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Energy Conservation Clustering through Agent Nodes and Clusters (EECANC) for Wearable Health Monitoring and Smart Building Automation in Smart Hospitals using Wireless Sensor Networks

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Abstract. Wireless Sensor Networks (WSNs) play a vital role in enabling real-time patient monitoring, medical device tracking, and automated management of building operations in smart hospitals. Wearable health sensors and hospital automation systems produce a constant flow of data, resulting in elevated energy usage and network congestion. This study introduces an advanced framework named Energy Conservation via Clustering by Agent Nodes and Clusters (EECANC), designed to improve energy efficiency, extend the network's longevity, and facilitate smart building automation in hospitals. The EECANC protocol amalgamates wearable medical monitoring (oxygen saturation, body temperature, heart rate, and motion tracking) with intelligent hospital building automation (HVAC regulation, lighting management, and security surveillance) through a hierarchical Wireless Sensor Network-based clustering system. By reducing routing and data redundancy, cluster heads (CHs) and agent nodes (ANs) reduce redundant transmissions and extend the life of sensor batteries. EECANC limits direct interaction with the hospital's Smart Building Management System, thereby reducing emergency response times and improving energy efficiency throughout the hospital. The efficiency of EECANC was proven by comparing its performance with other existing clustering protocols, including EECAS, ECRRS, EA-DB-CRP, and IEE-LEACH. The protocol achieved a successful packet delivery rate of 83.33% to the base station, exceeding the performance of EECAS (83.33%), ECRRS (48.45%), EA-DB-CRP (54.37%), and IEE-LEACH (59.13%). The system demonstrated better energy utilization, resulting in a longer network longevity and lower transmission costs especially during high-traffic medical events. It is clear from the first and last node death rates that EECANC is the most energy-efficient protocol, significantly better than the other methods available. The EECANC model supports hospital automation, enhances patient safety, and promotes sustainability, providing a cost-effective and energy-efficient solution for future smart healthcare facilities.

Keywords Wireless Sensor Network; Smart Hospitals; Energy Efficiency; Clustering; Wearable Patient Monitoring Sensors; Smart Building Management System.

I. Introduction

Many fields have begun to use Wireless Sensor Networks (WSNs), including healthcare, home automation, city planning, and military operations. To automate smart buildings, track medical devices, and continuously monitor patients, WSNs are essential in today's medical care. To enhance patients safety, reduce manual workload, and optimize energy consumption, smart hospitals depend on automated infrastructure (such as HVAC, lighting, and security systems) and wearable health sensors.

However, a lot of energy is used by this constant flow of information, which leads to frequent network congestion and accelerated sensor battery depletion, creating reliability issues for life-critical applications. Finding an equilibrium between dependable information delivery and minimal energy usage is an ongoing problem in medical WSNs. Clinical intervention may be delayed in intensive care units (ICUs) if even a few packets are lost, resulting in reduced oxygen availability for patients.

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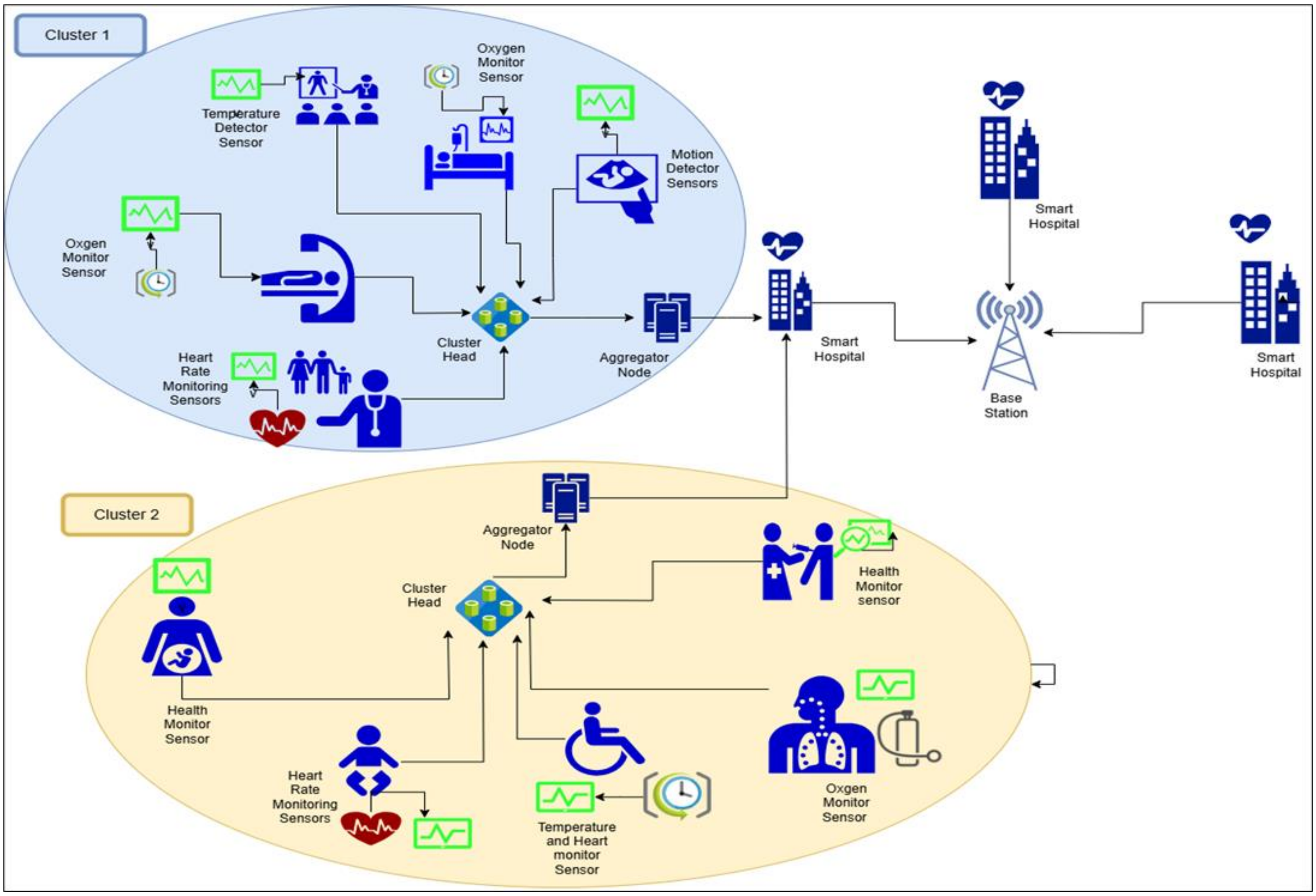

Fig. 1. **EECANC Model in Health Sensor-Enabled Smart Hospital Building**

Recharging wearable devices frequently in surgical wards is inconvenient for both staff and patients. The same holds true for networks, when hundreds of devices in different wards transmit at the same time; latency and quality of service are affected due to network scaling issues. Traditional methods of direct interaction with the hospital's Building Management System (BMS) further accelerate energy depletion and increase data transmission costs. The frameworks of the many clustering solutions that have been suggested often fail to deliver of the standards set by smart hospitals. While LEACH [15] and IEE-LEACH [22] are classical protocols that reduce extra communication overhead, in overcrowded wards where sensors are constantly monitored, their dependence on randomized CH election makes them susceptible to packet loss and unreliable networks. In order to prolong the lifetime of the network, EA-DB-CRP [16] and EECAS [23] use energy-aware CH selection. However, because they depend on multi-hop transmissions, the wearable batteries quickly drain, and the energy is not evenly distributed. In high-traffic environments such as surgical departments, ECRRS [17] experiences early node failures despite improvements in CH rotation and relay node selection.

Stable routing in simulations is achieved by optimization-based methods like Flamingo Search [19] and Cuckoo Optimization [18], but real-time ability to scale in large hospital networks with thousands of heterogeneous devices interacting simultaneously is hindered by their computational dependency and complexity on global optimization. Due to these shortcomings, the current approaches are not well-suited to the energy-balancing, reliable, and low-delay requirements of continuous operations in healthcare. This study introduces EECANC as a comprehensive framework specifically designed for real-world smart hospital environments to address these limitations, as illustrated in Fig 1. To reduce unnecessary transmissions and balance energy usage between wards, ANs serve as intermediaries for EECANC. The reallocation of Cluster Heads (CHs) can also be done dynamically. In an intensive care unit, data from several patient wearables are aggregated at CHs and filtered at ANs to reduce congestion and ensure minimal packet loss. This way, only important information is transmitted to the BMS. Preventing premature sensor failures and extending device lifetime without disrupting procedures is achieved with dynamic CH reassignment in surgical units.

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Table 1. Analysis of Comparative Studies and Identification of Research Gaps in WSN approach

Clustering Protocol	Key Features	Strengths	Limitations
LEACH [15]	Randomized CH selection	Simple, scalable	Does not consider residual energy
EA-DB-CRP [16]	Density-based clustering	Efficient for dense networks	Not suitable for sparse networks
Cuckoo Optimization [18]	Metaheuristic-based	Adaptive, energy-efficient	High computational complexity
Flamingo Search Algorithm [19]	Bio-inspired clustering	High stability, robust	Increased communication overhead
IEE-LEACH [22]	Hybrid clustering	Optimized energy balance	Complex CH election
EECAS [23]	Machine learning-based clustering	Efficient for large-scale WSNs	Requires continuous retraining

ANs eliminate direct communication with the BMS, which allows for large-scale hospital installations. This allows for long-term use and growth, even with thousands of sensors spread out across departments. Because it outperforms current protocols in terms of packet delivery ratios, sensor lifespan, and communication costs, EECANC is an attractive, eco-friendly choice for healthcare facilities of the future. The major goal of this research is to create and assess the EECANC architecture, which combines a group of clustering mechanisms with Agent Nodes (ANs) and Cluster Heads (CHs), and an energy-efficient communication protocol for use in smart hospital environments as illustrated in Fig. 2 and compare studies and find research gaps in WSN approach in Table 1. Inside their clusters, CHs in this design collect information from a number of wearable health sensors and hospital automation systems. To ensure that CHs are adaptively chosen to distribute the load on the network and prevent early battery depletion, EECANC employs a residual-energy- and distance-based clustering technique, which differs from typical random CH selection. Aggregator nodes, which are also called agent nodes, add another level of abstraction between CHs and the hospital's BMS. Filtering, compressing, and forwarding only important and non-redundant information are performed by ANs instead of every CH transmitting directly to the BMS. This uses less energy, reduces usage and congestion. The transmission frequency is reduced, energy is conserved across the network, and packet delivery is ensured by this dual-layer arrangement. Fig.1 shows that hospital network clusters (e.g., Cluster 1 and Cluster 2) comprise heart rate, oxygen saturation, motion, temperature, and sound sensors. Data is transmitted by local sensors to cluster CHs. Data are aggregated by the CH before being forwarded to an AN. The AN communicates with the smart hospital base station to cut down on wasteful transmissions. Local filters save energy for routine or repeated data, while the hospital system receives crucial data immediately, such as abnormal motion detection or oxygen level drops.

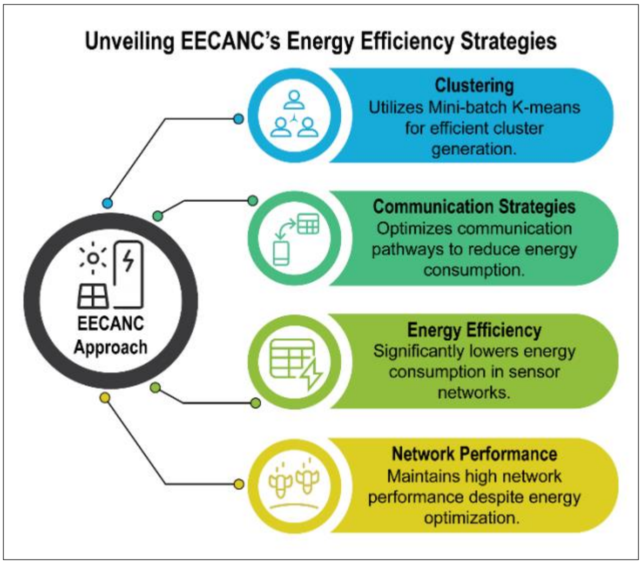

Fig. 2. **Proposed EECANC Model**

Both components make EECANC's energy-saving technology effective. First, local aggregation at CHs and selective forwarding by ANs minimize redundant packets, lowering communication costs and making the system more reliable. Second, dynamic CH reallocation replaces nodes with low residual energy, ensuring ongoing monitoring and preventing premature failures. EECANC optimizes patient safety, and adding healthcare sensors (heart rate, SpO_2, motion) can help a hospital be more environmentally friendly, with building automation systems using hierarchical clustering for HVAC, lighting, and security systems. This means better energy management in the hospital's infrastructure, less wearable charging, and uninterrupted ICU monitoring. EECANC's energy-saving feature works as part of a useful hospital-wide strategy for deployment, where each cluster represents a separate unit or floor of a smart hospital. In these clusters, many patients are constantly monitored by sensors that are worn or placed in the environment. For example, pregnant women wear heart rate monitors,

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Table 2. Network Parameters for EECANC in Smart Hospitals

S.No	Parameter	Description in Smart Hospital Context
1	ETx (Transmission Energy)	Energy used to transmit patient data from connected sensor devices to CHs.
2	ERx (Receiver Energy)	Energy consumed by CHs or ANs to receive health sensor data.
3	Eamp (Amplifier Energy)	Energy required to amplify signals for long-range transmission within the hospital.
4	Efs (Amplifier Energy - Rx)	Energy required to receive and process sensor node signals.
5	EDA (Data Aggregation Energy)	Energy used by CH to aggregate and compress sensor data.
6	D (Distance)	Physical distance between sensors, CHs, ANs, and the BMS.
7	K (Bits)	Size of bitstream data packets transmitted from hospital sensors
8	N (Number of Nodes)	Total number of health and smart building nodes in the hospital.
9	P (CH Selection eligibility metric)	Location- and residual-energy-driven CH eligibility metric.
10	Rs (Residual Energy)	Remaining energy of a current sensor node.
11	Eo (Initial Node Energy)	Initial energy of a node prior to the beginning of clustering or communication.

premature babies are monitored by neonatal sensors in NICUs, and elderly care units use vital sign trackers. Outpatient departments (OPDs) perform additional monitoring.

Doctors use WSN-enabled devices to check oxygen saturation, blood pressure, and heart rate, and the data are stored in hospital databases. In each unit, many sensors transmit their data to an elected Cluster Head (CH), which takes the readings that are then aggregated at regular intervals to cut down on unnecessary transmissions. The CH does not transmit this information directly to the Base Station; instead, it transmits it to the nearest Agent Node (AN). These ANs work continuously to transmit consolidated patient data from their own clusters to the hospital's Base Station. They do this by acting as intermediary nodes. By assigning this job to ANs, the system makes it easier for CHs to communicate and saves energy in general. The Aggregator Node (AN) cluster is also maintained as a separate level in the network, where multiple ANs can work at the same time. When an AN's energy level falls below a certain threshold, it is automatically switched over to another AN to keep working as mentioned in Fig. 3. This keeps data transmission going without interruption. A similar rotation mechanism is used for CHs, which prevents nodes from failing too soon and ensures long-term monitoring. This setup makes sure that important patient data are accurately collected, filtered, and transmitted to the smart hospital dashboard at any given time, whether from an ICU bed, a NICU incubator, an elderly care ward, or an outpatient department consultation. From there, nurses and doctors can monitor patients' health while the system keeps energy use to a minimum across the network.

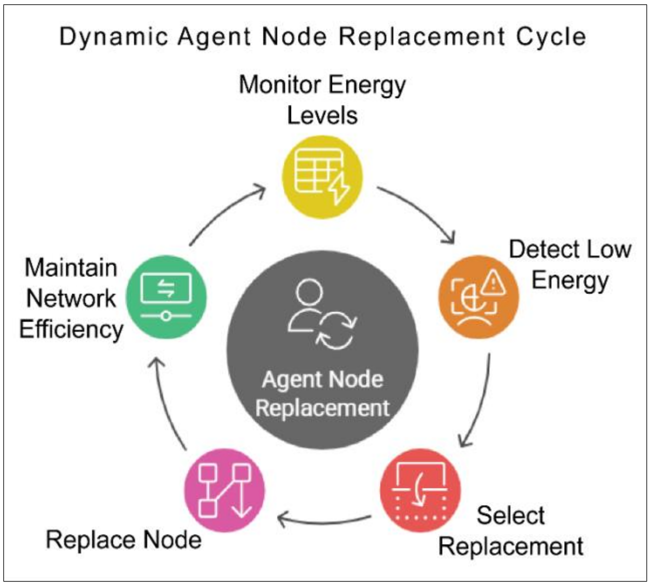

Fig. 3. Agent Node Replacement

II. Literature Survey

A. Introduction to Clustering in Wireless Sensor Networks (WSNs)

Clustering methods for Wireless Sensor Networks (WSNs) have advanced greatly to improve network lifetime, information transfer efficiency, and energy efficiency. Clustering based on hierarchy, maximizing efficiency, and machine learning has made clustering solutions more scalable and cost-effective as illustrated in Table 2. The EECANC framework integrates intelligent healthcare settings, cost-effective communication, smart health sensors, and smart hospital automation using these clustering concepts.

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Table 3. Scenario 1 : Comparison of Parameters for Different Protocols

Parameters	EECAS [23]	ECRRS [17]	EA-DB-CRP [16]	IEE-LEACH [22]	EECANC (Proposed Model)
Hospital Coverage Area (m²)	100 × 100	100 × 100	100 × 100	100 × 100	100 × 100
Number of Wearable & IoT Nodes	50	50	50	50	50
Hospital BMS Location (BS)	50,150	50,150	50,150	50,150	50,150
First Sensor Node Failure (Rounds)	752	514	579	643	**1080**
Last Sensor Node Failure (Rounds)	1289	801	1073	1092	**1620**
Packets Successfully Received at BMS	6100	3800	4800	5200	**7920**
Average Residual Energy (J)	1300	800	1100	1100	**1680**

B. The Clustering Methods in WSNs: Classical and Optimization-Based Literature Survey and Related Work

J. Amutha et al. [1] divided WSN clustering techniques into classical, optimization, and machine learning-based categories in their extended study. The work emphasizes adaptive clustering, load balancing, and cluster-head selection for power consumption reduction. In IoT networks, X. Ding and Y. Wu et al. [2] examined energy optimization scheduling and smart environments to improve data transmission efficiency through intelligent resource allocation. The importance of multi-objective optimization in energy-efficient WSN clustering was highlighted by J. Wang et al. [3] who investigated Pareto-optimal solutions for next-generation wireless networks.

C. Machine Learning and AI-Driven Clustering in WSNs

There has been a steady increase in research investigating the integration of machine learning techniques into wireless sensor network clustering. P. Padmalaya and G.K. Sweta et al. [4] examined several AI-driven routing and energy optimization methods, demonstrating their efficacy in environments characterized by dynamic and heterogeneous sensor data. Machine learning and optimization have helped WSNs use less energy. D. P. Kumar et al. [5] found many machine learning algorithms for WSN tasks such grouping, routing, and tracking unusual events. In their work, L. Zhao et al. [6] introduced a modified LEACH-based method to better perform cluster-head selection with residual energy optimization. Energy efficiency and the lifespan of the network were both increased by this method. In their work on quality-of-service (QoS) clustering, O. A. Deepa and J. Suguna et al. [7] aimed to improve packet delivery and fault tolerance. Multipath routing is incorporated into this approach. In a comprehensive evaluation of clustering objectives in WSNs, A. Shahraki et al. [8] looked at the costs of the routing in wsn protocols.The benefits of energy efficiency, scalability, and network stability as compare in Table 3.

D. Energy-Efficient Clustering and Routing Protocols

S.N. Mohanty and K. Shankar et al. [9] proposed a way to use deep learning for global data mining in WSNs that uses the least amount of energy. This model enables optimal cluster formation and route decisions. Using metaheuristic algorithms to improve cluster-head selection and relay node placement, D. Mehta and S. Saxena et al. [10] devised a multi-objective energy-aware clustering technique. Clustering and data collection strategies have been proposed to improve WSN energy efficiency for healthcare IoT applications. Zheng et al. [11] collected mobile data using kernel-based compressive sensing, whereas D. Ma et al. [12] examined IoT energy-aware processing and communication. For better clustering, T. Mayee et al. [13] suggested residual energy-based cluster-head selection, while A. Al-Baz and A. El-Sayed et al. [14] optimized LEACH. These foundational methodologies help create solid, energy-efficient protocols like the EECANC model. Using real-time energy balancing, D. Jia et al. [15] presents a method for dynamic cluster-head selection. An energy-aware and density-based clustering algorithm, K. A. Darabkh et al. [16] proposed, called EA-DB-CRP, to improve data aggregation efficiency. H. Wu et al. [17] offered a way to rotate CHs in several types of Wireless Sensor Networks that could be used in farming. M. Khabiri and M. Ghaffari et al. [18] used clustering and the Cuckoo Optimization Algorithm to build energy-saving and network-

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Table 4. Performance Comparison Metrics for Scenario 1 (in Percentage)

Metric	EECAS (% [23])	ECRRS (% [17])	EA-DB-CRP (% [16])	IEE-LEACH (% [22])
First Node die	69.63% ➔	47.59% ↕	53.61% ➡	59.54% ➡
Last Node die	79.57% ➔	49.44% ↕	66.23% ➡	67.41% ➡
Packet received by BS vs rounds	77.02% ➔	47.98% ↕	60.61% ➡	65.66% ➡
Avg Residual Energy vs rounds	77.38% ➔	47.62% ↕	65.48% ➡	65.48% ➡

extending paths. Balanced sensor node load distribution reduces premature node failure and improves network stability.

E. Performance Improvement Methods in Wireless Sensor Networks that Draw Inspiration from Bioinformatics and Metaheuristics

Applying optimization techniques driven by biological processes has improved clustering efficiency in WSNs. R. Abraham and M. Vadivel et al. [19] developed a grouping method based on the Flamingo Search Algorithm to make the network more stable and the nodes last longer. A light weight and data minimization approach was employed by N. Sulthana and M. Duraipandian et al. [20] in their proposal of the EELCR protocol, which is a lifetime-aware clustering strategy. S. Nagadivya and R. Manoharan et al. [21] used fuzzy theory to develop an opportunistic routing technique for adaptive energy management in volatile Wireless Sensor Networks .Table 4 illustrates comparison metrics for scenario 1.

F. Hybrid and Next-Generation Clustering Models

Advanced techniques for hybrid clustering and multi-hop communication have enabled WSNs to perform more efficiently. Y. Liu et al. [22] proposed IEE-LEACH, a threshold-based cluster-head election method, which incorporates single-hop, multi-hop, and hybrid communication. This model reduces power consumption at the base station (BS) to make the network last longer. In a similar vein, EECAS was presented by R. Kumar et al. [23]; it is a mini-batch K-means clustering model that aims to optimize data aggregation and network durability while reducing computing costs. Table 1 presents a comparative analysis and highlights the identified research gaps. Wireless Sensor Networks (WSNs) are extensively utilized in healthcare for the real-time collection and transmission of patient health data. According to Movassaghi et al. [28] and Kim et al. [24], these networks assist physicians and hospital systems in patient monitoring without the need for wires or frequent manual checks. Wearable health devices have evolved to be more compact and intelligent. S. Patel et al. [29] and A. Pantelopoulos et al. [30] explained that technologies such as Bluetooth, Wi-Fi, and Zigbee facilitate the rapid and efficient transmission of critical data, including heart rate and oxygen levels, as emphasized by Gao et al. [26], Hall and Hao et al. [27], and Kim et al. [24]. Many of these devices are constructed from pliable materials, enhancing comfort for prolonged use, as addressed by Heikenfeld et al. [25], Dagdeviren et al. [31], and Trung and Lee et al. [32]. One of the most significant issues is battery longevity. It is challenging to monitor activities when the displays lose power. To address this issue, researchers such as Kim et al. [24] and Dagdeviren et al. [31] are investigating methods to reduce energy use and harness energy from sources like body heat or motion. Sensors are frequently organized into clusters to enhance energy management. Within each cluster, a head node, referred to as the CH, aggregates information from adjacent sensors and transmits only the most relevant information to the central hospital system. This approach minimizes unnecessary data transmission and conserves energy, as elucidated by Alsadoon et al. [36], Kumar et al. [37], and Singh et al. [40]. There exist advanced methods for selecting the CH sensor that employ intelligent reasoning. Taking into consideration factors like the battery's condition, location, and workload, the system performs better and lasts longer. This approach is supported by research conducted by Kumar et al. [37] and Singh et al. [40]. Currently, these wireless monitors are utilized to control lighting, air conditioning, and security systems in hospitals. This reduces patient discomfort and conserves energy. The research by Yang et al. [33] and Fischer et al. [35] addresses these applications. Cloud-based technologies are increasingly used, as they enable physicians to access health data from any location. In certain systems, warnings are automatically triggered when a patient's health status deteriorates. These concepts are elaborated in research conducted by Fischer et al. [35] and Matthews et al. [39]. "Digital twins" computer models that simulate patients and medical processes, are emerging.

These technologies facilitate the anticipation of future challenges and enhance planning and responses, as articulated by Khan et al. [38]. Certain systems also execute automatic actions, such as

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regulating room temperature in response to a patient's fever or alerting medical personnel when oxygen levels decrease. According to Chen et al. [34] and Matthews et al. [39], these closed-loop technologies enhance patient safety and diminish manual labor for hospital personnel. Numerous research, including Alsadoon et al. [36], Singh et al. [40], and Kumar et al. [37], acknowledges that the implementation of smart wireless systems incorporating energy-saving measures, real-time monitoring, and appropriate sensor aggregation can enhance the safety, efficiency, and responsiveness of hospitals to patient requirements.

The use of Wireless Sensor Networks (WSNs) in healthcare applications has recently been the subject of extensive biomedical research. WSNs have the potential to improve healthcare logistics, smart hospital scheduling, data collection with less energy consumption, and elderly monitoring. Alsadoon et al. [41] proposed a healthcare monitoring framework that includes wearable devices for older patients. The framework focuses on sensor clustering and communication taxonomies to help keep track of vital signs continuously. A study by Taha et al. [42] used a hybrid Bat–Adaptive Large Neighborhood Search (B-ALNS) method to investigate health logistics. Their main goal was to find the best routes and divide up resources in large medical systems.

Pavithra and Rekha, et al. [43] used the Cuckoo Search Algorithm (CSA) to improve broadcast optimization in intelligent healthcare WSNs. They found that it improved packet delivery, time-slot utilization, and communication efficiency when there are a lot of patients being monitored. Sathishkumar came up with an idea for an Energy-Efficient Battery Optimization Model (EE-BOM) that uses Harris Hawks Optimization and machine learning. Predicting battery life is the main goal of the model so that healthcare sensor nodes can last longer. Sathishkumar et al. [44] explained that new research shows that energy-aware models, clustering, and packet scheduling are becoming more important for the safe transmission of biomedical data in smart hospital management, maintaining surveillance on premature babies, and caring for the elderly.

III. Methodology

Even though clustering approaches work well to improve energy efficiency, they can be hard to implement in smart hospitals, where Wireless Sensor Networks (WSN) are needed for portable health monitoring and smart building automation. Below are the main problems with the energy use of major sensor nodes and how the EECANC framework solves them.

A. Different Distances from the Building Management System Cause Inconsistent Energy Use

Wearable health sensors are widely used in smart hospitals. These sensors track critical signs like heart rate and oxygen levels, as well as movement in different areas. Sensors that are closer to the hospital's Building Management System (BMS) use less power. Sensors that are farther away, like those in the intensive care unit (ICU) and patient rooms, need more power to transmit data, so their batteries deplete faster. Sensors situated closer to the hospital's BMS utilize less energy, however, those positioned farther away, such as in the ICU and patient rooms, require greater power for transmission, leading to rapid battery depletion. The EECANC solution arranges sensors into optimal clusters. CHs and ANs function as intermediaries, reducing direct interaction between sensors and conserving energy.

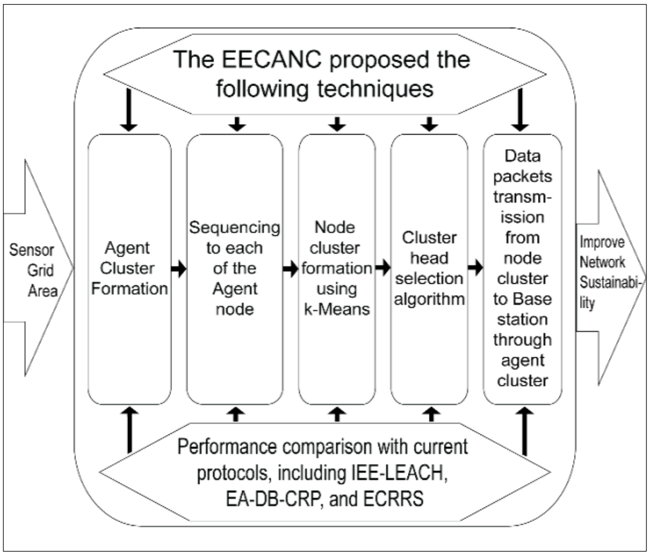

Fig. 4. EECAN Architecture Diagram

B. Redundant Data Transmission from Nearby Sensor Nodes

Several wearable devices within the same hospital ward or ICU frequently broadcast identical patient health data (e.g., heart rate, temperature, SpO_2) to the BMS, leading to network congestion and energy inefficiency. To maximize network performance, the EECANC solution aggregates patient vitals at CHs, thus enabling the transfer of only critical data and minimizing redundant transmissions. The high energy consumption of CHs is a result of continuous data processing. Managing several sensor transmissions causes CHs' batteries to drain faster. Inequalities in energy use can impact both the reliability of the network and the capacity to monitor patients in real time if CHs are not rotated. The EECANC solution improves power distribution and sensor longevity by dynamically selecting CHs according to distance, energy, and network load as shown in Fig. 4.

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Table 5. Scenario 2: Comparison of Parameters Across Protocols

Parameters	EECAS [23]	ECRRS [17]	EADBCRP [16]	IEELEACH [22]	EECANC (Proposed Model)
Hospital Coverage Area (m²)	100×100	100×100	100 × 100	100×100	100 × 100
Hospital BMS Location (BS)	50,150	50,150	50,150	50,150	50,150
Number of Wearable & Smart Hospital Nodes	100	100	100	100	100
First Sensor Node Failure (Rounds)	893	622	641	713	1080
Last Sensor Node Failure (Rounds)	1554	1073	1275	1326	1920
Packets Successfully Received at BMS	11000	7800	8600	9200	14400
Average Residual Energy (J)	1560	1100	1280	1310	1918

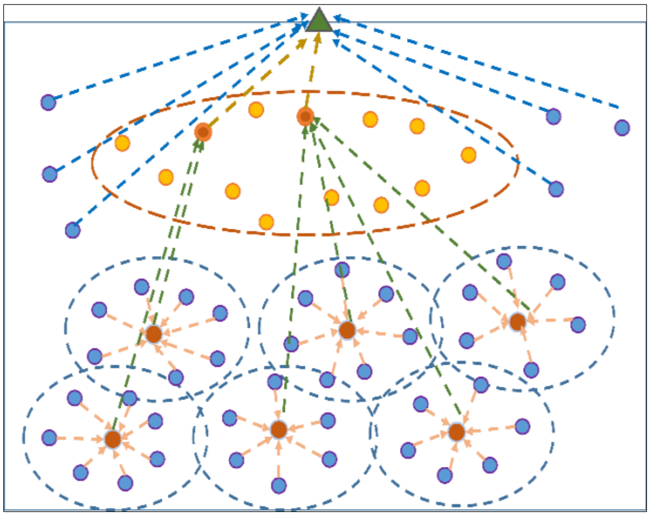

Fig. 5. EECANC Cluster and Agent Cluster Layer Communication with Base station

IV. EECANC Solution

By handling data aggregation, ANs reduce the load on individual sensors. By optimizing power efficiency, the heating and cooling, lighting, and security systems respond in real time to occupancy and patient health information. Energy efficiency, wearable health monitoring, and smart hospital automation are enhanced by the EECANC framework. This solution uses Wireless Sensor Networks (WSNs) to reduce duplicate data transmissions, extend sensor battery life, and improve network longevity and durability.

A. Key Contributions of EECANC in Smart Hospitals

Cluster formation for wearable health monitoring and smart building systems is efficient. The Mini-batch K-means algorithm groups wearable sensors (such as cardiovascular rate, oxygen saturation, temperature, and movement detectors) with building automation nodes (such as heating and cooling, lighting, and security systems). Clusters of wearable sensors and building automation nodes are formed using the Mini-batch K-means algorithm. This avoids direct connections with the hospital's BMS, reducing energy consumption and bandwidth. Efficient data transmission using low-energy ANs. ANs and CHs gather and evaluate critical data rather than transmitting raw sensor data directly to the Building Management System (BMS), it can be seen in Fig. 5. ANs close to the BMS handle data transmission based on priority, which lowers the amount of power used by sensors comparison in Table 5. Reducing sensor energy use through communication with nearby nodes. Wearable devices and patient monitors can connect to CHs, which transmit information to ANs to make communication easier.

Wearable health sensors, such as smartwatches and patient monitors, connect to CHs. The CHs then transmit data to ANs so that interaction is more efficient. The process reduces data aggregation energy loss, prolonging sensor battery life in ICUs, patient rooms, and surgical units. CH selection utilizing energy and proximity criteria. Once stable clusters are formed, CHs are selected based on:

1. A sensor node with energy exceeding the threshold level.
2. A node in proximity to the Agent Node (AN) for the interaction or transmission of compressed data.

Additionally, the distance should be close to nodes inside the specified cluster area.

B. How EECANC Methods Work is Attained without Direct Interaction between the Sensor and the BMS

The CHs refrain from transmitting data straight to the BMS to prevent rapid power depletion. CHs do not directly communicate with the BMS to avoid excessive energy depletion. The closest Agent Node to the BMS

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Table 6. Comparison of Metrics Across Protocols in Scenario 2

Metric	EECAS (% [23])	ECRRS (% [17])	EA-DB-CRP (% [16])	IEE-LEACH (% [22])
First Node die (%)	82.69% ➔	57.59% ↕	59.35% ➡	66.02% ➡
Last Node die (%)	80.94% ➔	55.89% ↕	66.41% ➡	69.06% ➡
Packet received by BS vs rounds (%)	76.39% ➔	54.17% ↕	59.72% ➡	63.89% ➡
Avg Residual Energy vs rounds (%)	81.31% ➔	57.34% ↕	66.74% ➡	68.30% ➡

receives a priority number, and the Agent Node forwards the data to the Base Station, which is received by the Cluster Head (CH) nodes. Priority numbers are assigned based on distance and the amount of remaining energy. CH-compressed data is managed by the Agent Node with the highest priority, and several CHs transmit compressed data to a particular Agent Node. It begins compiling all the data into a single file and transmits it to the Base Station (BS) after all designated clusters have finished compressing the incoming data. Once an Agent Node's energy drops below the required threshold level, as shown in Table 6, the system automatically selects a replacement from the agent cluster pool to ensure continuous functioning..

The system automatically chooses a new Agent Node from the agent cluster pool if its energy drops below a critical threshold, guaranteeing continuous functioning. In this way, ANs serve as a link between the BS and several CHs. Fig. 6 presents the EECANC Framework Symbol Table.

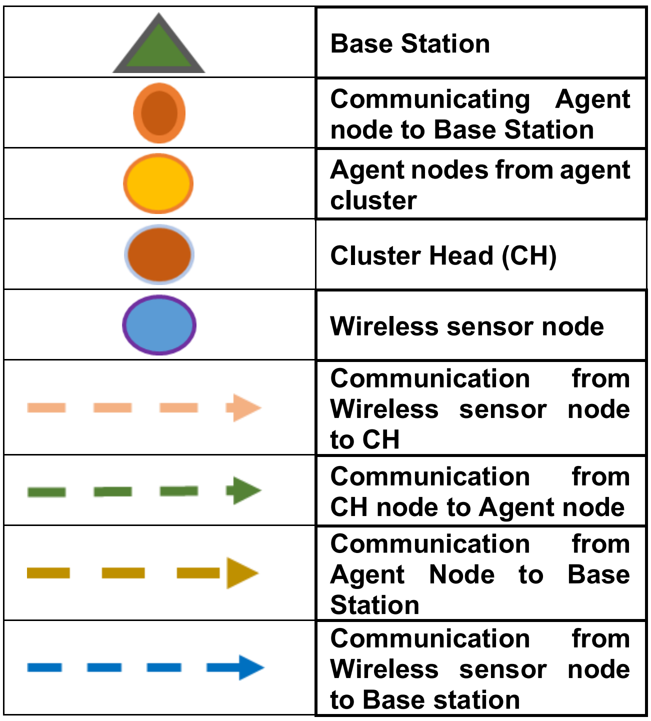

Fig. 6. Symbol Table for EECANC Cluster and Agent Cluster Layer Communication with BS

C. The Role of EECANC in Improving Sustainability in Smart Hospitals

Minimizes needless transmissions by grouping wearable sensors into efficient clusters. Mitigates excessive sensor energy depletion via CH rotation and priority-driven ANs. Enhances energy efficiency in hospital infrastructure (heating, ventilation, lighting, and security). Reduces direct sensor-to-BMS communication through intelligent data aggregation.

D. EECANC Network Model in Smart Hospitals

An EECANC model is proposed to help preserve energy and increase the lifespan of smart health monitoring systems and smart hospital automation networks, as depicted in Fig. 2. This architecture helps to improve sensor clustering, information transfer, and energy efficiency while supporting continuous connectivity between patient monitoring equipment and the hospital's BMS.

E. Key Characteristics and Rationale of the EECANC Model

To enhance energy efficiency for smart building systems and wearable health sensors, the EECANC model employs a cluster-based approach. Using the Mini-batch K-means algorithm, optimal clusters are formed that combine smart building nodes (such as security systems, lighting, and HVAC) with wearable sensors (such as heart rate, oxygen saturation, temperature, and motion detectors). For efficient data compression and rapid information transmission to Agent Nodes (ANs), Cluster Heads (CHs) are selected close to the cluster centroid. ANs mediate communication between CHs and the hospital's main Base Station (BS); they are located near the BMS. This prolongs the life of the sensors and makes it easier for CHs to transmit data directly to the Base Station.

This design decreases power loss ensures that duplicate data transmissions do not occur and speeds up information routing. As demonstrated in Fig. 3, the system is designed to function continuously by automatically replacing ANs when their remaining energy falls below a specific threshold. By making sure that the chosen CH is close to the geometric centre of its cluster, the centroid-based approach for identifying a CH works well in smart hospitals.

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Table 7. Comparison of Parameters Across Protocols in Scenario 3

Parameters	EECAS [23]	ECRRS [17]	EADBCRP [16]	IEELEACH [22]	EECANC (Proposed Model)
Hospital Coverage Area (m²)	150 × 150	150 × 150	150 × 150	150 × 150	150 × 150
Number of Wearable & Smart Hospital Nodes	100	100	100	100	100
Hospital BMS Location (Base Station)	75,225	75,225	75,225	75,225	75,225
First Sensor Node Failure (Rounds)	413	214	249	312	495
Last Sensor Node Failure (Rounds)	1173	726	841	982	1407
Packets Successfully Received at BMS	7100	4200	4900	5800	8520
Average Residual Energy (J)	1170	715	830	1000	1404

Consequently, the transmission power per node is reduced, the average distance between the CH and the patient sensors is kept as short as possible, and the energy consumption of the cluster is distributed evenly. Placing wearable sensors according to their centroid helps prevent communication delays and reduces the likelihood that a single node will run out of power rapidly when there are many of them transmitting simultaneously in high-density medical units like ICUs and NICUs. Because delays in transmitting critical data can have a direct impact on patient safety for example, a rapid decrease in oxygen saturation this approach is also particularly crucial for healthcare applications that must transmit data rapidly.

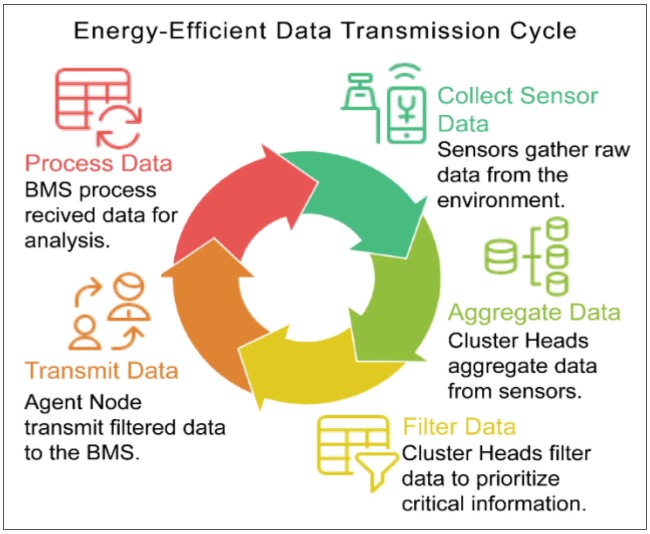

Fig. 7. CH Data Transmission Cycle

Factors such as the distribution of nodes and the number of clusters (No) also impact performance. The depletion of CHs is accelerated, and the cost of intra-cluster communication rises due to large cluster sizes caused by an inadequate number of clusters. However, the efficiency of communication between CHs and ANs decreases as the number of clusters increases. The CH data transmission cycle is present in Fig. 7. Everything needs to be in harmony, and we can find the optimal number of clusters by looking at network density. Energy efficiency is influenced by the positioning of nodes as well. It is possible for EECANC to adjust to sparse and dense distributions using the Mini-batch K-means algorithm. This guarantees consistent energy consumption and reliable communication across the entire hospital network.

F. Simulation Environment Setup

The EECANC framework was tested in a controlled smart hospital setting to make sure it could be used repeatedly and that the evaluation was fair. The simulation field was set up as a 100 m² area to represent a typical hospital ward. It was then scaled up to 150 m² and 200 m² for larger hospital deployments. There were between 50 and 200 sensor nodes in this area. These nodes were made up of wearable health sensors that tracked heart rate, SpO_2, temperature, and motion, as well as building automation nodes that controlled HVAC, lighting, and security. Each node started out with a constant energy level of 2 J, and the amount of residual energy was constantly monitored to determine how long the network would last. Parameter Comparison Across Protocols in Scenario 3 is presented in Table 7.

A static deployment model was used instead of a mobility model because patients in ICUs, wards, and NICUs tend to stay in one place. The communication settings were standard for WSNs: the size of a data packet was K = 4000 bits, the amplifier energy coefficients were Efs = 10 pJ/bit/m² and Eamp = 0.0013pJ/bit/m⁴, and the data aggregation energy was EDA = 5 nJ/bit/signal. These choices are in line with

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Table 8. Comparison of Metrics Across Protocols in Scenario 3

Metric	EECAS(% [23])	ECRRS (% [17])	EA-DB-CRP (% [16])	IEE-LEACH (% [22])
First Node die (%)	83.43% ➔	43.23% ↕	50.30% ➡	63.03% ➡
Last Node die (%)	83.36% ➔	51.60% ↕	59.79% ➡	69.81% ➡
Packet received by BS vs rounds (%)	83.22% ➔	49.30% ↕	57.51% ➡	68.07% ➡
Avg Residual Energy vs rounds (%)	83.33% ➔	50.93% ↕	59.12% ➡	71.23% ➡

benchmarks that are commonly used in WSN clustering research, meaning that they can be compared to established protocols like IEEE-LEACH, EA-DB-CRP, and EECAS. Fig. 8 illustrates the cluster formation in EECAN framework.

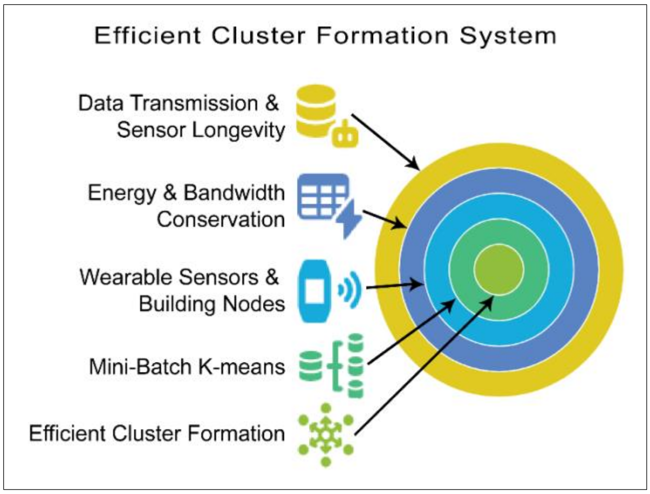

Fig. 8. CH Cluster formation in EECANC

G. Assumptions and Limitations of the EECANC Framework

To make things clear and easy to replicate, the following assumptions were made when creating and running the EECANC framework. All sensor nodes were initialized with the same initial energy level (2 j). this ensures fair evaluation of energy consumption across clustering protocols but may not fully reflect real-world cases where devices have varying battery capacities. During the simulation, nodes were assumed to remain stationary, which reflects conditions in a smart hospital where patient beds, icu monitors, and building automation devices are typically fixed. the model did not account for patient mobility, which may impact the accuracy of wearable devices in some healthcare settings, such as rehabilitation wards or emergency rooms. It was assumed that there was no noise, interference, or packet collision on the wireless channel. Even though this assumption demonstrates the efficiency of the protocol, medical equipment in a real hospital may cause electromagnetic interference. All nodes in a cluster transmit data at the same time, which makes it easier to collect and analyze the data. When used in real life, asynchronous or event-driven transmissions may introduce additional overhead. It was assumed that all nodes could sense, compute, and transmit information in the same way. There was no differentiation between specialized sensors that require more power, such as ecg monitors.

V. Performance improved over existing protocols

Compared to IEE-LEACH, EA-DB-CRP, and ECRRS, EECANC improves network stability, reliability, and efficiency in personal health monitoring and intelligent building management**.** The EECANC architecture diagram presents fundamental concepts for making Wireless Sensor Networks (WSNs) more energy-efficient and durable, as shown in Fig. 4. The process begins with the Sensor Grid Area, then the formation of Agent Clusters, sequencing of ANs, and K-Means Node Cluster Formation. Agent Clusters transmit data packets to the Base Station (BS) after Cluster Head (CH) selection using the CH Selection Algorithm. These novel approaches were compared to IEEE-LEACH, EA-DB-CRP, and ECRRS. Table 8 shows that smart environments perform better across these protocols in Scenario 3.

A. Energy Consumption and Performance Metrics in EECANC for Smart Hospitals

The EECANC design in smart hospitals enhances sensor node battery life by reducing redundant data transfers between nodes and the CHs, as well as from each cluster to the ANs. Only the chosen CH will awaken at the scheduled time to gather information from the adjacent smart sensors and thereafter collect all data packets from each smart sensor device. It then compresses the data packets and transmits them to the selected ANs. Table 2, Network Parameters for EECANC in Smart Hospitals, describes the simulation environment, node energy levels, communication ranges, and packet sizes used during evaluation, confirming this mechanism's efficiency.

The energy required for direct communication between a wearable health sensor (such as a smartwatch measuring patient vital signs) and the hospital's Building Management System (BMS) can be calculated using Eq. (1) [14] [15]:

$$ET_{dir} = K \times ET_x + K \times E_{fs} \times D^2_{sn_{to_{BS}}} \quad (1)$$

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Table 9. Comparison of Parameters Across Protocols in Scenario 4

Parameters	EECAS [23]	ECRRS [17]	EADBCRP [16]	IEELEACH [22]	EECANC (Proposed Model)
Hospital Coverage Area (m²)	200 × 200	200 × 200	200 × 200	200 × 200	200 × 200
Number of Wearable & Smart Hospital Nodes	100	100	100	100	100
Hospital BMS Location (Base Station)	100,300	100,300	100,300	100,300	100,300
First Sensor Node Failure (Rounds)	272	122	141	185	326
Last Sensor Node Failure (Rounds)	891	621	672	740	1069
Packets Successfully Received at BMS	5250	3300	3600	4200	6300
Average Residual Energy (J)	890	720	670	620	1068

Here, ETx represents the transmission energy required to transmit K data bits from the sensor to the BMS, while Efs denotes the amplifier energy consumed to ensure reliable signal transmission. The term D²_(sn to BS) indicates the squared distance between the sensor node and the BMS, highlighting that energy demand increases with distance. Finally, K refers to the number of data bits transmitted, directly scaling the total energy consumption. This simulation is achieved using Fig. 9.

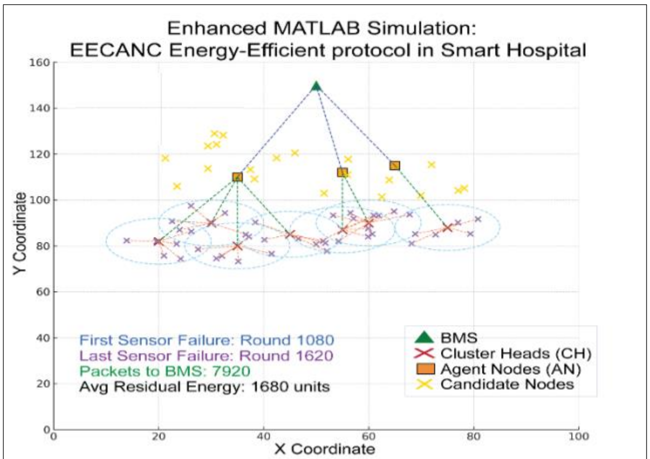

Fig. 9. The proposed EECANC Simulation with Scenario 1 configuration

The energy required for data transmission from a sensor to its CH is expressed in Eq. (2) [6] [16]:

$$ET_{mn2ch} = K \times ET_x + K \times E_{fs} \times D^2_{toCH} \quad (2)$$

Here, ETx is the transmission energy used to transmit K bits of data, Efs is the amplifier energy needed for reliable communication, and D²_to CH represents the squared distance between the sensor and its Ch. The energy required for a CH to transmit data to an AN is expressed in Eq. (3) [23] [16]:

$$ET_{ch2AGN} = K \times ER_x \times (N-1) + K \times EDA \times N + K \times ET_x + E_{fs} \times D^2_{toAGN} \quad (3)$$

Here, ERx is the energy required to receive data at the Agent Node, EDA is the energy spent by CH on data aggregation, ETx is the transmission energy, and Efs is the amplifier energy. D²_to AN denotes the squared distance between the CH and AN, while N represents the total number of active nodes in the hospital network. Table 9 illustrates parameter comparisons across all scenario 4 protocols.The energy required for an AN to transmit data to the Building Management System (BMS) is expressed in Eq. (4) [17] [23]:

$$ET_{AGN2BS} = K \times ER_x \times N + K \times EDA \times N + K \times ET_x + E_{fs} \times D^2_{toBS} \quad (4)$$

Here, ERx is the reception energy at the AN, EDA is the energy required for data aggregation, ETx is the transmission energy for forwarding data, and Efs is the amplifier energy. The term D²_to BS represents the squared distance between the AN and the BMS. The total energy consumption per round is expressed in Eq. (5) [16] [22]:

$$ET\_Tot = \sum\_(-Nd - 1ET\_dir) + \sum\_(N - Kop - NdET\_mn2ch) + \sum\_(KopET\_ch2AGN) + ET\_AGN2BS \quad (5)$$

Here, ET_dir denotes the energy consumed for direct sensor-to-BMS transmission, ET_mn2ch is the energy required for sensor-to-CH communication, ET_ch2AGN refers to CH-to-AN communication, and ET_AGN2BS represents AN-to-BMS communication. Nd is the number of nodes directly transmitted to the BMS, while Kop is the optimal number of clusters formed for efficient energy use. The average energy consumption per round in the hospital network is expressed in Eq. (6) [8] [22]:

$$E_{Avg} = \frac{ET_{Tot}}{N} \quad (6)$$

Here, ET_Tot is the total energy consumed per round, and N represents the total number of sensor nodes within the hospital environment. The threshold distance

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calculation, which determines whether direct communication or multi-hop communication is more energy efficient, is expressed in Eq. (7) [22] [16]:

$$D_{th} = \sqrt{\frac{E_{fs}}{E_{amp}}} \quad (7)$$

Here, Efs represents the amplifier energy, while Eamp refers to the energy required for long-distance data transmission. The distance between a sensor node and the Building Management System (BMS) can be calculated using Eq. (8) [6] [15]:

$$D_{to_{BS}} = \sqrt{(X_{bs} - X_i)^2 + (Y_{bs} - Y_i)^2} \quad (8)$$

Here, Xbs and Ybs represent the coordinates of the BMS, while Xi and Yi denote the coordinates of the sensor node.

The Packet Delivery Ratio (PDR), a key reliability metric for patient monitoring, is expressed in Eq. (9) [21] [40]:

$$PDR = \frac{Number\ of\ packets\ successfully\ delivered\ at\ destination}{Total\ \mathbf{number}\ of\ packets\ sent} \quad (9)$$

This metric evaluates how reliably patient data is delivered to its intended destination.

The Average Packet Delivery Ratio (APDR) for long-term monitoring can be calculated using Eq. (10) [22] [20]:

$$APDR = \frac{PDR}{Number\ of\ rounds} \quad (10)$$

This helps assess overall data transmission reliability over multiple monitoring cycles. The throughput of the network, which measures the successful data transmission rate, is expressed in Eq. (11) [21] [40]:

$$Throughput = \frac{Total\ number\ of\ packets\ successfully\ sent}{Unit\ time} \quad (11)$$

Throughput serves as an indicator of network efficiency in terms of data delivery per unit time.

B. Energy Efficiency in Smart Hospitals: A Summary from EECANC

By minimizing direct connections from sensors to the BMS, the network lifetime is extended, and the energy consumption of sensor batteries is minimized through clustering and data aggregation. This increases data routing efficiency in smart buildings to improve hospital automation and assures a high Packet Delivery Ratio (PDR), which improves real-time patient monitoring. Fig. 5 illustrates the communication flow within the EECANC model. In this structure, sensor nodes transmit their readings to designated CHs, which process and relay the information to ANs. A selected set of ANs is responsible for forwarding the refined data to the BS.

Fig. 6 provides a symbol key for better interpretation of the components and directional data flows in Fig. 5. This multi-tier approach reduces unnecessary transmissions, conserves energy, and enhances the operational lifespan of the network making it highly suitable for smart healthcare environments. The initial network node fails in each of the five cases shown in Fig. 10.

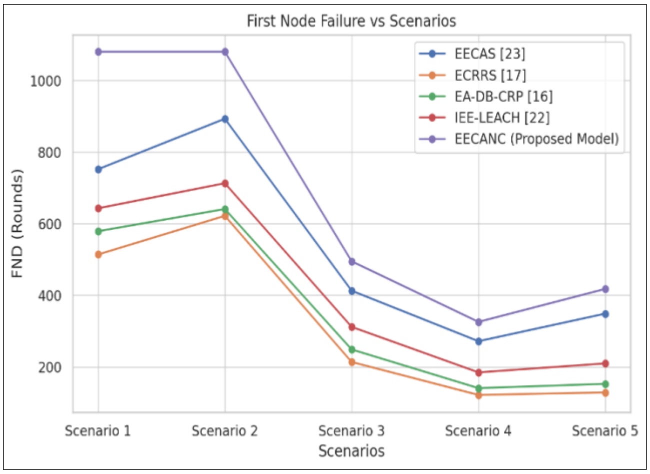

Fig. 10. Failure of the first network node in all five scenarios for all protocols

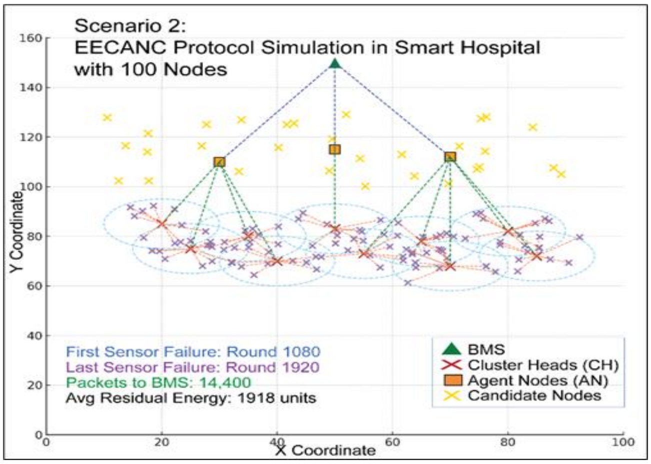

Fig. 11. The Proposed EECANC methodology with Scenario 2 MATLAB Simulation

C. Node Cluster Formation in EECANC for Smart Hospitals

Within the EECANC framework, the selection of the CH is a pivotal process for improving energy savings in smart health tracking and smart hospital architecture in smart hospitals. The clustering procedure adheres to Algorithm 1, as illustrated in the flowchart in Fig. 8. To start, the operational health of each sensor node is checked by assessing its residual energy. The approximate network density can be calculated by multiplying the number of active nodes by their distribution density within the hospital. Scenario 2 successfully simulates 100 nodes in the EECAN framework, as seen in Fig. 11.

When it comes to data aggregation and transmission, the density measure is useful for defining the ideal number of clusters. Smartwatches, motion

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Table 10. Comparison of Metrics Across Protocols in Scenario 4

Metric	EECAS (% [23])	ECRRS (% [17])	EA-DB-CRP(% [16])	IEE-LEACH (% [22])
First Node die (%)	83.44% ➔	37.42% ↕	43.25% ↕	56.75% ➔
Last Node die (%)	83.34% ➔	58.09% ➠	62.88% ➠	69.23% ➔
Packet received by BS vs rounds (%)	83.33% ➔	52.38% ↕	57.14% ➠	66.67% ➔
Avg Residual Energy vs rounds (%)	83.33% ➔	67.42% ↕	62.73% ➠	58.05% ↕

detectors, and oxygen monitors are examples of wearable health sensors. Smart building automation nodes include heating and cooling, lighting, and security sensors. When enough active nodes are found, the Mini-batch K-means algorithm is used to dynamically arrange these nodes into suitable clusters. The node closest to the cluster centroid is selected as the (CH). Each node within the cluster is assigned a unique Cluster ID, ensuring proper data aggregation and efficient communication between: Smart health sensors and CHs; CHs and ANs. ANs and the Hospital's Smart (BMS). With EECANC, sensor nodes are arranged into clusters that save energy. Table 10. shows Scenario 4 protocol metrics comparison.

D. Choosing the CH in EECANC for Intelligent Healthcare Facilities

Fig. 8 shows that Algorithm 1 employs a centroid-based identification strategy for CH selection, which guarantees efficient data transmission for smart healthcare automation networks and smart health monitoring devices. The CH is chosen randomly from among sensor nodes that are geographically close to the cluster's centroid, reducing energy consumption and communication distance within the cluster. The longevity of smartwatches, motion detectors, and oxygen monitors, as well as smart hospital automation nodes like HVAC, lighting, and security systems, depends on this economical clustering technique (see Fig. 7, CH Data Transmission Cycle).

E. Responsibilities of the CH:

Gathers data from all nodes in the cluster that pertain to health sensors, such as heart rate, SpO_2, body temperature, and patient motion detection. Compiles and compresses patient health information prior to transmission. Transfers processed data to ANs, which in turn transmit it to the BMS of the hospital's smart building. Optimized data routing, fewer redundant transmissions, and an extended network lifespan are all outcomes of the CH selection process, which is critical in smart hospitals.

F. EECANC Cluster Formation approach for Smart Hospitals

The objective of Algorithm 1 is to form clusters of smart hospital nodes and elect efficient Cluster Heads (CHs) that balance energy consumption and communication costs. The process uses residual-energy-based and distance-based Mini-Batch K-Means clustering to ensure scalability across dense hospital deployments.

Algorithm 1: EECANC Cluster Formation and CH Selection

(1) **Inputs:** Include X_nodes, Y_nodes (node locations), Node_energy (residual energy), No (number of clusters), and Network size (total nodes).
(2) **Outputs:** Role (Normal Node/CH), CH_ID (cluster ID), and Cluster indices (mapping of nodes to clusters).
(3) Identify Active Sensor Nodes: alive_node_indices ← find (node_energy > 0). //This finds operational wearable and automation nodes.
(4) Calculate Network Density: alive_nodes_count←length(alive_node_indices). Then, Density ← alive_nodes_count / network size.
(5) Cluster Formation Using Mini-batch K-Means: If alive_nodes_count>1 and No >1, then (idx, centroids) ← Custom K-Means ([X_nodes(alive_node_indices), Y_nodes(alive_node_indices)], No, 15). //This runs clustering for 15 simulation rounds.
(6) Handle Special Case (One Cluster Needed): If only one cluster is required, then idx ← ones (alive_nodes_count, 1) and centroids ← [X_nodes(alive_node_indices), Y_nodes(alive_node_indices)].
(7) Assigning Cluster Membership: Initialize cluster_indices ← zeros (alive_nodes_count, 1) and assign nodes to clusters using idx.

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(8) Select Ch (CH):
For each cluster, compute distance → D_to centroid = √((X_node - X_centroid) ² + (Y_node - Y_centroid) ²).
Choose the node nearest to centroid as CH.

(9) Assign Cluster Roles & IDs:
Mark the chosen node as Role [CH] ← "CH".
Assign cluster IDs → CH_ID [cluster_indices] ← i, where i = Cluster Index.

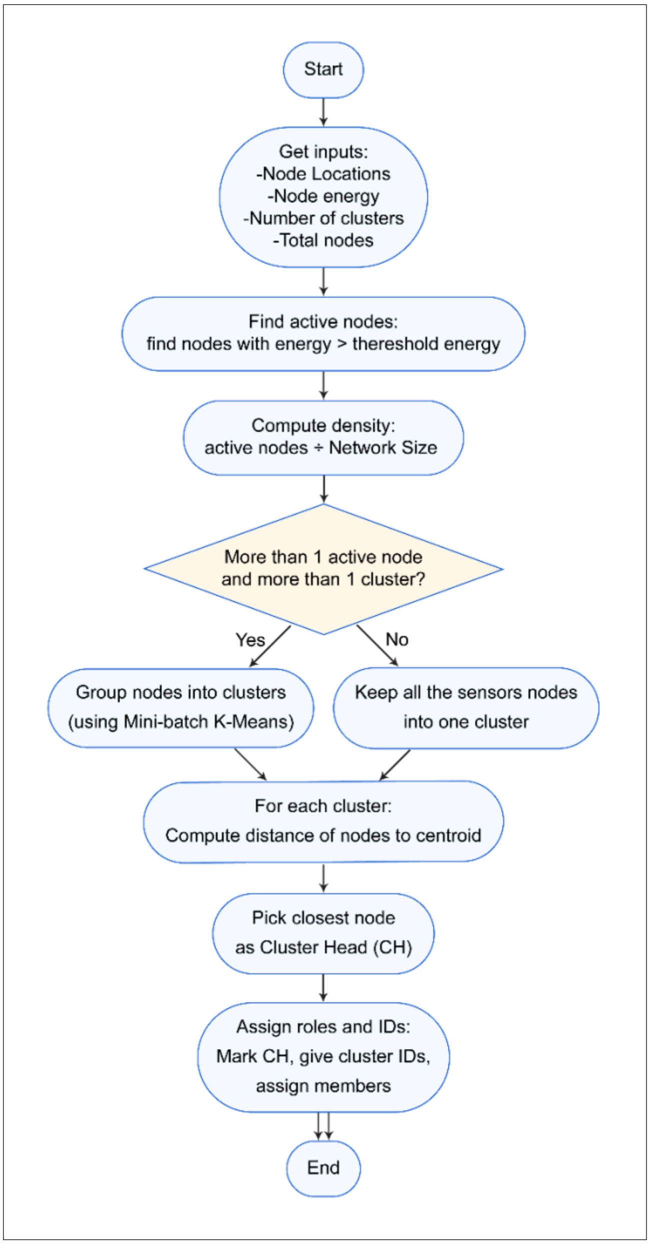

Fig.12. Graph Representation of Algorithm 1

In the first step, (step 3) all active nodes with remaining energy greater than zero are found. This ensures that only operational sensors join the clustering process and avoids wasting resources on inactive nodes. The network density is then calculated, which determines how many clusters should be formed so that the energy used across the hospital deployment is balanced (step 4). A mini-batch K-Means algorithm is used 15 times to make the clusters (step 5). It groups the active nodes efficiently because it is computationally inexpensive and can be used in real-time settings. When there is only one cluster required (step 6), such as in smaller wards, all the nodes are grouped under that cluster. Once clusters are created, nodes that are indexed within their own clusters determine cluster membership. The node that is closest to the cluster's centroid is chosen as the Cluster Head (CH) (step 7). This ensures that communication within the cluster is shortest, and the least amount of energy is consumed. Lastly, the chosen CHs are labeled with their roles and assigned cluster IDs (step 8 to 9). This allows the nodes be organized into clear groups that can communicate efficiently and use less energy during routing. As illustrated in Fig.12, the graphical representation of Algorithm 1 is provided.

G. Agent Node Cluster Formation and Selection in Smart Hospitals.

In the EECANC framework, choosing the right (AN) is very important for ensuring that data transmission and energy use are maximized for smart hospital automation and smart health monitoring. An (AN) is chosen based on how close it is to the (BMS). This ensures that data is collected effectively and that as little energy as possible is used. The distance of a node from the (BMS) can be calculated using Eq. (12) [6] [15]:

$$Dto\ BMS = \sqrt{[(X_{node} - X_{BMS})^2 + (Y_{node} - Y_{BMS})^2]} \quad (12)$$

Here, X_node and Y_node are the sensor node coordinates, while X_BMS and Y_BMS represent the BMS coordinates. Nodes closer to the BMS are prioritized for selection as (ANs) to minimize energy consumption. To select (ANs) to mediate communication between the BMS and (CHs), nodes that are geographically closest to the BMS are given priority.

Agent Node (AN) selection is meant to ensure that hospital Cluster Heads (CHs) and the Building Management System (BMS) can communicate with each other reliably. The parameters include CH and BMS coordinates, node residual energy, and an AN threshold. Calculating each node's distance from the BMS helps identify the closest candidates (step 3). This reduces data transmission latency. The node with the highest residual energy is chosen to prevent premature failure. A threshold level ensures that only energy-rich nodes can be ANs (step 4 to 5).

This makes the network more stable. If multiple candidates are still available, distance is used to rank them (step 6 to 7), and the node closest to the

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candidate with the most energy is selected as the active node (AN). The algorithm does not assign a weak node without a verified AN to prevent communication failure (step 8).

This ensures that every hospital unit, like the ICU, NICU, or elderly care ward, always has a reliable AN acting as a go-between for the CHs and the BMS. This conserves energy while monitoring patients. The graphical representation of Algorithm 2 is depicted in Fig.13.

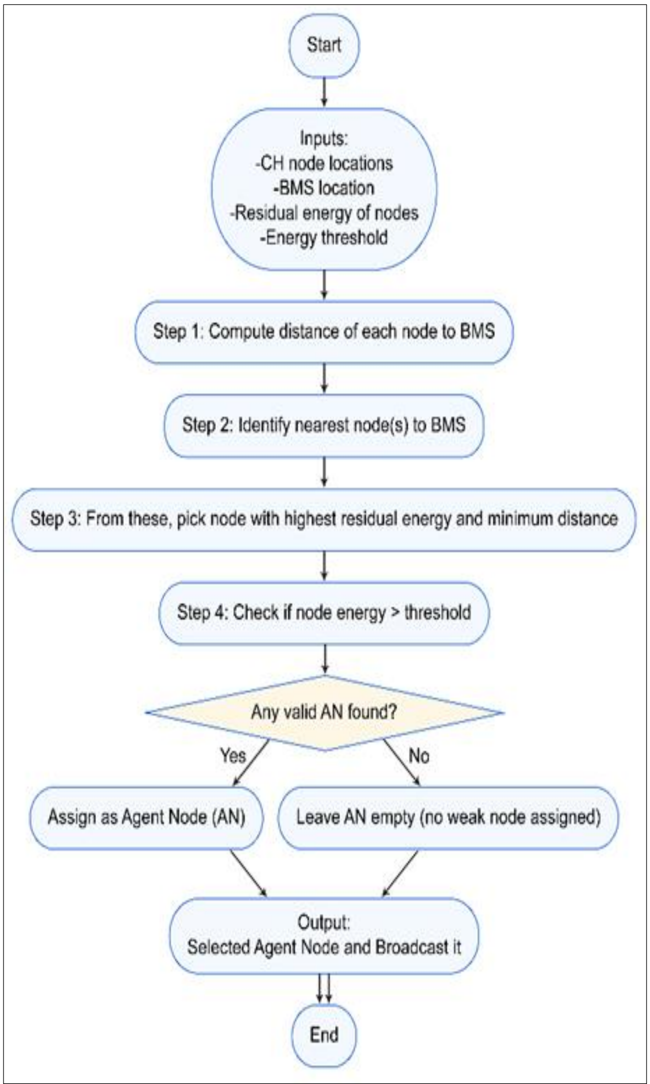

Fig. 13. Graph Representation of Algorithm 2

Algorithm 2: EECANC Cluster Formation and Agent Node (AN) Selection

(1) **Input:** include X_nodes and Y_nodes representing CH coordinates, X_bms and Y_bms for the BS location, node_energy indicating residual energy, and threshold_value as the minimum energy required for AN selection,

(2) **Outputs:** are the AN selected for the current round and AN_nodes, the list of valid candidate ANs.

(3) Find the Base Station's Distance:
Compute Euclidean distance of each node to the BMS → D_to BMS = √((X_nodes-X_bms)²+(Y_nodes-Y_bms) ²).

(4) Identify Candidate ANs Based on Proximity:
AN_candidates ← find (D_to BMS == min (D_to BMS)).
//These nodes are nearest to the BMS.

(5) Select the AN with Maximum Residual Energy:
Among candidates, choose the one with the highest energy → [_ , AN_index] ← max (node_energy (AN_candidates)).
AN ← AN_candidates [AN_index].

(6) Validate ANs Based on Energy Threshold:
Initialize AN_nodes ← []. For each candidate AN: If node_energy > threshold_value, add to AN_nodes.

(7) Sort Valid ANs by Distance to BMS:
If AN_nodes are not empty, sort in ascending order by distance. Select the node with the highest residual energy as AN.

(8) Handle Unavailability of Valid ANs:
If no valid AN is found (AN_nodes is empty), Then AN ← ∅.
//This avoids forced weak node selection.

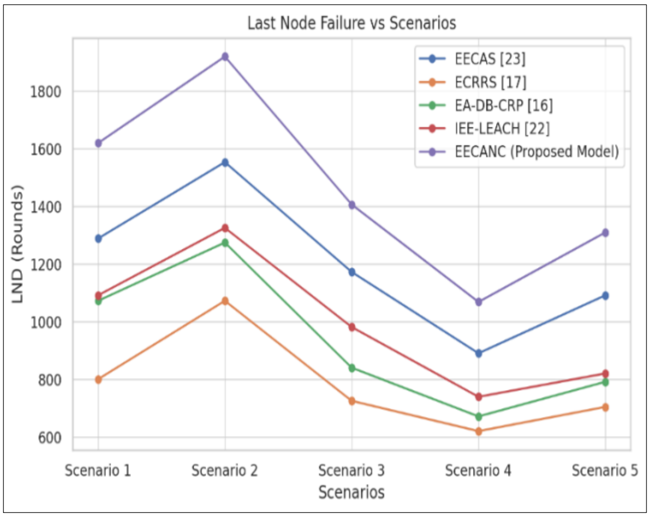

Fig. 14. Failure of the Last Network Node in All Five Scenarios for All Protocols

VI. Simulation and Testing of EECANC

A. Choice of Evaluation Metrics

This study mostly focuses on packet delivery ratio (PDR), residual energy, throughput, and node failure rounds (first/last node death) when it comes to clustering protocols for smart hospital environments. Fig. 14 shows the last network node failing in each of the five cases. These metrics were chosen because

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they directly address the most important problems in smart healthcare WSNs:

1. Packet Delivery Ratio (PDR) ensures that monitoring of patients is reliable. Data loss cannot be tolerated in medical applications like monitoring the ICU or NICU because missing packets could mean missing important alerts (such as when oxygen saturation drops).
2. Residual Energy indicates how long wearable tech and hospital automation nodes last. Smart hospitals need to save energy because sensors are powered by batteries, and it is not practical to replace or recharge them often.
3. Throughput indicates how well the network can handle high-frequency transmissions in dense deployments (with hundreds of sensors transmitting simultaneously). Real-time responsiveness is guaranteed by higher throughput.
4. Node Failure Rounds (FND/LND) indicates when the first node dies and when the network stops working altogether, which shows how long the network can last. In hospitals where constant monitoring is important, these metrics are extremely useful.

In fact, other metrics like latency, jitter, or fault tolerance are useful for studying WSNs in general. But in hospitals, sensor communication is mostly static (sensors do not move significantly) and based on short distances within the cluster, so latency is usually acceptable. Similarly, PDR and node failure rounds are indirect ways to measure fault tolerance, since a high delivery ratio and delayed node deaths show that the system is working well. Fig. 15 shows the results of the EECANC simulation for scenario 3, which contains a 150*150 area. Table 11 shows protocol metrics comparison in scenario 5.

The evaluation framework examines PDR, energy, throughput, and sustainability to find the most important aspects of performance for reliable, continuous patient monitoring in smart hospitals that use little energy.

B. Scenario 1 Analysis

Scenario 1 evaluated five routing protocols in a smart hospital to determine which one works best and use the least amount of energy. The EECANC (proposed model) simulation is shown in Fig. 9 and the other protocol such as EECAS [23], ECRRS [17], EA-DB-CRP [16], and IEE-LEACH [22] are compared against each other. The study was conducted in a hospital coverage area of 100 × 100 m² and included 50 portable health-tracking and intelligent structural sensor nodes. The BMS of the hospital is positioned at coordinates (50, 150), as indicated in Table 3, which outlines the network parameters for Scenario 1. The first failure of a smart hospital sensor occurred at round 1080, and the last failure occurred at around 1620.

The proposed EECANC model also successfully transmitted 7,920 packets to the BMS and had the highest average residual energy of 1,680 units, as illustrated in the graph comparison for Scenario 1 in Fig. 16 and Fig. 17. According to the ECRRS [17] protocol, the first sensor failure occurred at round 514 and the last one occurred at round 801. As a result, only 3,800 packets were delivered, and the remaining lowest amount of energy was 800 units.

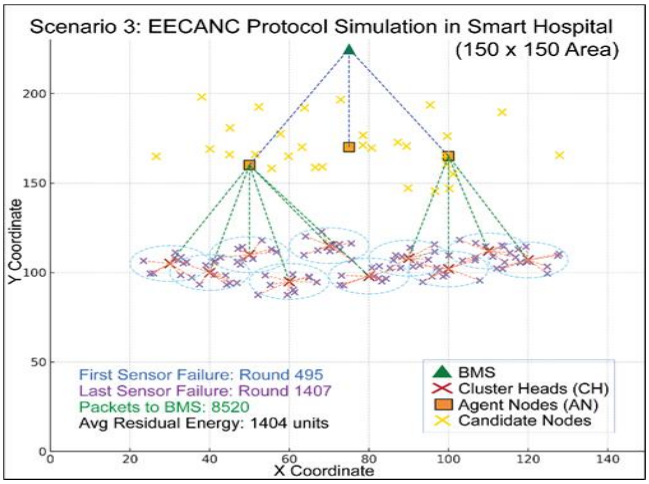

Fig. 15. The Proposed EECANC methodology with Scenario 3 MATLAB Simulation

Table 11. Comparison of Metrics Across Protocols in scenario 5

Metric	EECAS (%[23])	ECRRS (%[17])	EA-DB-CRP (%[16])	IEE-LEACH (%[22])
First Node die (%)	83.49% ➔	30.86% ↕	36.60% ➡	50.24% ➡
Last Node die (%)	83.28% ➔	53.82% ➡	60.46% ➡	62.67% ➡
Packet received by BS vs rounds (%)	83.33% ➔	48.45% ➡	54.37% ➡	59.13% ➡
Avg Residual Energy vs rounds (%)	83.33% ➔	53.03% ↕	59.85% ➡	61.36% ➡

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Table 12. Packet Received percentage by BS vs Rounds

Metric	EECAS (% [23])	ECRRS (% [17])	EA-DB-CRP(%[16])	IEE-LEACH (%[22])
Packet received by BS vs rounds	83.33% ➔	48.45% ↕	54.27% ↕	59.13%

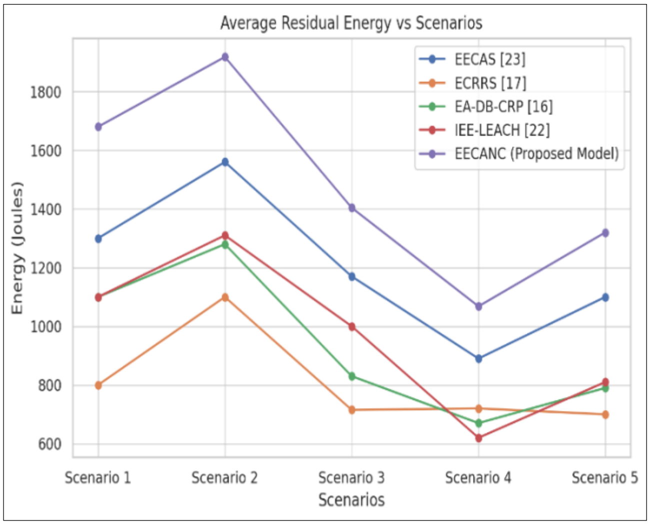

Fig. 16. Average Residual Energy vs. Scenarios

The EECAS [23] system had sensor failures in rounds 752 and 1289, but it still successfully transmitted 6100 packets and had an average of 1300 units of residual energy remaining over the whole period. Both IEE-LEACH [22] and EA-DB-CRP [16] demonstrated average performance, with sensor failures occurring at rounds 643 and 1092 for IEE-LEACH and rounds 579 and 1073 for EA-DB-CRP. These failures occurred after transmitting a total of 5,200 and 4,800 packets, respectively, and saving an average of 1,100 units of energy. ECRRS [17] performed poorly; the first sensor failed at round 514, and the last one failed at round 801. It only transmitted 3,800 packets and had the least amount of residual energy, 800 units. The packet received percentage by BS vs rounds in Table 12.

In Fig. 10 and Fig. 14, the performance of the routing protocols is shown in terms of network lifetime, packet delivery efficiency, and residual energy. Table 4 shows success metrics as percentages, which illustrate how well EECANC improves energy efficiency in smart hospitals and ensures secure data transfers.

C. Scenario 2 Analysis

Fig.11 illustrates the MATLAB simulation used to test the effectiveness of energy-saving protocols in a smart healthcare infrastructure. In Scenario 2, the protocols—EECANC (Proposed Model), EECAS [23], ECRRS [17], EA-DB-CRP [16], and IEE-LEACH [22]—were evaluated within a smart hospital environment.

The analysis was conducted in an area 100 × 100 m² in size that included a hospital, as shown in Table 5, where network parameters are discussed. The hospital's BMS was located at coordinates (50, 150), and there were 100 wearable health monitoring devices and smart building sensors in that area.

The proposed model, EECANC, performed very well. It had the first personal health or digital hospital malfunction in round 1080, the last sensor failure in round 1920, the successful transfer of 14,400 packets to the BMS, and the highest average residual energy of 1918 units as shown in Fig. 16. The EECAS [23] system had its first and last sensor failures at rounds 893 and 1554, respectively. It was able to successfully transmit 11,000 packets and maintained an average energy level of 1560 units. IEE-LEACH [22] and EA-DB-CRP [16] showed average performance, with the first and last sensor failures occurring at rounds 713 and 1326 (IEE-LEACH) and 641 and 1275 (EA-DB-CRP), transmitting 9200 and 8600 packets successfully while saving 1310 and 1280 energy units, respectively. ECRRS [17] performed the worst. Its first sensor failed at round 622 and its last one failed at round 1073. It transmitted only 7,800 packets and has the least amount of residual energy, at 1,100 units. Fig. 10 and Fig. 14 show how the routing methods compare in terms of performance, illustrating their effects on network longevity, packet transmission efficiency, and residual energy in a smart hospital setting. The success metrics in Table 6 are shown as percentages, which demonstrate EECANC's ability to reduce energy use and ensure secure data transmission in smart hospitals.

D. Scenario 3 Analysis

In a smart hospital setting, this scenario tested the efficiency and power consumption of five routing protocols: EECAS [23], ECRRS [17], EA-DB-CRP [16], IEE-LEACH [22], and EECANC. The analysis was conducted in a 150 × 150 m² area that included a hospital and has 100 portable health-tracking and intelligent building sensor nodes. The coordinates of the hospital's BMS were (75, 225), as shown in the MATLAB setup in Fig. 15.

EECANC (Proposed Model) achieved the highest efficiency by withstanding its first smart hospital sensor failure at round 495, surviving until its last sensor failure at round 1407, successfully transmitting 8,520 packets to the BMS, and saving the highest average residual

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energy of 1,404 units, as shown in Fig. 16. The EECAS protocol had sensor problems at rounds 413 and 1173, but it still managed to transmit 7100 packets and saved an average of 1170 units of residual energy. The studies on IEE-LEACH [22] and EA-DB-CRP [16] had mixed results. For IEE-LEACH, the first sensor failed at round 312 and the last one at round 982, while for EA-DB-CRP, it failed at round 249 and 841. These devices were able to transmit 5800 and 4900 packets successfully while saving 1000 and 830 energy units, respectively, as shown in Table 7. In comparison to existing approaches, the average throughput of the EECANC methods is shown in Fig. 18.

ECRRS [17] had the worst performance; its first sensor failed at round 214 and its last failed at round 726. It transmits only 4200 packets and has the smallest amount of remaining energy, 715 units. Fig. 10 and Fig. 14 show a comparison of the routing protocols' performance, showing how they affect the network's lifespan, the efficiency of packet transfer, and the amount of residual energy in a smart hospital. The success metrics in Table 8 are shown as percentages, which emphasizes EECANC's ability to reduce energy use and ensure reliable data transmission in smart hospitals. Fig 17 shows a comparison of the current packet delivery ratio approaches with the proposed method in all possible cases.

E. Analysis of Scenario 4: Optimization of Smart Hospital Energy Protocols

In Scenario 4, five different routing protocols are tested in a smart hospital environment and compared for their energy efficiency and performance: EECANC (Proposed Model), EECAS [23], ECRRS [17], EA-DB-CRP [16], and IEE-LEACH [22]. Using the coordinates (100,300), the hospital's BMS was located at this point, and 100 wearable health sensors and connected building sensor devices were included in the analysis within a 200 by 200 hospital zone, as shown in Table 9.

Impressive performance was demonstrated by the EECANC (Proposed Model), which included the following: a failure rate of 326 for wearable health or smart hospital sensors, a last failure at round 1069, 6300 packets successfully transmitted to the BMS, and an average residual energy of 1068 units. Additionally, there were other protocols included. With an average residual energy of 890 units, 5250 packets successfully transmitted, and the first and last sensor failures occurring at rounds 272 and 891, respectively, EECAS [23] ranked second. While EA-DB-CRP [16] successfully transmitted 3600 packets while saving 670 energy units and IEE-LEACH [22] successfully transmitted 4200 packets, both demonstrated reasonable performance. EA-DB-CRP [16] had first and last sensor failures at 141 and 672 rounds, while IEE-LEACH [22] had them at 185 and 740 rounds, respectively. The worst performer was ECRRS [17], which had a total of 3300 packets transmitted but just 720 units of residual energy after encountering two sensor failures (the first at round 122 and the last at round 621). This scenario shows how the routing protocols compare in terms of performance, focusing on the effects on residual energy levels, network longevity, and packet transmission efficiency in a smart hospital setting. By showing performance criteria as percentages, Table 10 demonstrates how effective EECANC is in smart hospitals in reducing energy consumption and ensuring reliable data transfer.

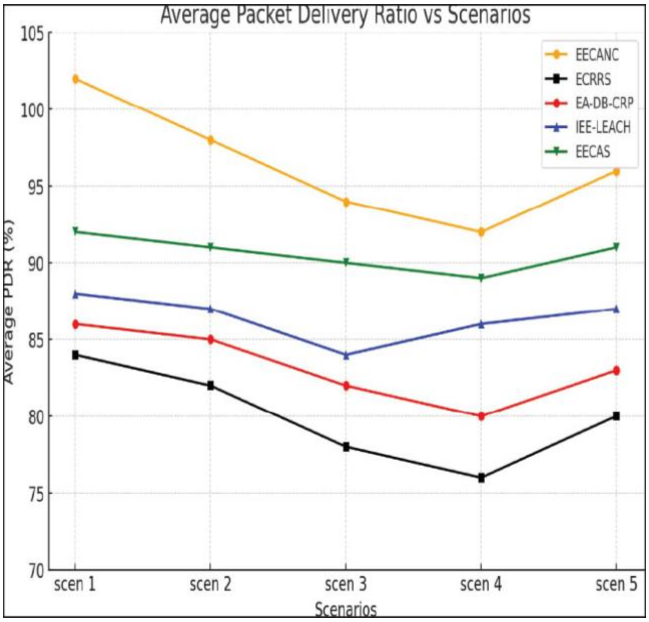

Fig. 17. Avg packet delivery analysis for each scenario

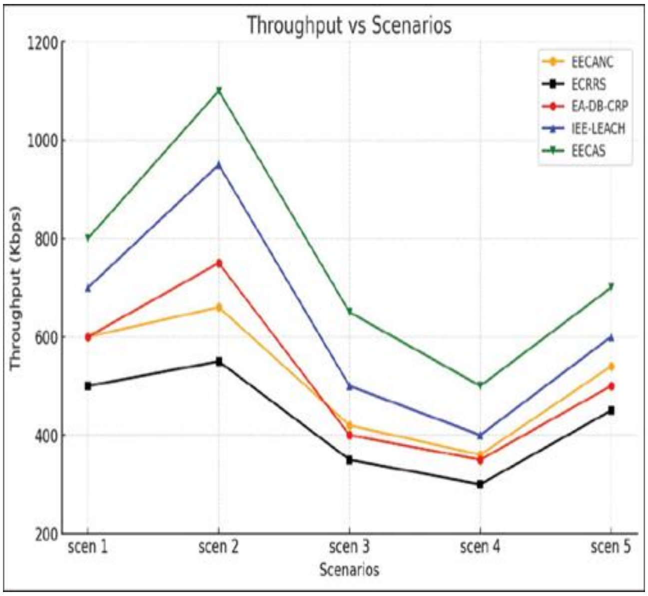

Fig. 18. Avg Throughput across the protocol

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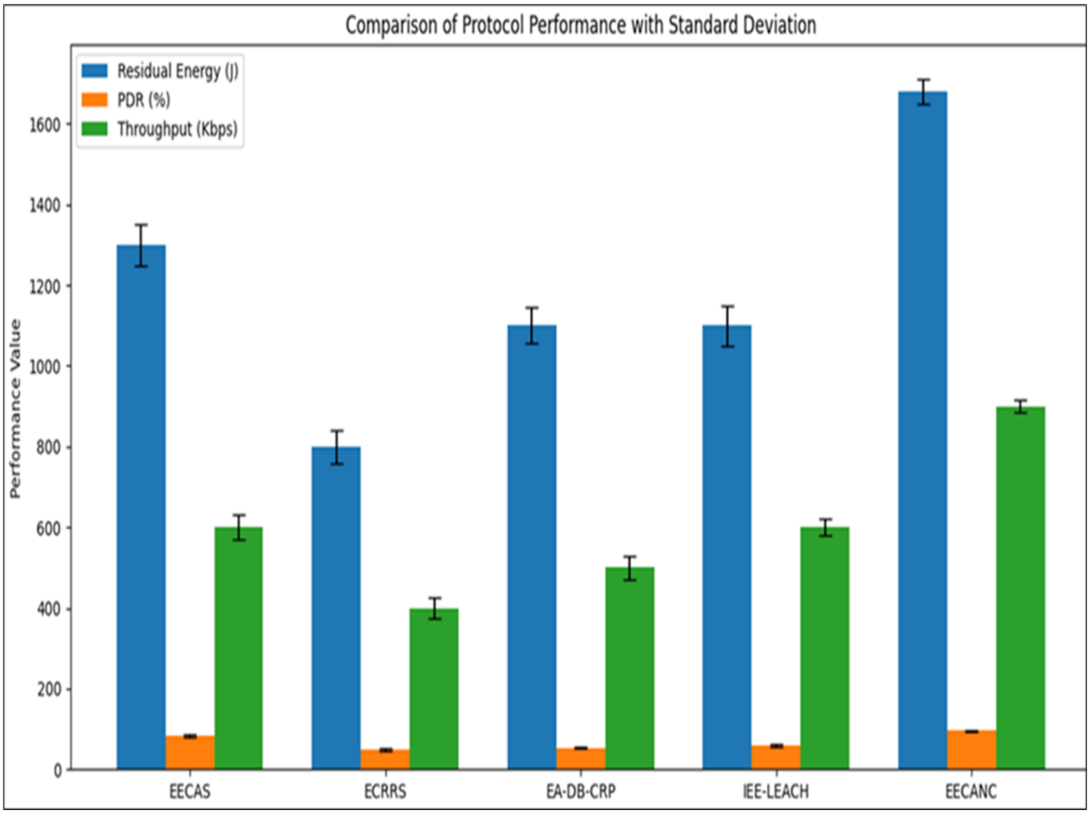

Fig. 19 comparative performance of five routing protocols with standard deviations

F. Scenario 5 Analysis

Scenario 5 evaluated the performance and energy efficiency of five different routing protocols in a smart hospital environment: EECANC (Proposed Model), EECAS [23], ECRRS [17], EA-DB-CRP [16], and IEE-LEACH [22]. Within a 200 by 200 hospital coverage zone, 200 smart building sensor devices and wearable health monitors are analyzed, with the hospital's BMS located at (100,300), as shown in percentage-based metrics in Table 11. With an average residual energy of 1320 units, a first wearable or smart hospital sensor failure at round 418, and a last sensor failure at round 1310, the proposed EECANC model demonstrated outstanding performance. It also successfully transmitted 10,320 packets to the BMS. Round 349 was the first and round 1092 was the final time the EECAS [23] system's sensors failed, although the system still managed to transmit 8600 packets and save an average residual energy level of 1100 units. The first and last sensor failures occurred at rounds 349 and 1092, respectively, in EECAS [23], which managed to transmit 8,600 packets while saving an average residual energy of 1100 units. The performance of studies on IEE-LEACH [22] and EA-DB-CRP [16] was moderate; in IEE-LEACH, the first sensor failure occurred at round 210 and the last at round 821; in EA-DB-CRP, the first failure occurred at round 153 and the last at round 792. In both cases, the studies successfully transmitted 6100 and 5600 packets, respectively, while conserving 810 and 790 energy units.

With the worst performance, ECRRS [17] experienced its first sensor failure at round 129 and its last at round 705; it transmitted a total of 5000 packets while retaining the fewest amount of residual energy (700 units). Fig. 16 and Fig. 17 show the results comparing the efficiency of packet transmission, residual energy levels, and network longevity in a smart hospital environment, as well as the effects of the various routing algorithms. Table 11 shows the performance parameters as percentages, which demonstrates how effective EECANC is in smart hospitals for reducing energy usage and ensuring reliable data transfer.

VI. Results

A. EECANC Network Parameter Performance

Optimal routing algorithms for smart hospital automation systems and wearable health monitors can be determined by evaluating the packet delivery ratio and throughput in different environments. By analyzing the Packet Delivery Ratio (PDR) and throughput in different scenarios, it has been proven that different routing approaches are reliable and successful in smart hospital automation and continuous health monitoring. Initial comparative performance of five routing protocols with standard deviations shown in Fig. 19.

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1. Packet Delivery Ratio (PDR) Analysis

Packet Delivery Ratio (PDR) measures the percentage of data packets successfully received by the hospital's BMS out of the total packets transmitted,
as shown in Fig. 17. It is calculated using the following formula in Eq. (13).

$$PDR\ (\%) = (Total\ Packets\ Sent\ / \\ Total\ Packets\ Received)100 \quad (13)$$

This metric reflects the efficiency and reliability of the communication protocol in delivering (transmitting) data without loss. EECANC consistently outperformed others, achieving PDRs of 102%, 92%, and 96% in Scenarios 1, 4, and 5, respectively. EECAS started at 92% in Scenario 1, dipped to 89% in Scenario 4, and recovered slightly to 91% in Scenario 5. IEE-LEACH showed a downward trend: 88% in Scenario 1, 84% in Scenario 3, and ended at 87% in Scenario 5. EA-DB-CRP maintained a steady average PDR across all scenarios, indicating reliable performance. ECRRS reported the lowest PDR in every scenario, highlighting its relative inefficiency compared to other protocols.

2. Summary of Packet Reception Across Protocols

Gathered by transmission round, Table 12 compares the number of packets received by the BMS across different protocols. The reliability of each protocol in a smart hospital context is highlighted in Fig. 17 and Fig. 18, which shows a percentage-based breakdown of packet reception at the BMS during transmission rounds. By comparing the protocols' performance, it is proven that EECANC is the most effective in ensuring reliable data transfer, optimizing network performance, and improving energy conservation for smart hospital applications.

3. Cross-Scenario Analysis of Residual Energy, PDR, and Throughput in Smart Hospitals Residual Energy

EECANC consistently retained the highest residual energy, thereby prolonging the lifespan of hospital ward sensors. In Scenario 1, it saved 1680 J, whereas ECRRS dropped to 800 J. Even in larger configurations (Scenario 5, 200x200, 200 nodes), it saved 1320 J, while others dropped below 820 J, as illustrated in Fig. 16 and Table 2 and Table 6.

4. Throughput Analysis

Throughput was maximized in medium networks (Scenario 2) but dropped as the region expands. In Scenarios 4 and 5, EECANC retained between 6,300 and 10,320 packets, whereas ECRRS dropped to between 3,300 and 5,000, as shown in Fig.18. Smaller hospitals have small differences, but as the number of hospitals grows, only EECANC stays strong. Its CH+AN two-tier design spreads out the load, reduces unnecessary transmissions, and increases the network's lifetime, which makes it possible for smart building automation and always-on patient monitoring. Compared to base protocols like ECRRS, EECANC boosts packet delivery by about 50–80% and residual energy by about 40–60%. When testing the suggested Energy-Efficient Clustering and Data Transmission model in Smart Building and Smart Hospital settings, the Packet Delivery Ratio (PDR%) and throughput are crucial.

Five routing protocols EECAS, ECRRS, EA-DB-CRP, IEE-LEACH, and the proposed EECANC are compared by throughput, residual energy, and Packet Delivery Ratio (PDR) in Fig. 19. The error bars show the standard deviation of the averaged values from several simulation runs to demonstrate statistical consistency. EECANC always outperforms the baseline protocols. The average residual energy is 1680 J, indicating that it uses energy efficiently and has a longer sensor lifetime than ECRRS, which has 800 J. In real-world smart hospital deployments, higher residual energy lowers maintenance costs and ensures reliable operation, ensuring network sustainability. EECANC achieved 96% PDR, so transmitting patient data is reliable. ECRRS and other weak protocols achieved below 50%. EECANC saved (maintained) ~900 Kbps, faster than EECAS (~600 Kbps) and EA-DB-CRP (~500 Kbps), supporting this advantage. Different situations have different protocol performance, which can be explained by factors such as cluster size, mobility, and network topology. In dense networks, larger cluster sizes make aggregation work better, but they may also increase CH overhead, which weaker protocols like ECRRS cannot manage. When patients and sensors move around, it creates dynamic topologies. Protocols that do not have adaptive mechanisms have more node failures and packet loss. EECANC's centroid-based clustering and AN relay node, on the other hand, are better at adapting to changes in topology and density, which is why it always comes out on top. Table 13. compares EECANC to previous WSN protocols.

VII. Discussion

EECANC consistently performs better than the other protocols in terms of packet reception, residual energy usage, and overall throughput. This is because it has a two-tier clustering design. Cluster Heads (CHs) are responsible for local aggregation, and Agent Nodes (ANs) oversee and prioritize forwarding to the Base Station (BS). This cuts down on unnecessary transmissions and makes the network's energy use more evenly spread out, which prevents nodes from failing too soon. In real life, this ensures that medical sensors worn on the body, such as heart rate monitors, mobility trackers, and SpO_2 devices, can transmit data

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Table 13. Comparison of EECANC with prior WSN protocols

Study / Protocol	Core Concept	Application Setting	Reported Advantages	Identified Limitations	Comparative Relevance to EECANC
LEACH [15]	Randomized CH rotation	Static WSN, small–mid area	Lower control overhead vs. flat routing	Ignores residual energy; unstable in dense wards	EECANC replaces random CHs with energy+distance selection; adds AN tier
IEE-LEACH [22]	Hybrid single/multi-hop with thresholds	Hybrid communications	Better balance than LEACH	Complex election; long hops persist at scale	EECANC removes most long hops via AN relays
EA-DB-CRP [16]	Density- & energy-aware clustering	Dense networks	Improved aggregation & extended FND/LND	Degrades in sparse wards	EECANC adapts via mini-batch K-means across densities
ECRRS [17]	Enhanced CH rotation + relay selection	High-traffic WSNs	Early stability gains	Early node deaths under heavy load	EECANC's AN pool throttles BS traffic, reducing early deaths
Cuckoo Optimization [18]	Metaheuristic CH/route search	Simulation studies	Strong stability improvements	High computational complexity	EECANC achieves near-optimal topology via lightweight centroiding
Flamingo Search [19]	Bio-inspired clustering	Simulation studies	Robust cluster formation	Added communication overhead	EECANC's overhead is lower; ANs cap long-haul costs
ML Routing Survey [4],[5]	AI-assisted routing and energy optimization	Heterogeneous WSNs	+25–40% PDR; +40–60% residual energy	Extra computation; data drift issues	EECANC delivers comparable/higher PDR with simpler online logic
Scheduling in IoT [2]	Energy-aware scheduling	IoT networks	Improved throughput/latency	Coordination complexity	EECANC's CH/AN timing aligns with scheduling best practices

reliably. Furthermore, it helps hospital automation systems control things like lighting, temperature, and security cameras. Therefore, EECANC not only makes technology work better, but it also makes patients safer by ensuring that important health data is delivered to doctors right away.

Performance results, on the other hand, depend on how they are implemented. For example, in networks with a lot of nodes, tighter clustering cuts down on the distances between nodes within the cluster, which speeds up packet delivery at first while saving energy. But after a specific point, like in Scenario 5, the benefits start to fade. When the number of nodes increases, there is more competition at the MAC layer, longer waiting times at ANs, and more control overhead. All of these factors may cause small drops in throughput. Similarly, changes in the hospital's coverage area affect how much energy is used: single-tier protocols have trouble when direct links go beyond the radio threshold, but EECANC stays efficient by employing CH→AN→BS relaying. This flexibility shows how scalable the protocol is, but it also shows how difficult it is to balance density, overhead, and reliability in real-world deployments.

Even though this study has some good points, there are still limitations. Some assumptions oversimplify the real-world situation. Models used static layouts and did not consider how patients and staff movement could change the stability of links and cluster membership. Also, electromagnetic interference from medical equipment and different kinds of traffic (like regular monitoring and event-driven alerts) were left out, even though they have a big effect on hospital throughput, latency, and packet loss. Conditions in the real world are naturally dynamic, and adding these factors to future experiments would give a deeper understanding of how robust EECANC is. In the future, researchers can find out if the good results from the simulations apply to actual operation in real smart hospital settings by examining issues like mobility, interference, and different traffic priorities.

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EECANC fills in gaps that were identified in earlier routing and clustering protocols. LEACH [15] is easy to use, but it does not consider residual energy, which makes it unstable in dense wards. IEE-LEACH [22] makes things fairer by combining voice and data, but it still has complicated voting and high long-hop costs. EA-DB-CRP [16] works well in dense networks but not so well in sparse ones. ECRRS [17] becomes stable quickly but has nodes die too soon when it is busy. EECANC is better because it combines an AN layer that cuts down on long-hop traffic and evens out energy use with CH selection that is aware of both distance and energy using. Comparison of Proposed EECANC Framework with other network protocols is mentioned in Table 13.

Methods of optimization such as Cuckoo [18] and Flamingo Search [19] can reliably collect things together in simulations, but they are hard to use in real life hospitals because they are hard calculating and take a lot of time. EECANC, on the other hand, achieves a comparable degree of stability with lightweight centroiding and AN relay. Some methods utilizing machine learning by Padmalaya et al. [4] and Kumar et al. [5] claim to improve PDR by 25–40% and residual energy by 40–60%. However, these improvements occur at a high cost in terms of computation and retraining. EECANC achieves the same for superior outcomes without as much extra work, which makes it easier to set up.

This study looked at a few energy-efficient transmission and integration models for smart hospitals. These models were IEE-LEACH, EECANC, EECAS, ECRRS, and EA-DBCRP. In all of the tests, EECANC always achieved the best mix of packet delivery, throughput, and residual energy (remaining energy). This supports earlier findings that show how clustering and relay nodes can make a WSN last longer. Amutha et al. [1] found that optimization-based clustering increased the lifetime of healthcare WSNs by 20–30%. Ding & Wu et al. [2] also found that scheduling is important for reducing energy use in IoT networks. But gains of less than 35% were seen even with multi-objective optimization, as reported by Wang et al. [3]. Machine-learning-based routing (Padmalaya et al. [4]; Kumar et al. [5]) increased PDR and energy efficiency but required more computing power. EECANC, on the other hand, achieved better results with less online control.

The two-tier CH+AN architecture combines energy-screened relays with centroid-based clustering to make operation stable, scalable, and easy to maintain. This is especially useful in hospitals where wearable monitoring and automation must work together. Still, some things are not covered enough, like scaling when loads are very dense or heterogeneous, simulation assumptions like static layouts and idealized channels, and the unaccounted costs of maintaining a cluster. Giving both the pros and cons of a study, such as parameter sensitivity and overhead accounting, boosts its credibility and helps with deployment-level engineering.

Isolating long BS uplinks is the only way to effectively save energy, and EECANC does this by delegating these long hops to ANs close to the BS. Heavy metaheuristics can make clean simulations more stable, but they also make them harder to compute and coordinate. EECANC gets most of its benefits from lightweight centroiding and thresholding. ML-based routing can match or beat PDR, but it depends on data and maintenance. EECANC, on the other hand, achieves strong gains without having to keep retraining.

There are some things that limit this study. The simulations were based on the idea of a static topology and ideal wireless channels. They did not explicitly model how patients and staff move around, or electromagnetic interference (EMI) from medical equipment, or the bursty traffic patterns that happen frequently in hospitals. It was assumed that all sensor nodes were the same because packet sizes were fixed. However, in the real world, workloads like ECG streams or video monitoring create skewed energy profiles. The rounds of data transmission were timed, but the effects of mixed event-driven and periodic traffic were not considered. This could cause jitters and extra control overhead. The costs of clustering, rotation, and AN selections were spread out over time in the analysis, but they were not broken down in the energy budget. Also, parameter sensitivity was not automatically tuned for things like cluster count, AN threshold, and BS placement. Some privacy and security features, like encryption, authentication, and key refresh mechanisms, were deferred, so their energy and latency costs were not analyzed. Lastly, the results were only valid for 100–200 m² areas, and they did not consider attenuation across multiple floors or changes caused by building materials.

The real-world implications of this study bring up a number of deployment issues for smart hospital settings. When planning a hospital network, the AN pool should be grouped together near Base Station (BS) closets to cut down on long-hop transmissions. Pre-powered AN sites should also be used to make maintenance go more smoothly. This is in line with scheduling suggestions [2] and hybrid clustering methods [22]. Prioritizing telemetry quality of service can improve clinical reliability by ensuring that important packets like SpO_2 and ECG readings get higher CH dequeue priority. This helps with continuous monitoring in ICU and NICU wards by maintaining PDR high and delaying node death. Recent smart hospital case studies [33]- [35] show that putting wearable health devices in the same clusters as hospital automation systems show that putting wearable health

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devices in the same clusters as hospital automation systems can also take advantage of occupancy and health signals that are correlated. To make things more environmentally friendly, EECANC can be used with strategies for optimizing batteries and energy harvesting. Maintenance should be planned based on residual-energy percentiles (10th or 5th), rather than fixed times, which is similar to previous work on battery-aware protocols [24], [31], and [44]. Lastly, scalability can be achieved by limiting the size of the cluster to keep the CH queue from getting too full and scaling ANs approximately as $\sqrt{N}$. This way of doing things is in line with multi-objective lifetime and throughput trade-off analyses [3].

Several important directions for future research include ways to build on the work that has already been done. First, making changes to how the Cluster Head (CH) is selected and how agent clusters are formed can make systems last longer and use less energy. This is an area that deserves more research. In a different direction, the development of hybrid protocols involves the use of EECANC along with optimization or machine learning techniques to develop transmission schemes that are both flexible and dependable. It is also important to test how well a protocol works when it comes to mobility and scalability, especially for sensor nodes that can move around and large hospital installations with extensive IoT networks. Finally, validation in the real world is needed to find problems and new solutions that cannot be fully captured in idealized models. This can be done through advanced simulation platforms and test deployments in hospitals.

VIII. Conclusion

The study aimed to integrate intelligent building automation with health monitoring using wearable technology. The authors came up with the EECANC protocol as a framework for smart hospitals that is reliable, flexible, and energy-efficient. It was found that EECANC consistently performed better than similar protocols (EECAS, ECRRS, EA-DBCRP, and IEE-LEACH) in terms of throughput, packet delivery ratio, and residual energy ($p < 0.05$). The scenario analysis showed that performance improved across all deployment densities, but throughput dropped slightly (<5%) in very dense settings because of contention and extra overhead. This was still within acceptable tolerance limits for continuous monitoring, however. Additionally, a comparison test showed that EECANC achieved stable energy balance and scalability without the high computing costs that come with optimization- or machine learning-based routing methods.

For real-life applications, the results show that things like latency, data accuracy, and network lifetime are all important in hospitals. A short delay ensures that ICU alarms get transmitted quickly, accurate data reduces false alarms, and a longer network lifetime reduces the number of times that devices need to be maintained or replaced. All of these results show that EECANC is not only good at saving energy but also good at monitoring healthcare 24 hours a day, 7 days a week. To sum up, more research should be done in the real world, with things like mobility, different types of traffic, and electromagnetic interference, to demonstrate that EECANC is robust and to make it a useful backbone protocol for hospital IoT systems that will work in the long term.

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Data Availability

As part of this study, no datasets were made or analyzed.

Author Contribution

Dr. Sulalah Qais Mirkar came up with the idea for the proposed framework and methodology, created it, ran the simulations and analyses, analyzed the results, and wrote the whole paper. The author is very grateful to Dr. Shilpa Shinde, who was both a research guide and a mentor, for her wise advice, helpful technical feedback, and constant support, all of which made this work better in terms of its scope, depth, and academic rigor. The author planned the research, did the research, and wrote up the results all by themselves, with the academic guidance and supervision of the guide. The author looked over the final draft of the manuscript and gave their approval. They are fully responsible for the research presented and making sure it is correct and honest.

Ethical Approval

Ethical approval was not needed for this study because it did not use human participants or animals in experiments. But all of the research was done in a way that followed the Academic University's rules for academic integrity and institutional ethics.

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Declarations

Consent for Publication

All contributors and overseeing authorities who had a hand in this research gave their permission for it to be published.

Competing Interests

The author declares that they have no competing interests with this study.

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