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Review of Energy-Efficient Model Hybrid Clustering Technique in WSNs

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ABSTRACT

This review article explores advancements in energy-efficient hybrid clustering techniques for Wireless Sensor Networks (WSNs), highlighting their significance for optimizing energy consumption and extending network longevity. As WSNs become integral to various applications, efficient energy management is crucial for prolonging node lifespan and ensuring reliable data transmission. The purpose of this review is to analytically examine previous energy-efficient hybrid clustering techniques in WSNs, with a specific emphasis on their mathematical modeling, this serves as a unifying framework for quantitatively evaluating energy efficiency, network lifetime, and transmission performance to enhance network stability. We analyze existing models and compare their effectiveness in minimizing energy use while maximizing data delivery efficiency. Related literature was identified through a methodical search of scientific databases covering publications from 2022 through 2025. Keywords such as hybrid clustering, energy efficiency, wireless sensor network, and energy consumption models were used to ensure comprehensive coverage of the field. The analysis shows that most studies focus on protocols such as LEACH, DCO-EEN-SCGA, FIS, BWOA, and BeeCluster, as well as parameter metrics such as node density, dead nodes, network lifetime, and so on, while equation-based modeling is rarely used. We also discuss the challenges in implementing these techniques, including scalability and network dynamics. This review synthesizes current research to highlight emerging trends and future directions in energy-efficient clustering strategies, offering practical guidance for researchers and practitioners aiming to enhance the sustainability and performance of WSNs.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have become essential technology for a range of applications, including smart cities, healthcare, environmental surveillance, and industrial automation. These wireless sensor networks consist of many sensor nodes that are grouped together and send packets to a central base Station (BS), thereby facilitating immediate monitoring and smart decision-making. As wireless sensor networks grow in scale and application domains, their contribution to modern infrastructure and vital systems becomes increasingly important [1]-[4]. Despite the potential, WSNs face significant challenges due to the limited energy resources of sensor nodes. Conventional clustering techniques often overburden specific nodes, such as CHs, leading to energy holes and early network failure. Various existing models do not

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accurately capture the realistic energy utilization trends of nodes during packet transmission, reception, aggregation, and multi-hop transmission, leading to suboptimal energy distribution. Additionally, traditional communication strategies such as direct and multi-hop are absent for proper balancing techniques, which causes high transmission overhead, data loss, and reduced throughput, as these nodes are typically battery-operated and situated in remote or harsh environments, frequent recharging or replacement is impractical. High energy consumption not only reduces data reliability but also shortens the network's overall lifespan. Traditional data transmission techniques tend to hasten energy depletion, further restricting the long-term sustainability of WSN operations. As a result, energy-efficient design has emerged as a key research focus, aimed at prolonging node lifespan while ensuring reliable communication [5]-[8]. Clustering has emerged as a widely studied solution to address energy efficiency in WSNs. By grouping sensor nodes into clusters, clustering minimizes redundant transmissions, balances energy consumption, and enhances scalability.

However, current clustering techniques often struggle to balance network conditions, leading to uneven energy distribution, premature node failures, and reduced overall efficiency. Therefore, while clustering enhances energy management, its limitations underscore the necessity for more adaptable and robust approaches [9][10]. To address these limitations, researchers have proposed hybrid clustering strategies that combine the strengths of various models. Hybrid approaches are designed to optimize energy usage, adapt to fluctuating network conditions, and extend node and network lifespan [11]-[25]. By integrating multiple techniques, hybrid clustering enables systematic evaluation and improvement across three key areas: energy-efficient clustering methods, network energy consumption modeling, and data transmission effectiveness. These aspects not only enhance energy management but also improve scalability, flexibility, and the reliability of data delivery.

This review aims to provide a thorough examination of energy-efficient hybrid clustering algorithms in WSNs, with comparative analyses to identify best practices and areas requiring further investigation. The main contribution of this article is to formulate an equation model to assess energy efficiency, network lifetime, and data transmission efficiency. This serves as a unifying framework to for quantitatively evaluating the aforementioned network-stability parameters. By doing so, the review offers valuable insights for both researchers and practitioners aiming to design more sustainable and high-performing WSNs. Ultimately, the findings of this study may guide future innovations that ensure reliable and energy-efficient operation of sensor networks across diverse application domains.

Despite the advancements made in developing hybrid clustering techniques for energy efficiency in WSNs, prior works exhibit notable limitations:

- Lack of a model equation for Energy-Efficient Hybrid Clustering Techniques. Prior studies have proposed clustering schemes, but they have not developed a satisfactory mathematical model ~~to~~ for systematically evaluating and optimizing energy efficiency. This limitation hinders its ability to optimize energy utilization and ensure reliable network operation.
- Lack of a comprehensive model equation for Network Energy Consumption. Without a precisely specified model equation, network design cannot accurately identify energy-use inefficiencies. This gap limits the ability to reduce operating costs, maximize the node's lifetime, and deploy wireless sensor networks more reliably.
- Failure to initiate a model equation for Data Transmission Efficiency. Previous scholars have not adequately grasped the relationship between energy management and data delivery efficiency. As a result, the decision-making regarding the transmission technique remains unknown.
- This review aims to fill these gaps by highlighting mathematical models required for hybrid clustering, energy consumption modeling, and transmission efficiency analysis, thereby providing a structured basis for future improvement and performance enhancement in wireless sensor networks.

2. RELATED STUDIES

The authors presented a scheme for selecting the best cluster head from a collection of terminals. The cluster head election considers several criteria, including node degree, node centrality, distance to neighbors, and distance to the base station. Also, they emphasized Ant Colonization Optimization, which calculates the path between the cluster leader and the base station (BS) by selecting the most efficient route based on distance, remaining energy, and node degree. Comparing the average network lifespan to LEACH, Beecluster, iABC, and BeeSensor, the findings reveal significant improvements of 40.50%, 33.17%, 25.00%, and 15.49%, respectively. The proposed algorithm outperforms the existing algorithms: LEACH, Beecluster, iABC, and BeeSensor by 28.7%, 22.51%, 20.95%, and 12.47%, respectively, in terms of the number of active nodes.

The hybrid K-means and Lion optimization scheme for Energy-efficient clustering Routing (K-LionER) in WSNs supported by the Internet of Things. The researchers also highlight K-LionER's emphasis on increasing energy efficiency and network longevity. K-means is used to build the clusters in the WSN under study, and ant lion optimization is used to choose each CH. Cluster members provide data to CHs, which aggregate it and send it to the base station. MATLAB 2017a was used for the simulation. The proposed algorithm outperforms the existing algorithms. The simulation show improvements in several performance parameters, including active nodes, stability period, dead nodes, and network lifespan metrics. The developed K-LionER routing protocol extends the network's lifespan by 10% to 48% as compared to the existing algorithm.

The three main stages of the proposed methodology are cluster formation, optimal route selection, and intrusion detection. For CH selection, the adaptive shark smell optimization (ASSO) method was first applied with three input parameters. These factors include node density, distance to the base station, and residual energy. An energy-efficient WSN is produced by clustering and then using the salp swarm optimization (SSO) to select the best route for data transfer between clusters. The accuracy of this technique is 99.2%, and the performance results of quality of service (QoS) metrics are stated as dispersion value (0.8072), packet delivery rate (98%), average latency (160 ms), and network lifespan (3200 rounds). The developed protocol improves network lifespan by 77%, 60%, 45.4%, and 14.2%, respectively, compared with the existing protocols.

Smart computing has been especially noteworthy in the development of wireless sensor networks (WSNs), which have several uses, according to the researchers [26]. These networks are based on self-configuring, battery-powered sensor nodes. Additionally, researchers emphasized that sensors had limited energy and resources. The network's longevity is negatively affected by unbalanced nodes which consume more power. This paper proposes an enhanced cluster-based routing protocol that is energy efficient for Internet of Things-based heterogeneous wireless sensor networks (WSNs). The usefulness of the developed model was assessed using several performance metrics, including energy efficiency, active nodes, dead nodes, network lifespan, and residual energy. The comparison's findings were contrasted with the existing algorithm, where the proposed algorithm outperforms the existing algorithms, including hybrid PSO, PSO, and LEACH. The simulation results show that in networks with 50 and 100 nodes, the developed algorithm performs significantly better than the existing algorithms.

The evaluation metrics for energy, latency, distance, node centrality, and node degree were considered throughout the CH selection process using this multi-objective HBESAOA method. Compared with baseline CH selection methods that are independent of the sink node's location, the HBESAOA scheme shows a 26.78% improvement in average network lifespan Compared with the existing algorithms, the network's energy sustainability is also enhanced by 21.98%, even as the number of sensor nodes scales. There are two major phases in the developed technique. The first phase involves selecting a possible cluster head (CH) using a hybrid K-means and Grey Wolf optimization (GWO) method. The Firefly algorithm is used in the second stage to choose the most energy-efficient path between the BS and the sensor node. Comparisons between the developed method's performance and the FIGWO algorithm and the current PSO-based routing algorithm reveal that the developed algorithm performs better.

A variety of optimization strategies have been put forth. Unfortunately, many current algorithms lack sufficient security against malicious attacks, making network connections insecure and unreliable. This paper presents a low-power cluster-based routing protocol with a robust fault-detection mechanism for WSNs to overcome these issues. The protocol selects the Cluster Head (CH) using the fuzzy logic-enhanced Improved Whale Optimization Algorithm (IWOA). Improved Quality of Service (QoS) characteristics, including dispersion (0.3401), cost function (601.09), network lifespan (4100 rounds), and prediction accuracy (99.5%), were observed in the simulation results of the proposed method. The developed protocol outperforms the Mobile Sink-based Fault Diagnosis Scheme (MSFDS), Enhanced Clustering Hierarchy (ECH), Adaptive Energy Efficient Clustering (AEEC), and Quadrature-LEACH (Q-LEACH) protocols.

To enhance network performance in MANETs, the authors in [27] present a two-stage Hybrid Adaptive Clustering Algorithm for Dynamic MANETs (HACADM). Using the Gravity Search Algorithm (GSA), the first stage optimizes node degree, neighborhood distance, battery power, and mobility, and uses on the Weighted Clustering Algorithm (WCA) to select the best CHs. In the second phase, the Enhanced Density-Based Spatial Clustering of Applications with Noise (Enhanced-DBSCAN) algorithm, used to determine the member nodes and their functions of the chosen CHs. Additionally, by selecting gateway nodes for inter-cluster communication, this method improves cluster stability and reduces the burden on the CHs. By improving the resilience of clustering processes in MANETs under dynamic network conditions, this study marks a significant step towards increasing network lifetime and maximizing energy efficiency.

The authors propose an effective clustering-based routing technique [28]. The protocol accounts for energy, node degree, and distance parameters when selecting the best cluster head (CH) using a multi-objective binary whale optimization algorithm (BWOA). To improve energy efficiency, a Mamdani-type fuzzy inference system (FIS) is also used for cluster formation. The FIS output determines the likelihood that a sensor node will connect to a CH. The performance metrics are distance, neighborhood degree, and CH residual energy. For data packet transfer, a multi-hop shortest-path routing procedure is used. Their simulation results demonstrate the potential impact of the developed technique in the field, with the FND meter rising by 4.5%, the HND measure improving by 7.8%, and the LND benchmark rising by 1.5%.

Dynamic Clustering Optimization for Energy Efficient IoT Network: A Simple Constructive Graph Approach (DCO-EEN-SCGA) was developed by the authors [29]. In many parameters, the shortest valid path is found using the Mean Standard Deviation Shortest Path Problem (MSDSPP). Energy usage and transmission overhead are reduced by using Simple Constructive Graph Clustering (SCGC). Lastly, the suggested DCO-EEN-SCGA method's performance results in 17.45%, 18.72%, and 19.19% greater end-to-end latency, 16.35%, 18.62%, and 20.11% higher throughput, and 15.17%, 17.42%, and 19.25% higher energy consumption. In contrast, the following methods are currently in use: Clustering at the Edge: Load Balancing with Energy Efficiency for IoT (CE-LBEE-IOT), An Opportunistic Energy-effective Dynamic Self-Configuration Clustering Algorithm in WSN-based IoT Networks (OEDSCC-WSNN), and An Energy-effective Hybrid Clustering Technique for IoT-based Multilevel Heterogeneous WSN (EEHT-IOT-MHWN).

According to the literatures reviewed above, the majority of researchers concentrated on protocols like LEACH, DCO-EEN-SCGA, FIS, BWOA, and BeeCluster, as well as parameter metrics like node density, dead node, network lifetime, and so forth, to determine their simulation without considering model equations, this serves as a unifying framework to quantitatively evaluate and provide network stability, such as Energy-Efficient Hybrid Clustering Techniques, which enable systematic evaluation and improvement, ensuring optimal energy consumption and enhanced network sustainability. Energy Consumption enables network designers to identify and resolve inefficiencies in energy utilization, minimizing operating costs and extending node lifespan. Data transmission efficiency improves understanding of energy management's effect on data delivery and network lifespan, guiding decisions that enhance transmission efficiency and reduce maintenance needs.

2.1. Method of Review

Table 1. Summary of the reviewed Literature

Reference	Work Done	Method Used	Solution Provided	Limitation
[26]	Active node, dead nodes, network life time, and residual energy.	An enhanced, energy-efficient cluster-based routing protocol.	The results show that in networks with 50 and 100 nodes, the developed algorithm outperforms the existing one.	Low gains with model equations that lack the ability to quantitatively evaluate energy efficiency, network lifetime, and transmission performance for network stability.
[27]	Node degree, neighborhood distance, battery power	Hybrid Adaptive Clustering Algorithm for Dynamics MANETs (HACADM)	The developed algorithm improved network lifetime and maximized energy efficiency.	Low gains with model equations ~~lacking~~ that lack the ability to quantitatively evaluate energy efficiency, network lifetime, and transmission performance for network stability.
[28]	Energy, node degree, and distance	Multi-objective binary whale optimization algorithm (BWOA)	Improvement in the aforementioned metrics: 4.5%,7.8%, and 1.5%, respectively.	Low gains with model equations that lack the ability to quantitatively evaluate energy efficiency, network lifetime, and transmission performance for network stability.
[29]	End-to-end delay, throughput, and energy consumption	Means standard deviation shortest path problem (MSDSPP)	Improvement in terms aforementioned- metrics: 15.17%, 17.42%, and 19.25%, respectively.	Low gains with model equations that lack the ability to quantitatively evaluate energy efficiency, network lifetime, and transmission performance for network stability.

To ensure a comprehensive and unbiased review, a systematic search strategy was adopted, as outlined in Table 1. Relevant publications were identified and selected based on clearly defined keywords, a specific search period, and inclusion/exclusion criteria. The review article focused on recent manuscripts published between 2022 and 2025 to capture developments in energy-efficient hybrid clustering techniques for wireless sensor networks. The following informed our selection criteria: peer-reviewed journal manuscripts, book chapters published in reputable domains, studies that emphasize hybrid clustering models for energy efficiency, published work that includes model equations, simulation results on energy consumption and data transmission efficiency, and papers published in English. We limited our selection to studies from 2022 onward, as more significant progress and relevant contributions have been made in recent years compared to earlier works.

Overall, although the reviewed techniques achieved noticeable improvements across specific performance metrics, a common limitation is the absence of equation-based models to estimate energy efficiency, consumption, network lifetime, and transmission efficiency. This paper addresses that gap by introducing model equations.

3. Overview of Wireless Sensor Networks

To receive and transmit data to a central processing unit, also known as a sink or base station, wireless sensor networks (WSNs) consist of many spatially distributed sensor nodes that monitor physical or environmental conditions, such as temperature, humidity, light, and motion. WSNs are well-known for their real-time data collection capabilities and are used in a variety of applications, including smart agriculture, healthcare, military surveillance, and environmental monitoring [30]-[33].

3.1. Wireless Sensor Network

Sensor nodes, a communication network, and a sink (base station) are the three main components of a WSN [34].

- **Sensor Nodes**: Usually, each node has a power supply, a communication module, a processing unit, and a sensing unit. Since nodes are often battery-powered, energy efficiency is a crucial factor in both their formation and functionality [35]-[37].
- **Communication Infrastructure**: Wireless communication protocols are used by nodes to exchange information with the base station and with one another. This infrastructure needs to minimize energy usage while supporting reliable data transfer [38].
- **Base Station**: Before transmitting the data to end users or external networks, this central unit compiles data from the sensor nodes and may carry out additional processing [39].

Given that WSNs are most often deployed in inaccessible or remote areas, considerations such as scalability, resilience, and energy efficiency must be made throughout the configuration and implementation phases.

3.2. Clustering Techniques

In WSNs, clustering is a commonly used technique to enhance data transmission and energy efficiency. During clustering, sensor nodes are arranged into clusters, and each cluster is assigned a cluster head (CH). The CH is designated for aggregating and sending data to the base station from its members. By reducing the volume of data sent straight to the base station, this hierarchical structure saves energy and increases the network's operational lifespan [40].

Types of Clustering Techniques [41]-[50]

- **Homogeneous Clustering**: This technique makes the assumption that every node has the same energy resources and capabilities. To distribute energy usage equitably, nodes alternate as cluster heads via techniques such as LEACH (Low-Energy Adaptive Clustering Hierarchy).
- **Heterogeneous Clustering**: This technique takes into consideration nodes with different energy levels and capabilities. To ensure that more competent nodes manage clusters and improve overall efficiency, strategies that assign cluster head tasks based on node energy levels can be developed.
- **Hybrid Clustering**: Hybrid clustering techniques combine nodes of heterogeneous and homogeneous methodologies to maximize energy use while preserving network performance. These methods are appropriate for dynamic operations since they adjust to network conditions.

All things considered, the success of clustering strategies in WSNs is essential for attaining energy efficiency, extending network lifetime, and ensuring accurate data collection. The design and deployment of novel clustering techniques remain a crucial topic of study as WSN applications grow.

4. Energy Efficient Hybrid Clustering Techniques

In WSNs, hybrid clustering approaches have become a viable way to improve energy efficiency. These approaches overcome the drawbacks of conventional approaches by combining the advantages of several clustering techniques, offering a more flexible and energy-efficient framework for data transmission and reception. To maximize network performance and minimize energy consumption, hybrid clustering integrates features of both homogeneous and heterogeneous clustering techniques. These techniques usually the dynamic selection of cluster heads based on factors such as data aggregation capabilities, nodes' energy levels, and distance to the base station. The main advantage of hybrid clustering is that it can adjust to dynamic network conditions, ensuring balanced energy consumption and extending the network's operational lifespan [51]-[53]. Figure 1 illustrates a hybrid clustering model for WSNs, where sensor nodes are grouped into clusters, each managed by a CH. The CHs coordinate communication, with energy-efficient data transmission occurring between them.

We provide the following model equation to estimate the efficiency of an energy-efficient hybrid clustering strategy in Wireless Sensor Networks (WSNs): Energy efficiency hybrid techniques is given by the ratio of subtracting energy consumption from initial energy multiply by weight factor to subtracting network’s total active time in seconds from the amount of data successfully gather and sent in bits multiply by weight factor as seen in equation (1).

$$E_H = \frac{(E_i - E_{Con})).\alpha}{\beta D_{Co} + \gamma T_{Ac}} \tag{1}$$

Where;

- E_H defines the efficiency score of the hybrid clustering technique.
- E_i signifies the network's total initial energy, expressed in Joules.
- E_{Con} denotes the Total energy used in Joules for data transmission and clustering.
- D_{Co} identifies the total amount of data successfully gathered and sent to the BS in bits.
- T_{Ac} is the network's total active time in seconds.
- α defines the weighting factor (dimensionless, ranging from 0 to 1) for energy retention that indicates the significance of energy conservation.
- β signifies the data efficiency weighting factor (dimensionless, range 0 to 1) that reflects the importance of data collection.
- γ is the Operational time weighting factor, which indicates the importance of network longevity (dimensionless, 0 to 1).

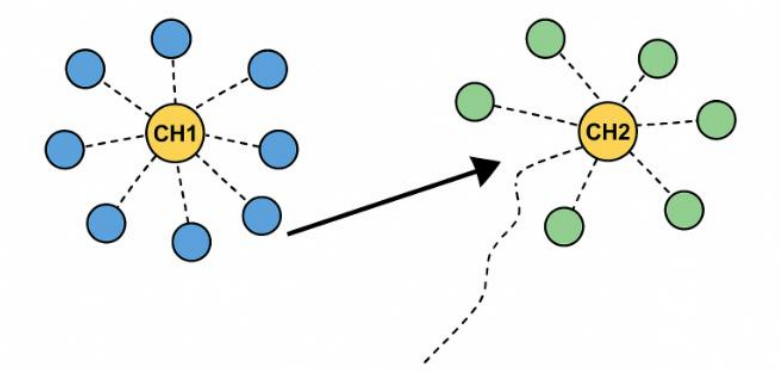

Figure 1. Energy-Efficient- Model Hybrid Clustering Technique in WSNs

By balancing several vital parameters, this equation holistically evaluates the energy efficiency of a hybrid clustering technique. It provides an estimate of energy retention by accounting for the initial energy available and deducting the energy used during the network’s activities. Effective energy management must also take into account the volume of data successfully transferred and the length of time the network is operational, since the denominator is a weighted sum of the total data gathered and the network's active time. By adjusting the weight factors α, β, and γ to meet the requirements of a particular application, researchers can tailor the model to prioritize data efficiency, energy savings, or operational lifespan. The resultant E_H score guides the design of more effective and sustainable WSNs by providing a thorough assessment for evaluating the efficacy of different hybrid clustering strategies. Longer-lasting and more reliable sensor networks are ultimately a result of a better balance between energy consumption and network performance, which is shown by a higher score.

4.1. Existing Hybrid Clustering Techniques

The literature has put forth several hybrid clustering strategies, each with its own advantages and techniques [54]-[57].

- **Hybrid Energy-Efficient Distributed Clustering (HEED):**
  Use node proximity and residual energy to select cluster heads, thereby maintaining energy-efficient clustering by evenly distributing the load among nodes, improving network longevity and reducing

energy usage. However, this protocol results in increased overhead due to the complexity of the clustering technique.

- **Cluster Head Election Framework (CHEF):**
  Employ a multi-criteria decision-making process to select cluster heads based on node density, distance, and energy, thereby enabling efficient energy management that adapts to the network's changing needs, reducing data transmission burden, and increasing clustering efficiency. However, this protocol can lead to uneven energy consumption among nodes, as a node may repeatedly be elected as CH.
- **Distributed Energy-Efficient Clustering (DEEC)**
  Takes into account nodes' initial energy and appropriately adjusts the likelihood of becoming the cluster head, thereby allowing nodes with higher energy to take more demanding tasks, thereby supporting heterogeneous networks, and also ensuring balanced energy use and a longer network lifetime. However, this protocol suffers from network partitioning issues.
- **Energy Aware Clustering Hierarchy (EACH)**
  Focuses on energy efficiency by modifying the cluster structure based on the current energy reserve, thereby prolonging lifetime by enabling nodes to switch tasks in response to energy depletion, and also includes ongoing energy and cluster formation optimization. However, this protocol may introduce a delay in data transmission due to multilevel communication between clusters and the base station.

4.2. Comparative analysis

Significant differences in performance parameters, including energy efficiency, network longevity, and hybrid clustering techniques, are evident in comparing previous works.

Table 2. Comparison of the previous work done in the research area

Author	WSN	CT	EEHCT	M.E for EEHCT	M.E for EC	M.E for NLT	M.E for D T E
[58]	✓	✓	✓	×	×	×	×
[59]	✓	✓	✓	×	×	×	×
[60]	✓	✓	✓	×	×	×	×
[61]	✓	✓	✓	×	×	×	×
[62]	✓	✓	✓	×	×	×	×
[63]	✓	✓	✓	×	×	×	×

Note: ✓ means it is present.
× Means it is absent.

- EEHCT stands for Energy Efficient Hybrid Clustering Techniques.
- CT stands for Clustering Techniques.
- M.E. for EEHCT stands for Model Equation for EEHCT.
- M.E. for EC stands for Model Equation for Energy Consumption.
- M.E. for NLT stands for Model Equation for Network Life Time.
- M.E. for DTE stands for Model Equation for Data Transmission Efficiency.

Based on Table 2, it was observed that the majority of earlier work focused on Clustering techniques, Energy-Efficient Hybrid Clustering techniques, and related techniques, with little attention paid to developing model equations to assess and enhance network stability.

5. Performance Metrics

A thorough grasp of several performance measures is necessary to assess the efficacy of energy-efficient hybrid clustering algorithms in Wireless Sensor Networks (WSNs). Data transmission efficiency, network longevity, and energy usage are important parameters to consider. When evaluating the overall effectiveness of clustering techniques, each indicator is essential [65]-[68].

5.1. Energy Consumption

The entire energy used by the sensor nodes for data sensing, processing, and transmission to the base station is referred to as energy consumption. The total energy consumption in the network is given by the total summation of energy utilized during the operation of sensing, processing, [69]-[71], and transmitting data as seen in equation (2).

Model Equation

$$E_{Total} = \sum_{i=0}^{n}(\mathrm{Es} + \mathrm{Ep} + \mathrm{Et}) \tag{2}$$

Where;

- Es is the amount of energy, in joules, required for each sensing operation.
- Ep denotes the energy in joules required for each data processing operation.
- Et defines the energy, in joules, required to transmit data.
- N denotes the total number of sensor nodes.

The total energy consumption of all network nodes is represented by this equation. A more effective clustering strategy is shown by lower overall energy use. To make targeted improvements, the energy consumption breakdown helps determine which stages of the operation (transmission, processing, or sensing) are the most energy-intensive.

5.2 Network Lifetime

The amount of time until the first node fails or until a specific proportion of nodes run out of energy is known as the network lifespan. The network lifetime of a system is given by the ratio of the network's initial energy to the average energy per round, in joules, multiplied by the number of rounds until the first node runs out of energy, as seen in equation (3).

Model Equation

$$\boldsymbol{L_{net} = \frac{E_i}{E_{av}} T} \tag{3}$$

Where;

- E_i identifies the network's total initial energy expressed in joules.
- E_{av} is the average energy used per round, in joules.
- T is the number of rounds till the first node runs out of energy.

This equation expedites the evaluation of network longevity based on initial energy reserves and average energy utilization. A longer network lifetime denotes effective energy efficiency in clustering techniques. The focus on average energy utilization helps to accentuate the efficiency of the clustering technique over time [72].

5.3 Data Transmission Efficiency

The ratio of successfully transferred data to the total amount of data received by the sensor nodes is known as data transmission efficiency. Data transmission efficiency is given by the number of bits transmitted successfully divided by the total number of bits generated by all nodes, multiplied by 100, as shown in equation (4).

Model Equation

$$D_{efficien} = \frac{D_S}{D_T} \cdot 100 \tag{4}$$

D_S indicates the number of bits of data successfully transmitted.
D_T stands for the total amount of data in bits generated by all nodes.

This metric evaluates how well the clustering strategy works in terms of communication efficiency and data reliability. The stability of the clustering strategy and its effect on network performance are demonstrated by higher data transmission efficiency, which shows that a greater percentage of generated data is effectively transmitted to the base station.

These performance metrics (data transmission efficiency, network longevity, and energy consumption) provide critical insights into how well energy-efficient hybrid clustering strategies perform in WSNs. Researchers can thoroughly evaluate and compare clustering techniques using these metrics and their corresponding equations, thereby guiding the development of more effective and long-lasting WSN techniques. By improving our understanding of energy dynamics in networks, this method aims to open the door to further advancements in sensor technology and clustering techniques. Table 3 summarizes of all the variable definitions used in the system.

Table 3. The Summary of variable definitions used in the system

Variables	Definitions	Relevance to Model
EH	Performance metric of an Energy-Efficient Clustering.	Hybrid Clustering for effective estimation
E_i	Initial energy node *i.*	For the evaluation of the remaining capacity and lifetime
E_{Con}	Energy utilized during the clustering operation.	Accounts for overhead in cluster formation
α	Weighting factor indicating the effectiveness of clustering.	Stabilizes the impact of residual energy and clustering cost
β	Weighting Factor indicating communication distance.	Modify the effect of transmission distance in the EH model
D_{Co}	Amount of data successfully sent to BS.	Determines intra-and inter-cluster energy cost
γ	Weighting factor indicating transmission activity cost	Stabilizes the impact of node transmission activity
T_{Ac}	Number of transmissions or duration	Workload of a node/CH
E_{Total}	Amount of Energy utilized in the network	Summarizes the overall network energy utilization
n	Number of nodes in the network	Defines scale total energy estimation
E_s	Sensing energy	Capture the cost of environmental data acquisition
E_p	Processing energy for computation and aggregation	Energy spent on data aggregation
E_t	Transmission energy for sending data	Accounts for wireless communication cost
L_{net}	Evaluated network lifetime	Estimates the sustainability of the WSN
E_{av}	Average energy utilization per node per round	Basis for estimating network lifetime
T	Number of operational rounds	Multiplier for network lifetime evaluation
$D_{efficien}$	Data transmission efficiency (%)	Assesses the effectiveness of data delivery
D_S	Successfully delivered data packets	Reflects reliable transfer
D_T	Total transmitted data packets	Denominator for efficiency estimation

6 Future Direction

To improve efficiency and robustness, future studies on energy-efficient hybrid clustering strategies in Wireless Sensor Networks (WSNs) should focus on adaptive algorithms that respond dynamically to dynamic network conditions. While investigating energy-receiving technologies can support sustainable operations, integrating artificial intelligence and machine learning can optimize decision-making for cluster formations. Strong security protocols are also necessary to safeguard data integrity, and methods for handling diverse nodes and scalability will enhance overall network performance. The efficiency of this technique in real-world applications will be further confirmed by thorough assessment frameworks and field tests.

7 Conclusion

This review paper emphasizes the importance of energy-efficient hybrid clustering strategies for improving the sustainability and performance of Wireless Sensor Networks. As demand for reliable efficient sensor networks continues to grow, integrating innovative clustering strategies offers a promising solution to the challenges posed by energy constraints and network scalability. By leveraging diverse clustering techniques, these hybrid models enhance network lifetime and data transmission reliability while optimizing energy consumption. The model equation provides a structured framework for quantifying and optimizing clustering decisions, thereby achieving balanced energy utilization across the network. Furthermore, it improves accuracy by addressing performance gaps that existing schemes cannot capture, such as energy efficiency, network lifetime, and data transmission efficiency. The area will continue investigating of potential future paths, such as AI-driven clustering, blockchain-based secure clustering, 6G-enabled WSN implementations, and energy-harvesting technologies. To fully utilize WSNs across a variety of applications and open the door to smarter, more robust networks, efficient hybrid clustering approaches must be developed.

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