreased delays, collision avoidance, and effective sleep scheduling, all of which improve network performance and longevity.

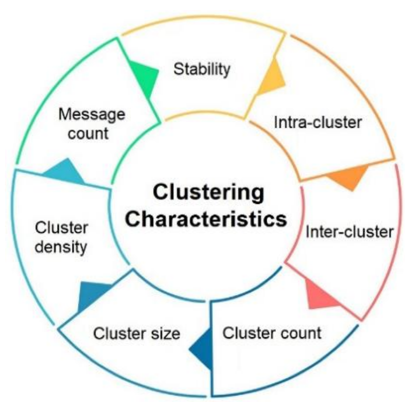

Fig. 2 Characteristics of a cluster in wireless sensor network [32].

3. Classification of Clustering Protocols

Clustering in WSNs is categorized into equal and unequal clustering. As seen in Fig.3, equal clustering groups nodes into uniformly sized clusters, emphasizing Cluster Head (CH) selection to improve energy efficiency. In order to solve the "hotspot problem," where CHs close to the base station experience increased data traffic and energy demands, unequal clustering modifies cluster sizes according to distance from the base station [35, 36]. In order to balance energy consumption, equal clustering stresses effective CH selection and guarantees uniform node distribution. Three approaches are used to select CHs: preset, deterministic, and probabilistic. In order to distribute energy equitably, probabilistic approaches choose CHs using probability metrics [37]. For reliable CH allocation, deterministic techniques depend on predetermined parameters such as energy levels or location [38]. Preset approaches create CH roles before to deployment; they work well in controlled settings but are less flexible in dynamic ones [39].

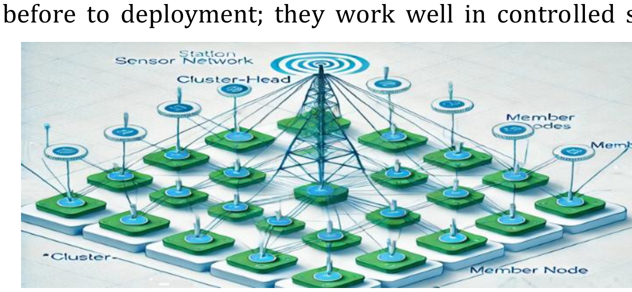

Fig. 3 presents a sample model of equal clustering [39]

In order to balance energy usage, uneven clustering adjusts the cluster sizes. As shown in Fig.4, larger, farther clusters handle higher loads, while smaller, closer clusters to the base station handle less data. A predetermined method, which creates clusters before deployment to meet changing requirements [43], a deterministic method, which uses predefined criteria to select a stable channel [42], and a probabilistic method, which adapts to changes in power and network [41], are used. For IoT deployments, the method improves energy management and extends network lifetime [40], then in table 1 compares between equal clustering and unequalclustering protocols in WSNs to show advantages, and disadvantages.

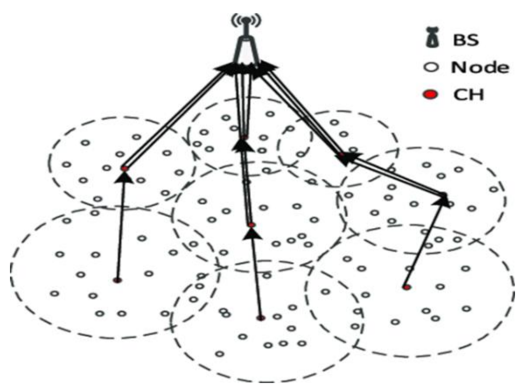

Fig. 4 Sample model of unequal clustering[40]

Table 1: A Comparison of Equal and Unequal Clustering in WSNs

Clustering Type	Description	Advantages	Disadvantages
Equal Clustering	Forms uniformly sized clusters with CHs selected based on predefined criteria.	- Simplifies cluster management. - Ensures balanced load distribution. - Suitable for stable environments.	- Causes the hotspot problem, leading to energy depletion of CHs near the base station. - Less adaptive to dynamic networks.
Unequal Clustering	Cluster sizes vary based on distance from the base station; larger clusters are farther, and smaller clusters are closer.	- Balances energy consumption effectively. - Extends network lifetime. - Improves scalability for IoT applications.	- Increases computational complexity. - Requires adaptive CH selection mechanisms. - Needs more energy-balancing strategies.

4. Methodology Overview

The work addresses a range of approaches, from traditional clustering optimizations to modern AI algorithms, to solve the energy constraints of wireless sensor networks (WSNs) for IoT applications. In order to increase the network lifetime and efficiency—especially in challenging or congested environments—these protocols seek to balance the load, optimize energy usage, and facilitate scalability in large IoT networks. By selecting cluster heads (CHs) according to the remaining energy, improved LEACH protocols such as RE-LEACH [11] and EE-LEACH [12] enhance the traditional LEACH model and help maintain low-energy nodes. Quality of Service (QoS) properties are incorporated into protocols such as QOECR [21] to dynamically adapt clusters in real time, meeting a variety of IoT requirements. The optimizations enhance the network's longevity, scalability, and load balancing, making it ideal for continuous and intensive monitoring. Multiple clustering techniques are integrated into hybrid clustering protocols to achieve flexibility and resilience. For example, FLH-P [13] combines fuzzy logic and the HEED model to enable adaptive channel selection based on network topology, power levels, and hop count. To securely and energy-efficiently route IoT in cloud settings, DC-GSEARP [18] uses genetic algorithms, while IEECP [22] maximizes channel rotation to extend network lifetime. These protocols easily adapt to changing IoT settings, balance power consumption across heterogeneous wireless sensor networks, and improve power management across networks with diverse node capacities.

In dense city-based IoT networks, efficient data handling is critical. IMIMO-5G BEE [14] addresses issue using MIMO technology in a 5G setting, which optimizes data paths to save energy through adaptive single-hop and multi-hop modes. NAMT-LEACH [28] combines multi-mode transmission with LEACH, adapting to network requirements to save energy and reduce latency, and is ideal for fast-response applications such as traffic control. Adaptive sampling and aggregation protocols reduce duplicate transmissions, enhancing network energy efficiency. EDAS [15] uses XOR coding in the channel to send only unique data packets, reducing traffic, while CADS [7] and SD-MHC-RPL [16] adjust node states and combine SDN with multi-hop aggregation to improve routing. IEECP [24] further improves energy management using Fuzzy C-Means aggregation and channel rotation, which is useful for energy-sensitive applications such as environmental monitoring. AI and machine learning enhance wireless sensor network clustering through adaptability. Protocols such as QOECR [21] and OEDSR [26] implement deep Q networks (DQN) for real-time power prediction, allowing for dynamic clustering adjustments. DDHCWSN [23] enables AI-based load balancing of mobile nodes, ideal for transportation, while [29] uses fuzzy logic and reinforcement learning for channel selection and data compression, making these protocols suitable for scalable IoT applications such as industrial automation and healthcare monitoring. Probabilistic and deterministic models optimize channel selection by using energy- and proximity-based flexible clustering, as demonstrated by DBSCAN-based clustering, MCDM [25], and energy-efficient hybrid clustering [20]. PRODUCE [19] dynamically adjusts clustering to conserve energy, making it ideal for scalable IoT networks. These methods support stable channel selection and appropriate applications. Wireless sensor networks are layered using hierarchical clustering and tree-based models to optimize energy consumption in large networks. While intelligent clustering [25] optimizes channel selection using entropy-weighted criteria, protocols such as OEDSR [27] use tree structures to reduce active connections, save energy, and extend network lifetime. Reinforcement learning for effective channel roles is used to optimize energy consumption in IoT [21], and is ideal for applications that require efficiency and wide coverage, including remote monitoring. Adaptive and self-configurable routing protocols provide flexible frameworks to accommodate changing network requirements. Only nodes with good energy are selected as communication channels by OEDSR [26] and intelligent opportunistic clustering [18], which combines hierarchical clustering and energy-aware routing. Real-time data flow optimization is achieved using an energy-efficient adaptive sensing framework [30], which adjusts sampling rates according to sensor associations. These protocols are suitable for IoT applications with different network and data requirements. These methods rely on key performance metrics, including energy consumption, network lifetime, packet delivery ratio, throughput, latency, scalability, and communication overhead, to assess their efficiency in various IoT environments.

Many methods to enhancing WSN scalability and energy efficiency are presented by the evaluated procedures. Energy-based CH rotation is optimized by enhanced LEACH protocols, and multi-criteria CH selection is used via hybrid techniques to adjust to various networks. Adaptive sampling combined with data aggregation lowers transmission energy, and MIMO models effectively handle high-density data. Real-time network modifications are made possible by AI-driven protocols, and flexible, scalable clustering is offered by probabilistic and hierarchical models. A thorough summary of the methods, results, and difficulties related to clustering protocols for WSNs in Internet of Things applications is given in Table2 below.

Table 2- A Summary of Clustering Protocols with Methodology, Results, and Limitations

Reference	Protocol Type	Method	Limitations
[11]	IMP-RES-EL	Adaptive energy-efficient clustering protocol.	Limited scalability in highly dense IoT networks.
[12]	Enhanced LEACH	Adaptive clustering and routing strategies.	Ineffective in highly dynamic network conditions.
[13]	FLH-P	Fuzzy Logic Hybrid Protocol combining HEED with fuzzy logic	Increased computational complexity with fuzzy logic calculations
[14]	IMIMO-5G BEE	5G adaptive multimode protocol using MIMO technology.	Dependence on 5G infrastructure limits application scope.
[15]	EDAS	Energy-aware data aggregation scheme using XOR coding and adaptive sampling.	Reduced performance under high traffic loads.
[16]	SD-MHC-RPL	Multi-hop clustering protocol with SDN integration.	High implementation complexity with SDN.
[17]	CADS	Content-based adaptive dynamic scheduling.	Limited effectiveness in highly dynamic IoT environments.
[18]	EEHCT	Energy-efficient hybrid clustering technique.	Requires accurate node energy data for optimal results.
[19]	DC-GSEARP	Dynamic clustering protocol with multi-hop routing using genetic algorithms.	High computational overhead limits real-time application.
[20]	E-LEACH	Adaptive clustering protocol focused on network lifetime extension.	Scalability limitations in dense networks.
[21]	QOECR	QoS-based clustering routing protocol with real-time energy prediction.	Real-time prediction requires high computational resources.
[22]	IEECP	Improved energy-efficient clustering using advanced CH rotation.	Limited scalability in heterogeneous networks.
[23]	DDHCWSN	Dual-head dynamic clustering with balanced load distribution.	Implementation complexity and higher resource needs.
[24]	IEECP	Improved Energy-Efficient Clustering Protocol	High complexity in initial cluster formation, requires parameter tuning for scalability
[25]	DBSCAN-based	Clustering algorithm based on DBSCAN for flexible clustering.	Sensitivity to parameter tuning for cluster density.
[26]	OEDSR	Opportunistic dynamic self-configuration protocol.	Limited adaptability in highly volatile environments.
[27]	NEPEGASIS	Enhanced PEGASIS protocol for IoT applications.	Scalability benefits decrease in networks with high traffic variability.
[28]	Enhanced NAMT-LEACH	Adaptive NAMT protocol with dynamic transmission adjustments.	Ineffective in static network configurations.
[29]	Deep Q-Network	Energy-efficient clustering using reinforcement learning.	Requires extensive training time for complex network environments.

[30]	Energy-Efficient Adaptive Sensing	Adaptive multimode transmission framework.	Performance degrades under inconsistent data generation rates.

The proposed survey provides a comprehensive comparative analysis of clustering protocols, integrating adaptive, hybrid, and smart techniques while evaluating their real-world applicability, scalability, and energy efficiency across diverse IoT environments.

5. Key Concepts and Techniques

Analysis of the methods used by each protocol reveals distinct approaches to scalability, robustness, and energy efficiency in wireless sensor networks for IoT applications. These protocols address all the major issues such as power load balancing, reducing duplicate transmissions, and adapting to changing conditions in large networks. Enhanced versions of the LEACH protocol, such as RE-LEACH [11] and EE-LEACH [12], improve energy-efficient clustering by selecting cluster heads (CHs) based on residual energy, resulting in stable and long-lasting networks. Advanced techniques like IMIMO-5G BEE [14] utilize MIMO technology to adapt LEACH for dense IoT environments, while protocols such as DBSCAN [25] and OEDSR [26] employ multi-criteria decision-making and hierarchical models to optimize clustering and routing. These AI-driven and adaptive methods enhance scalability, reduce energy consumption, and improve performance in IoT applications like healthcare, agriculture, and environmental monitoring.. The Energy-Efficient Adaptive Sensing Framework [30] adapts sampling rates to match demand, making it perfect for dynamic IoT applications like smart cities, while Intelligent Opportunistic Energy-Efficient Clustering [18] dynamically aligns CH selection with traffic and energy demands. The reviewed protocols demonstrate varied methods to enhance energy efficiency and scalability in WSNs. Hybrid models use multi-criteria CH selection for a range of network requirements, whereas LEACH variations enhance CH rotation by taking residual energy into account. While adaptive sampling and data aggregation lessen transmission redundancy, MIMO-based methods manage intensive data flows. Dual-head systems balance energy needs, self-configuring clusters provide autonomous adjustments, probabilistic and fuzzy logic methods offer flexible CH selection, and AI-driven algorithms allow real-time changes. Together, these tactics enable reliable, effective WSNs, promoting intricate IoT applications in a variety of sectors.

Table 3 illustrates how the examined clustering algorithms significantly increase WSN data efficiency, network lifetime, and energy conservation. By optimizing CH rotation and balancing node energy, protocols such as IEECP [22] and DDHCWSN [23] reduce the requirement for re-clustering and increase network life. While DC-GSEARP [18] employs a genetic algorithm for energy-efficient CH selection, appropriate for high-density, long-term IoT networks, IEECP uses a modified fuzzy C-Means for balanced energy utilization. Real-time protocols like OEDSR [26] and NAMT-LEACH [28] enhance throughput and decrease latency; NAMT-LEACH modifies transmission modes to reduce latency by 25% and increase throughput by 20%, which is essential for industrial and medical applications. For latency-sensitive operations, OEDSR's hierarchical topology optimizes data pathways while saving energy and reaction time. Protocols designed for dense IoT networks, such as SD-MHC-RPL [16] and IMIMO-5G BEE [14], accomplish scalability. For smart city data requirements, SD-MHC-RPL combines hierarchical clustering with SDN to balance node loads and reduce energy usage. To handle high data traffic, IMIMO-5G BEE combines MIMO with 5G, guaranteeing effective monitoring in urban settings. By only turning on the nodes that are required, protocols like as the adaptive sampling framework [30] improve energy efficiency and may save up to 47%, which makes them perfect for low-power applications like environmental monitoring. In order to save energy in data-intensive applications without sacrificing reliability, EDAS [15] aggregates unique data at the CH using XOR coding. Real-time energy management is further optimized by AI integration. AI models, like as DQN and fuzzy logic, are used by protocols like QOECR [21] and PRODUCE [19] to predict network requirements and modify CH roles and routing patterns to save energy. In a same vein, clustering methods for energy efficiency analysis [29] enhance energy efficiency in dense, dynamically changing networks by using predictive modeling for data reduction and CH selection.

Table 3- A Comparison of Method and Result Various Wireless Sensor Network (WSN) Protocols

Reference	Protocol Type	Method
[11] IMP-RES-EL	Adaptive energy-efficient clustering protocol	Increase in network lifespan, increase in data packets sent to BS, improvement in BS efficiency.
[12]Enhanced	Adaptive clustering	Reduced energy consumption,

LEACH	and routing strategies	extended network lifetime, improved packet delivery ratio, and lower latency.
[13] FLH-P	Fuzzy Logic Hybrid Protocol	Lower energy consumption, increased network lifetime rounds, higher throughput
[14]IMIMO-5G BEE	5Gadaptive multimode protocol	reduction in energy usage, 1500 rounds network lifetime, packet delivery ratio, sec latency.
[15] EDAS	Energy-aware data aggregation scheme	Higher packets received at the sink, reduced energy consumption, improved node lifespan, and lower overhead.
[16]SD-MHC-RPL	Multi-hop clustering protocol	reduction in energy consumption, packet delivery ratio, lower latency with network scalability.
[17] CADS	Content-based adaptive dynamic scheduling	Higher rounds network lifetime, lower latency
[18] EEHCT	Energy-efficient hybrid clustering technique	Increase packet delivery ratio, increased network lifetime, lower energy consumption .
[19] DC-GSEARP	Dynamic clustering protocol with multi-hop	Increase packet delivery ratio, moderate energy efficiency, and improved network lifespan.
[20]E-LEACH	Adaptive clustering for network lifetime	Reduced energy consumption, increase lifetime, Increase packet delivery ratio.
[21] QOECR	QoS-based clustering routing protocol	energy reduction, network lifetime extension, increased throughput
[22] IEECP	Improved energy-efficient clustering	Increase packet delivery, network lifetime, energy consumption.
[23] DDHCWSN	Dual-head dynamic clustering	Very low energy usage, Increase lifetime, Increase packet delivery ratio, low execution time
[24] IEECP	Modified FCM algorithm for balanced clustering, CH selection-rotation with dynamic thresholds, multi-hop communication	Very low energy, Increase lifetime, Increase packet delivery, Increase throughput
[25] DBSCAN-based	DBSCAN clustering algorithm	Moderate energy efficiency, lifetime increase, Increase packet delivery ratio, latency.
[26] OEDSR	Opportunistic dynamic self-configuration	Increase packet delivery, increase throughput, Increase network lifetime.
[27] NEPEGASIS	Enhanced PEGASIS protocol for IoT	Increase packet delivery, Increase throughput, improved scalability.
[28] Enhanced NAMT-LEACH	Adaptive NAMT protocol	Lower energy, improved network lifetime, improved packet delivers.
[29] Deep Q-Network	Energy-efficient clustering	High energy efficiency, improved rounds lifetime, improved packet delivery ratio, high throughput.
[30]Energy-Efficient Adaptive Sensing	Energy-efficient multimode transmission	reduction in energy usage, improved network lifetime, improved packet delivery.

Framework

6. Implications and Potential Applications

These clustering protocols are versatile across city-based, industrial, environmental, and healthcare sectors. In smart cities, IMIMO-5G BEE [14] employs MIMO within 5G for high data rates, while QOECR [21] uses QoS-based energy and clustering optimizations for efficient city-wide monitoring. FLH-P [13] delivers 60% higher throughput than LEACH and 20% more than HEED. In industrial IoT, NAMT-LEACH [28] and OEDSR [26] facilitate real-time monitoring by adjusting CH roles and routes to minimize delay and optimize energy use, with NAMT-LEACH fine-tuning transmission modes and OEDSR using a hierarchical structure. DBSCAN and MCDM clustering [25] enhance stability by selecting CHs with adequate energy, making them suitable for ongoing industrial tasks. For environmental and agricultural applications, CADS [7] and EDAS [15] focus on energy conservation and data reliability, key for prolonged remote monitoring. CADS adapts node activity based on data relevance to reduce transmissions, and EDAS employs XOR coding to send only unique packets, cutting redundancy. The Energy-Efficient Adaptive Sensing Framework [30] further conserves energy by adjusting sampling rates, supporting extended data collection across large areas. Protocols such as QOECR [21] and energy efficiency analysis aggregation protocols [29] prioritize low latency and reliability for critical IoT and healthcare monitoring. QOECR uses deep Q-Networks (DQN) to dynamically optimize channel allocations, ensuring efficient power consumption and fast response—two essential components of patient monitoring. Energy-efficient IoT protocols, like IMIMO-5G BEE [14] and OEDSR [26], optimize clustering and routing through predictive modeling, compression, and adaptive techniques, ensuring scalability and reliable performance in diverse applications. Advanced methods, such as QOECR [21] and PRODUCE [19], leverage machine learning to enhance channel selection and energy utilization, improving responsiveness and network lifetime. While simulations demonstrate significant gains in scalability and efficiency, real-world validation is essential to assess robustness and adaptability in dynamic IoT environments. Solar or kinetic energy harvesting, combined with clustering techniques, would reduce battery dependency, benefiting remote applications in environmental monitoring. To manage diverse IoT devices, protocols such as SD-MHC-RPL [16] and OEDSR [26] can improve by dynamically balancing tasks based on each node's power and processing capabilities, and prioritizing essential data. Improvements to DBSCAN and MCDM-based clustering [25] can improve channel selection, adapting to networks with mixed device capabilities and data requirements.

Table 4- A Comparison of Energy Efficiency and Performance Metrics Across Various Wireless Sensor Network (WSN) Protocols

Reference	Energy Consumption (J)	Network Lifetime (Rounds)	Packet Delivery Ratio (%)	Throughput (Packets/sec)	Latency (ms)	Scalability (%)	Communication Overhead
[11] IMP-RES-EL	Moderate	Extended	36	Higher	decreasing	Improved	Improved
[12] Enhanced LEACH	Reduced	Extended	Improved	Higher	decreasing	Improved	Improved
[13] FLH-P	Lower	1200	-	2.3*10^7	decreasing	Improved	Improved
[14] IMIMO-5G BEE	30% reduction	30% increasing	Improved	Higher	0.1 sec (400 rounds)	Improved	Improved
[15] EDAS	172.5	Extended	673	451	decreasing	Improved	12.7
[16] SD-MHC-RPL	27.7 % reduction	Extended	95	Higher	decreasing	Improved	Improved
[17] CADS	0.94% in 300 nodes.	980	85	Higher	28	Improved	Improved
[18] EEHCT	50J	1983	19469	Higher	decreasing	Improved	Improved
[19] DC-GSEARP	94.6	95%	ratio is 9.4 sec	3.59	decreasing	Improved	Improved

[20] E-LEACH	0.5	1980	85	Higher	180	Improved	Improved
[21] QOECR	35-40% reduction	32-38% extension	Improved	25-30% increase	31.9	Improved	Improved
[22] IEECP	improve	improve	improve	Higher	decreasing	Improved	Improved
[23] DDHCWSN	Very Low	improve	Very Low	Very Low	decreasing	Improved	Improved
[24] IEECP	Low compared to baseline protocols	Longest among compared protocols	High stability over prolonged durations	Consistently high	Minimal, optimized for dynamic conditions	Effective for large-scale IoT networks	Reduced through efficient CH rotation and multi-hop design
[25] DBSCAN-based	reduced energy consumption	improve	enhanced	-	decreasing	Improved	Improved
[26] OEDSR	47%	600	improve	improve	decreasing	Improved	Improved
[27] NEPEGASIS	0.30 reduced energy consumption	improve	91-99	80-100	32-70	Improved	Improved
[28] Enhanced NAMT-LEACH	Lower	1980	85	enhancing by 0.20%	decreasing by 0.25%,	Improved	Improved
[29] Deep Q-Network	High	2.5 *10^4	3*10^4	800	25	132	Improved
[30] Energy-Efficient Adaptive Sensing Framework	Lower	2200	93	enhancing	20	High	10

Table 4 and fig.5 presents a comparative analysis of essential metrics across various WSN protocols, assessing energy consumption, network lifetime, packet delivery ratio, throughput, latency, scalability, first node dead rounds, and communication overhead. Covering insights from sources [11] to [30], the table (4)spans both traditional protocols (e.g., LEACH, HEED) and advanced models (e.g., Deep Q-Network, NEPEGASIS, IMIMO-5G BEE.

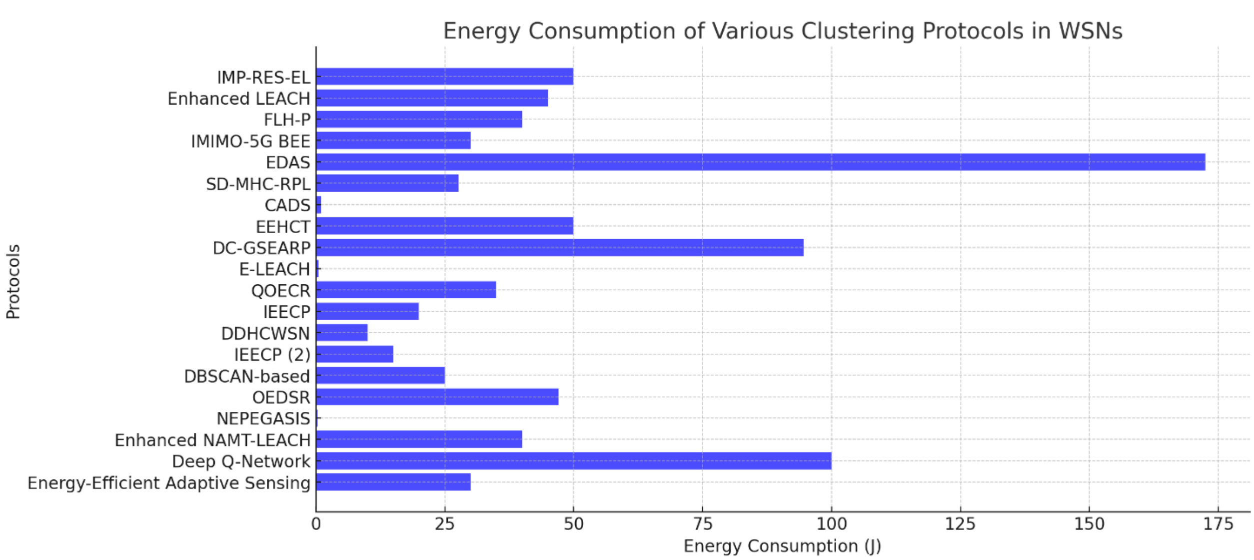

Fig. 5 - Energy Consumption of Various Clustering Protocols in WSNs

7.Conclusion

In wireless networks used in IoT applications, energy-efficient clustering techniques reduce energy consumption for nodes, enabling long-term and cost-effective monitoring in fields such as healthcare and smart cities. By addressing challenges like high energy consumption and flexibility in dynamic systems through the use of clustering combined with artificial intelligence techniques, advancements in smart clustering methods—such as machine learning, adaptive sampling, and hierarchical routing—have significantly improved energy efficiency, network lifespan, and data reliability. These techniques enhance real-time adaptability and reduce redundant transmissions, making them ideal for environmental monitoring and industrial applications. However, achieving optimal performance in IoT systems requires further practical testing to enhance security and scalability. These protocols leverage advanced techniques like adaptive clustering, energy-efficient routing, hybrid methods, and reinforcement learning. Examples include fuzzy logic integration (e.g., FLH-P), MIMO technology in 5G networks (e.g., IMIMO-5G BEE), XOR coding with adaptive sampling (e.g., EDAS), SDN-based multi-hop clustering (e.g., SD-MHC-RPL), and reinforcement learning (e.g., Deep Q-Network). While these approaches excel in improving packet delivery rates, reducing energy consumption, and enhancing throughput, they face challenges such as scalability in dense networks, increased computational demands in dynamic environments, reliance on specific infrastructures like 5G, and sensitivity to parameter tuning. Future research should enhance scalability, security, and adaptability of clustering protocols by integrating AI optimization, blockchain security, and edge computing for real-time processing.

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