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LEACH-Based Approach Using First Order Model for Energy Efficient Routing in WSNs for Mobile Diabetes Patient Monitoring

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Abstract

About the last decade or so, Wireless Sensor Networks (WSNs) have found a place as an enabling technology in modern healthcare systems. Case in point is the real-time monitoring processes for chronic diseases like diabetes. To get at continuous monitoring of diabetic patients, reliable and energy-efficient communication between sensor nodes and healthcare must occur to guarantee uninterrupted data collection and be able to obtain timely medical intervention with these data. But insufficient energy in sensor nodes creates a real challenge, especially in dynamic environments that have mobility among both patients and healthcare providers. This research aims at developing and simulating an energy-efficient WSN framework for mobile diabetic patient treatment in association with the Low-Energy Adaptive Clustering Hierarchy (LEACH) Protocol with the First-Order Radio Model for consumption estimation. This research simulates diabetic patients as mobile sensor nodes moving within a defined room while representing the doctor as a mobile base station within a wider hospital environment. The simulation considers critical factors influencing communication performance, including cluster head (CH) selection, varying transmission distances, environmental loss factors, packet size variability, and adaptive data rates. Energy consumption for data transmission and reception is calculated using the First-Order Radio Model, considering both free-space and multipath propagation environments based on the distance threshold d0. Additionally, a realistic loss factor (ranging between 0.9 and 1.1) is applied to simulate the effects of environmental interference and signal attenuation on energy efficiency. Dynamic packet sizes and randomly selected data rates determine transmission latency. The experiments run in MATLAB for about 20 communication rounds would yield results demonstrating that the proposed framework balances the energy consumption of the sensor nodes, increases the lifetime of the network, and guarantees dependable data transmission under various environmental and mobility conditions. Nodes acting as CHs suffer from a greater energy depletion and reducing overall energy consumption can be aided by optimizing the selection of CHs and routing adaptation in the performance. An area further elaborated in this study describes the tradeoffs between increased data rates and decreased latencies at a cost of greater energy consumption on larger packet sizes. This study gives some useful

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perspectives for designing and deploying robust energy-aware WSNs for health solutions that will help in the monitoring of diabetic patients in naturalized mobile environments. Future research directions will look at machine learning-based methods of CH selection with dynamic transmission control to improve the performance of the network.

Keywords: Wireless Sensor Networks (WSNs), LEACH, Diabetes, Patient.

1 Introduction

With the merging of wireless sensor networks (WSNs) into the healthcare system, patient monitoring has become a revolution of sorts with real-time data collection and analysis. This change certainly gains importance for the management of chronic diseases like diabetes, where continuous monitoring of physiological parameters is necessary for management and prevention of complications. WSNs enable wearable and implantable devices for monitoring of vital signs and timely delivery of information for decision-making by health professionals (Verma et al., 2023; Verma, 2022; Khan and Awan, 2022). On the flip side, the deployment of WSNs in various healthcare settings faces several challenges, one of the most important being energy consumption (Shetty & Kapoor, 2024). Sensor nodes are mostly battery-powered and hence possess limited energy resources, thus energy efficiency must be a design and operational consideration for these networks (Giji Kiruba et al., 2023). To extend the operational lifetime of sensor nodes without frequent battery replacement is very helpful in ensuring continuous patient monitoring and cost reduction related to maintenance (Rajaram et al., 2025). Various routing protocols have, therefore, been proposed, among the most well-known of which is the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. The LEACH protocol is hierarchical, in that it forms clusters of sensor nodes, each presided over by a cluster head (CH). The CH aggregates data received from its member nodes before forwarding this aggregated data to the base station, thus saving energy by minimizing direct transmissions to the base station (Rana et al., 2024; El-Sayed et al., 2021). LEACH, nevertheless, has its own limitations, especially for dynamic environments such as healthcare where both healthcare staff and patients are mobile (Mathboob, 2024). Random cluster head selection regardless of the nodes' residual energy and the distance between the nodes and the base station would interfere with even energy depletion and, therefore, the network lifetime. Moreover, the static node assumption of LEACH does not capture the mobility patterns of healthcare environments (Ayehu et al., 2020; Kim et al., 2014). To overcome these limitations, a number of enhancements to the LEACH protocol have been proposed. For instance, the Enriched Energy Optimized LEACH (EE-OLEACH) protocol utilizes optimization algorithms for CH selection and routing to improve energy efficiency. Similarly, Neural Network-based Improved LEACH (NN_ILEACH) protocol also utilizes machine learning algorithms to select CHs dynamically using node residual energy levels and network topology (El-Sayed et al., 2024; Malhotra & Mahadik, 2024). Besides protocol optimization, energy consumption models with high efficiency are required for designing energy-efficient WSNs. The First-Order Radio Model is commonly used to estimate the energy required for data transmission and reception (Agarwal & Singh, 2024). According to this model, the energy consumed to transmit a k-bit message over a distance d is given by Equation 1:

$$E_{tx}(k,d) = \begin{cases} k.E_{elee} + k.\mathcal{E}_{fs}\,.d^2, & if\ d < d_0, \\ k.E_{elee} + k.\mathcal{E}_{mp}\,.d^4, & if\ d \geq d_0, \end{cases} \qquad (1)$$

Where Eelec is the energy consumed by the electronic circuitry, ϵfs and ϵmp are the energy consumption coefficients for free space and multipath fading channels, respectively, and d0 is the threshold distance that determines the channel model to be used. The energy consumed to receive a k-bit message is given by Equation 2:

$$E_{tx}(k) = k.E_{elee} \quad (2)$$

In medical applications, specifically in monitoring diabetic patients, patient and caregiver mobility is involved (Sánchez-Ancajima et al., 2023). Sensor nodes must deal with changing network topologies and varying distances to the base station. Furthermore, the diversity of data transport requirements, such as different packet sizes and rates, necessitates adaptive protocols for efficiently managing energy consumption while achieving good data deliverability (Bhola et al., 2020; (Ramesh et al., 2022). Herein, energy-efficient WSN framework development and evaluation are given special attention geared toward mobile monitoring of diabetic patients. The proposed system combines a modified LEACH protocol and the First-Order Radio Model to realize optimal energy utilization. The model takes mobility of nodes, varying parameters of transmission, and environmental factors affecting signal propagation into account. Based on MATLAB simulation for a number of scenarios, the study compares the performance of the system in terms of energy efficiency, network lifespan, and reliability of data transmission.

2 Experimental Setup

Network Model and Simulation Scenario

In our experimental setup, we simulate a wireless sensor network (WSN) designed for mobile diabetic patient monitoring. In this network, each diabetic patient is modeled as a sensor node and is assumed to be mobile within a confined “room” (with spatial boundaries defined on the x and y axes). A doctor—functioning as the base station—is modeled as a mobile entity moving within a larger “hospital” area. The simulation is conducted in MATLAB over a total of 20 rounds. In each round, patient nodes update their positions by a random step (up to 0.5 m per round), and the doctor’s position is similarly updated over a larger area (e.g., between 10 and 20 m in both x and y directions).

In this simulation: Number of sensor nodes (patients): N=5 and Number of rounds: R=20

Cluster Head Selection via LEACH Protocol

We use a LEACH-based protocol to elect a Cluster Head (CH) in each round. The CH is responsible for aggregating data from all patient nodes and transmitting this aggregated data to the doctor (base station). The selection process is probabilistic—each node that has not been a CH in the recent $1/\rho$ rounds is eligible, where ρ is the desired probability of becoming a CH. When multiple nodes meet the criteria, the one nearest to the doctor is chosen to minimize the energy expenditure for the long-range transmission (El Ouadi and A. Hasbi, 2020).

Energy Consumption Model

Energy consumption for data transmission and reception is computed using the First-Order Radio Model. In this model, the energy required to transmit a k-bit message over a distance d is given by Equation 3:

$$E_{tx}(k,d) = \begin{cases} k.E_{elec} + k.\epsilon_{fs}.d^2, if\ d < d_{0,} \\ k.E_{elec} + k.\epsilon_{mp}.d^4, if d \geq d_{0.} \end{cases} \quad (3)$$

The energy consumed to receive a k-bit message is modeled as in Equation 4:

$$E_{rx}(k) = k.E_{elee} \quad (4)$$

Where:

- Eelec is the energy consumed by the electronics (in J/bit).
- ϵfs is the free-space amplifier parameter (J/bit/m2^22).
- ϵ_{mp} is the multipath fading amplifier parameter (J/bit/m4^44).
- d0 is the threshold distance, computed by Equation 5

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (5)$$

For our experiments, we set:

- E_{elec}=50×10^{-9} J/bit
- ϵ_{fs}=10×10^{-12} J/bit/m^2
- ϵ_{mp}=0.0013×10^{-12} J/bit/m^4

Thus, d_0 is calculated accordingly.

Transmission Parameter Models

To capture realistic channel conditions and variability in data transmission, we incorporate the following transmission parameters:

Loss Factor L

A loss factor is introduced to account for environmental effects (e.g., interference, obstacles) that impact signal quality and energy consumption. The loss factor is randomly generated in the range [0.9,1.1] for each round. The effective transmission energy becomes (Equation 6):

$$E_{tx,effective} = E_{tx}(k, d) \times L. \quad (6)$$

1. Packet Size k: The simulation cycles through a set of predetermined packet sizes (e.g., 2000, 4000, and 8000 bits) which directly affect both energy consumption (linearly with k) and communication latency.
2. Data Rate R: Data rates are randomly selected from a discrete set (e.g., 1000,5000,10000). The data rate is used to compute the transmission latency (Equation 7):

$$Latency = \frac{k}{R} \quad (7)$$

3 Experimental Procedure

In every simulation round:

- Patient nodes and the doctor update their positions randomly within their respective regions.
- Transmission parameters (packet size, data rate, loss factor) are generated for the round.
- A LEACH-like algorithm selects a Cluster Head (CH) based on eligibility criteria and proximity to the doctor.
- Energy consumption is calculated for:
  - ➢ Each non-CH node transmitting data to the CH.

- ➢ The CH receiving data from other nodes.
- ➢ The CH transmitting aggregated data to the doctor.

- The computed energy consumption is subtracted from each node's energy budget (initially set to 2 J per node).
- The positions and connectivity for each round are captured and later combined for network topology visualization.
- Energy levels of the nodes, along with transmission parameters, are stored for later plotting and analysis.

Data Acquisition and Analysis

During simulation, the following data are acquired:

- **Node Positions:** The spatial coordinates of the patient nodes over 20 rounds.
- **Doctor's Positions:** The trajectory of the doctor, tracked separately.
- **Energy Levels:** The energy remaining in each sensor node after every round.
- **Transmission Parameters:** The loss factor L, data rate RRR, packet size k, and calculated latency for each round.

For example, in one experimental round, a sensor node transmitting a 4000-bit message over a distance of 2 m (with $< d_0$) will have its transmission energy calculated as:

$$E_{xt} = 4000 \times 50 \times 10^{-9} + 4000 \times 10 \times 10^{-12} \times (2^2) \approx 0.0002J + 0.000016J = 0.000216J$$

With a loss factor L=0.9 (best-case scenario), the effective energy is

$$E_{tx,effective} = 0.000216J \times 0.9 \approx 0.000194J.$$

Latency for the round might be computed (if, e.g., packet size k=4000 bits and data rate R=10000 bps) as in Equation 8:

$$Latency = \frac{4000bits}{R10000pbs} = 0.4sec. \qquad (8)$$

Over 20 rounds, energy depletion curves indicate that nodes may see their energy decrease from 2 J to approximately 1.7–1.8 J, depending on the frequency of CH selection and the transmission distances.

4 Results and Discussion

Data Rate

The simulation represents a dynamic wireless sensor network designed for mobile diabetic patient monitoring, where each diabetic patient is modeled as a sensor node moving within a confined room and the doctor—serving as the base station—moves within a broader hospital area. The network employs a LEACH-based protocol for selecting a cluster head (CH) among the patient nodes. Patients communicate data with their doctors one at a time, which reduces the range of transmission and evenly shares energy consumption among all nodes, according to Saikia et al. Energy consumption was derived from the First-Order Radio Model set forth to minimize the complexity of estimating transmission and reception energy. This approach indicates the energy used to transmit a k-bit message over a distance d (Daanoune et al., 2021; Veera Boopathy et al., 2024). Transmission parameters such as packet size (randomly assigned to values such as 2000, 4000, and 8000 bits), data rate (randomly assigned to values such as 1000, 5000, or 10000 bps), and a loss factor (randomly generated between 0.9 and 1.1) are chosen in every round of simulation to emulate the environmental impacts on signal quality. Although in the First-Order Radio Model, energy consumption is mainly affected by packet size and distance, including a loss factor accounts for extra energy consumption under real channel conditions (Jyothi and Usha, et al., 2019).

For each round, the simulation updates the positions of both the diabetic patient nodes and the doctor, and then selects a CH using a LEACH-like algorithm. Patients send their data to the selected CH, and the CH then forwards the aggregated data to the doctor. The energy used for these transmissions and receptions is deducted from each node's initial energy, which was set uniformly for all nodes (for instance, 2 Joules per node). The energy model helps in understanding how varying transmission distances (both from node to CH and from CH to doctor) and the introduced transmission parameters influence the lifetime of the network (Sajwan et al., 2019). Figure 1represents the data rate variation across 20 simulation rounds representing the dynamic selection of transmission speed in the proposed wireless sensor network. Higher data rates (up to 10,000 bps) reduce latency but may increase energy consumption, while lower data rates (down to 1,000 bps) enhance energy efficiency at the cost of increased transmission delay. The attached simulation results, therefore, display multiple aspects: the network topology changes due to the mobility of the diabetic patients and the doctor, the rotation of the CH over the rounds ensuring balanced energy consumption, and separate plots for loss factor, data rate, packet size, and the resulting latency. These plots illustrate how the random selection of transmission parameters contributes to the fluctuating latency and overall system performance. First-order radio model calculations associated with energy consumption, data-dependent routing ensured by the LEACH protocol, and dynamic movement of nodes represent highly attractive prospects for balancing energy efficiency with signal quality and timeliness of data transfers in a healthcare monitoring scenario. In brief, this integrated perspective shows how mobility among patients and physicians is critical for the effective mobile monitoring of diabetic patients, taking into account both space and the tradeoffs between transmission parameters and energy consumption. It would extend operational lifetime in real healthcare while providing services relevant to timely delivery of patient data.

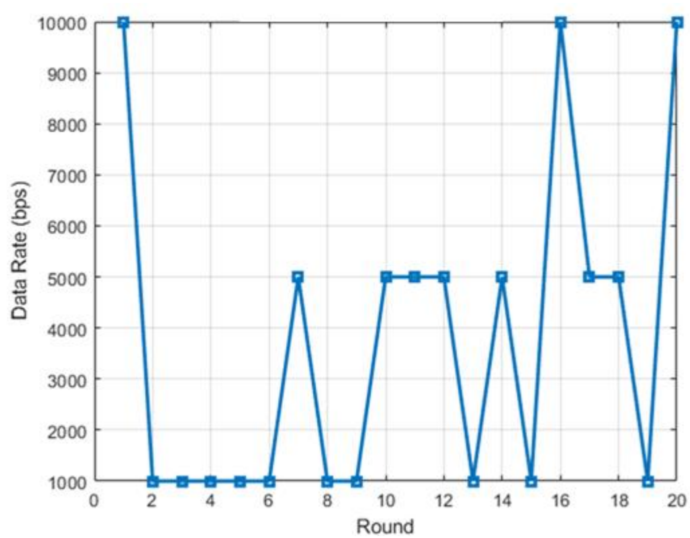

Figure 1: Variation of Data Rate per Round in the Mobile Diabetic Patient Monitoring Wireless Sensor Network

Figure 2 represents the network topology for mobile diabetic patient monitoring using LEACH in a Wireless Sensor Network (WSN). The figure illustrates the positions of diabetic patients (sensor nodes), the selected Cluster Head (CH), the Base Station (hospital), and the Doctor (mobile sink). Figure 2 also shows the communication paths: data aggregation from patients to the CH, transmission from the CH to the Base Station, and finally to the Doctor, highlighting the dynamic routing and energy-efficient data transmission in the proposed system.

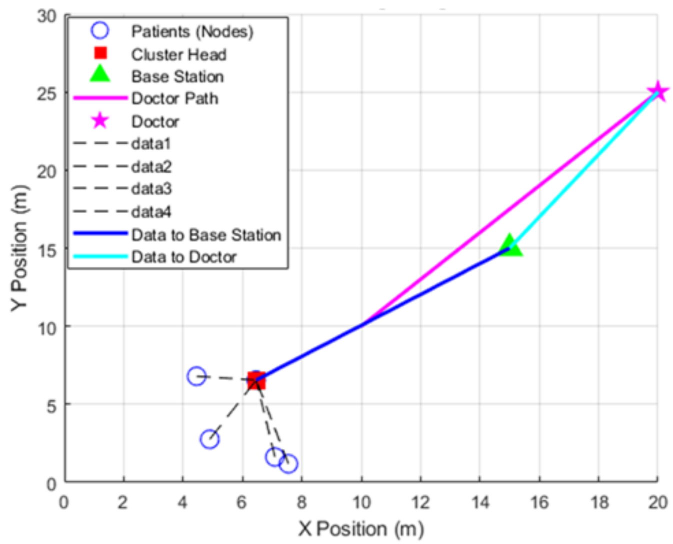

Figure 2: "Network Topology and Data Transmission Paths in Diabetic Patient Monitoring Using LEACH Protocol

Loss Factor

In this simulation, each round introduces a randomly selected Loss Factor from a defined range (0.9 to 1.1) to emulate real-world environmental effects—such as signal attenuation, interference, and obstacles—on data transmission between mobile diabetic patient nodes and the mobile doctor (acting as the base station). The attached loss factor plot, which exhibits a fluctuating, spiky pattern, is a direct result of this random selection (Tomar and Shukla, 2019). From the perspective of the First-Order Radio Model, the energy required for any data transmission (whether from a patient node to the chosen cluster head or from the cluster head to the doctor) is calculated as a base value (Sajwan et al., 2020). In this context, achieving a lower Loss Factor is beneficial. The best-case value in our simulation is 0.9, which represents optimal transmission conditions. A Loss Factor of 0.9 implies minimal additional energy expenditure—only a 10% penalty over the base transmission cost—thus leading to better energy efficiency. This means that when the Loss Factor is at its ideal value, the sensor nodes (each representing a diabetic patient) use less energy per data transmission. This is critical for extending the operational lifetime of the network, ensuring that health data is reliably delivered to the doctor with minimal energy drain. In our LEACH-based system, diabetic patient nodes dynamically move within a room, and one node is periodically selected as the Cluster Head (CH) based on predefined criteria (including proximity to the doctor). The CH aggregates data from the other nodes and forwards the information to the doctor. With a lower Loss Factor, the energy cost associated with this multi-hop transmission (node to CH and CH to doctor) is reduced, thereby improving overall network reliability and longevity (Tomar and Shukla et al., 2020).

The attached loss factor plot clearly shows the fluctuating values that may occur due to variable environmental conditions. While these fluctuations are inherent to the simulation's random design, ensuring operational conditions that consistently approach the best-case value (0.9) would be highly desirable for a real-world healthcare monitoring system. In summary, the spiky behavior observed in the loss factor plot reflects the dynamic and unpredictable nature of the wireless channel. However, our analysis confirms that a Loss Factor of 0.9 is optimal—minimizing energy consumption per transmission and enhancing overall system efficiency. This is particularly important for a mobile diabetic patient monitoring system, where preserving the energy of sensor nodes is crucial for continuous and reliable communication between the patients and the doctor. Figure 3 refer to the loss factor variation across 20 simulation rounds, representing the environmental effects on signal quality during data transmission in the proposed wireless sensor network (WSN) for diabetic patient monitoring. The loss factor fluctuates between 0.9 and 1.1, where lower values indicate favorable transmission conditions with minimal energy loss, while higher values reflect adverse environmental impacts increasing energy consumption.

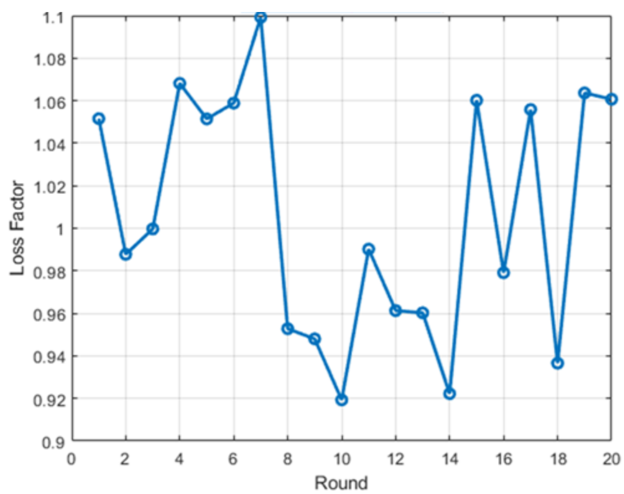

Figure 3: Variation of Loss Factor per Round in the Diabetic Patient Monitoring Wireless Sensor Network

Packet Size

In this wireless sensor network simulation for monitoring diabetic patients, the packet size is deliberately cycled through three distinct values (e.g., 2000, 4000, and 8000 bits) in each round, yielding a repeating pattern in the attached figure. This setup mimics different volumes of data being sent—perhaps representing lighter or more detailed patient readings—and provides insight into how packet size impacts both energy consumption and communication overhead. Larger packets carry more information in one transmission but consume additional energy when using the First-Order Radio Model; smaller packets save energy on each send but could increase overhead through more frequent transmissions if data is segmented (Maitra et al., 2018). In the LEACH-based approach used here, each diabetic patient node (moving within a room) either sends its readings to a selected cluster head (CH) or, if it is chosen as the CH, aggregates data from the other patients and forwards it to the doctor (acting as the base station, also mobile). Each node's energy expenditure is calculated based on distance (d) and packet size (k). Thus, when the simulation enters rounds with a packet size of 8000 bits, transmission energy jumps accordingly especially for nodes transmitting over longer distances. Conversely, a smaller packet size (2000 bits) yields lower energy use but might need more frequent sends if real-world data cannot be compressed into small packets (El Idrissi et al., 2020). In real healthcare systems, packet size may depend on the granularity of patient data (e.g., vital signs vs. full waveform data). The cyclical pattern seen in the plot underscores the chosen design in the code (cycling packet sizes each round) and helps evaluate how energy consumption and network overhead respond to different message lengths. Ultimately, this trade-off influences how effectively diabetic patients' data is delivered to the doctor—balancing the need for detailed health information against the limited energy resources of mobile sensor nodes. Figure 4 is the packet size variation across 20 simulation rounds in the proposed wireless sensor network (WSN) for diabetic patient monitoring. The packet size cycles between 2000, 4000, and 8000 bits, directly impacting energy consumption and transmission latency. Larger packet sizes increase energy consumption but may reduce overhead, while smaller packet sizes are more energy-efficient but lead to higher transmission frequency.

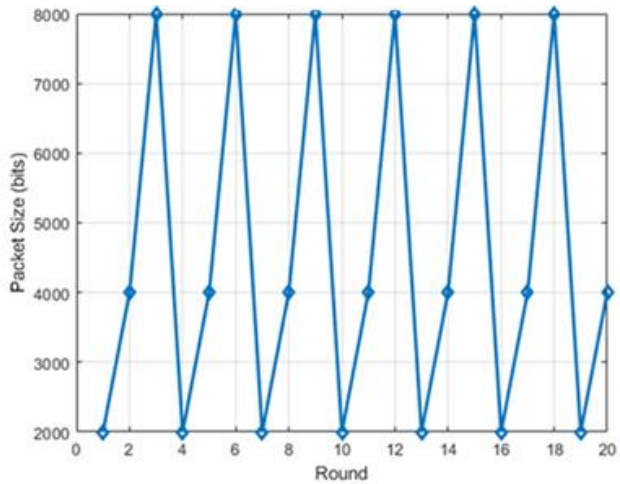

Figure 4: Variation of Packet Size per Round in the Wireless Sensor Network for Diabetic Patient Monitoring

The combined network topology figure overlays the positions of the diabetic patient nodes across all 20 rounds. For example, if we assume that patient nodes started within the room (with coordinates typically between 0 and 10 on both axes) and moved with a maximum step of 0.5 per round, you might see node positions shifting by up to about 5 meters over the full simulation. The LEACH-based algorithm selects a cluster head (CH) in each round. In one particular round, the simulation might select a CH that is 2.0 meters away from another patient node, while the CH's distance to the doctor (who moves within the hospital area defined approximately between 10 and 20 on both axes) might be around 8 meters. In the overlay, each round is color-coded (using, for example, a jet colormap), so you can observe how the locations evolve over time. Although the doctor's positions were removed from this combined plot for clarity, note that on average, the CH is selected to minimize the distance to the doctor—often reducing the long-range transmission costs (Gülbaş et al., 2023). The combined network topology of diabetic patient nodes and the selected Cluster Heads (CH) during the 20 simulation rounds using LEACH protocol. Figure (a) excludes the doctor's positions for clarity. The movement of nodes within the monitoring area and the dynamic selection of CHs are shown. Figure (b) is the trajectory of the doctor's movement across 20 rounds within the hospital area. The mobility of the doctor (base station) affects the selection of Cluster Heads and the routing of data from patient nodes. Figure (c) represents the evolution of energy levels for each patient node during the 20 simulation rounds. The energy consumption is calculated based on the First-Order Radio Model, where nodes acting as Cluster Heads (CH) show higher energy depletion compared to other nodes.

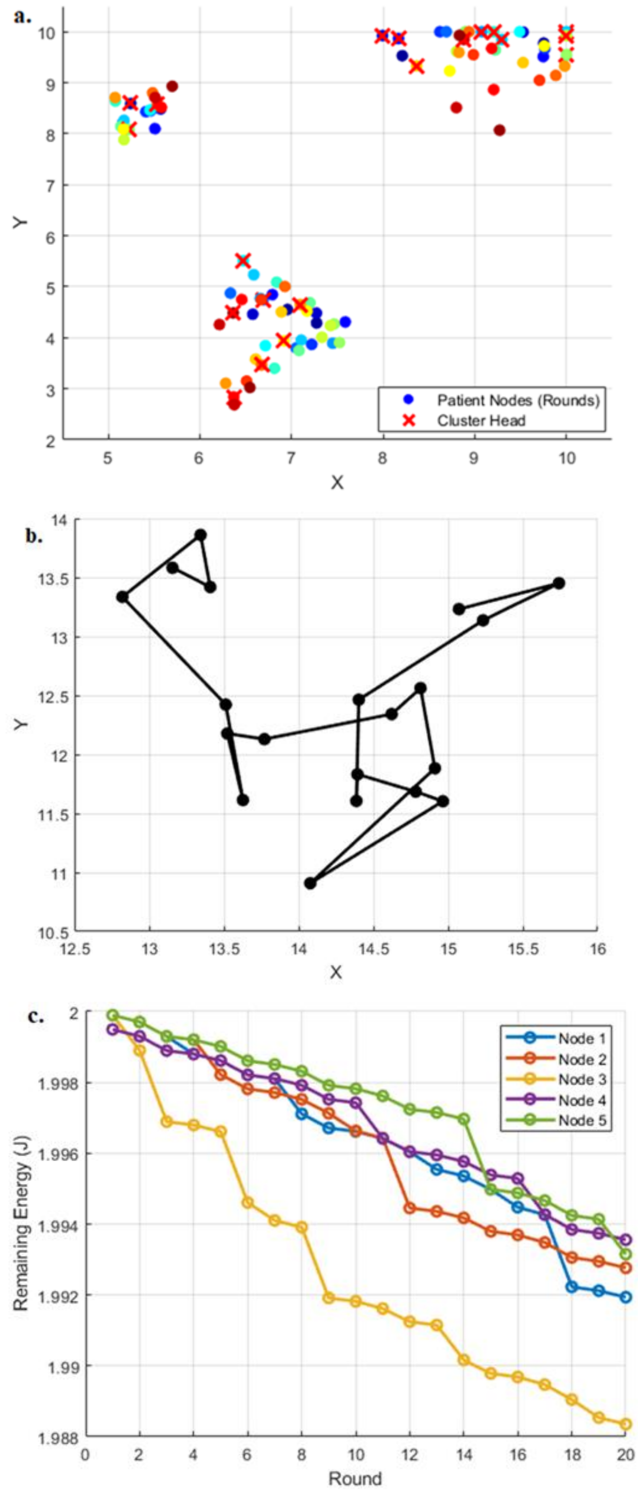

Figure 5: (a) is the Combined Network Topology of Patient Nodes and Cluster Heads over All Simulation Rounds (Excluding Doctor Position), (b) is the Doctor's Mobility Pattern and Positions Over Simulation Rounds in the Monitoring Environment and (c) is the Energy Consumption and Remaining Energy Levels of Patient Nodes Over Simulation Rounds

Transmission Delay

In this wireless sensor network simulation for monitoring diabetic patients, the packet size is deliberately cycled through three distinct values (e.g., 2000, 4000, and 8000 bits) in each round, yielding a repeating pattern in the attached figure. This setup mimics different volumes of data being sent—perhaps representing lighter or more detailed patient readings—and provides insight into how packet size impacts both energy consumption and communication overhead. Larger packets carry more information in one transmission but consume additional energy when using the First-Order Radio Model; smaller packets save energy on each send but could increase overhead through more frequent transmissions if data is segmented. In the LEACH-based approach used here, each diabetic patient node (moving within a room) either sends its readings to a selected cluster head (CH) or, if it is chosen as the CH, aggregates data from the other patients and forwards it to the doctor (acting as the base station, also mobile). Thus, when the simulation enters rounds with a packet size of 8000 bits, transmission energy jumps accordingly especially for nodes transmitting over longer distances. Conversely, a smaller packet size (2000 bits) yields lower energy use but might need more frequent sends if real-world data cannot be compressed into small packets (Sureshkumar and Sabena, 2020). In real healthcare systems, packet size may depend on the granularity of patient data (e.g., vital signs vs. full waveform data). The cyclical pattern seen in the plot underscores the chosen design in the code (cycling packet sizes each round) and helps evaluate how energy consumption and network overhead respond to different message lengths. Ultimately, this trade-off influences how effectively diabetic patients' data is delivered to the doctor—balancing the need for detailed health information against the limited energy resources of mobile sensor nodes. Figure 6 is the variation of transmission delay over 20 simulation rounds in the proposed wireless sensor network (WSN) using LEACH protocol. The transmission delay (in seconds) is influenced by the dynamic changes in packet size and data rate. Higher packet sizes combined with lower data rates increase the delay, while smaller packets and higher data rates minimize it. The delay directly affects the responsiveness of patient data delivery to the doctor (base station).

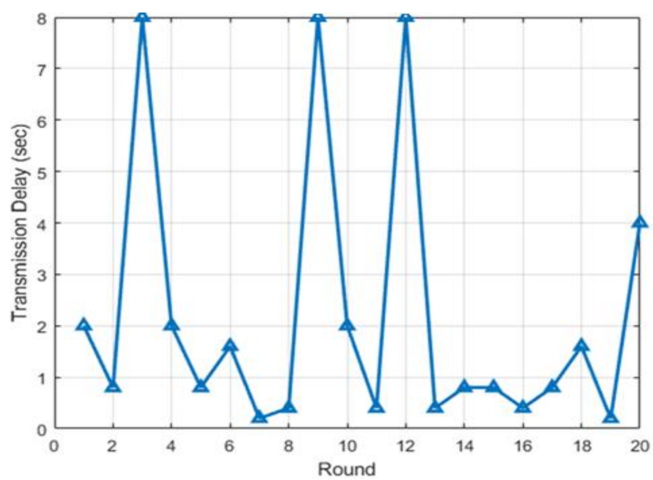

Figure 6: Transmission Delay per Round in the Wireless Sensor Network for Diabetic Patient Monitoring

5 Conclusion

Together, these results demonstrate a realistic simulation of a mobile healthcare monitoring system. Diabetic patient nodes, represented as mobile sensors, and the doctor, serving as the mobile base station, form a dynamic network where routing decisions (via a LEACH-based protocol), energy consumption (computed by the First-Order Radio Model), and variable transmission conditions (reflected by loss factors, data rates, and packet sizes) interplay to define system performance. The combined topology and energy evolution plots illustrate spatial dynamics and energy efficiency over time, while the doctor's trajectory underscores the impact of base station mobility. The individual transmission parameter plots provide deeper insights into how variations in channel conditions and configuration choices affect energy use and communication delay. This integrated analysis is valuable for optimizing network performance in real-world healthcare applications by balancing the trade-offs between energy efficiency, transmission reliability, and timely data delivery—a critical consideration for effective mobile diabetic patient monitoring systems.

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Authors Biography

Haydar Abdulameer Marhoon, The Ph.D. in Information and Communication Technology, specializing in Computer Networks, was awarded to Dr. Haydar Abdulameer Marhoon in 2017 at Universiti Utara Malaysia (UUM). This expert boasts a very well-set foundation as an academic professional with about 15 years of experience working in research and development of several cutting-edge domains. His primary research interests include wireless and sensor networks, especially WSN, WBAN, and IoT. Besides designing and optimizing routing protocols, Dr. Marhoon has made significant contributions in the field for cloud computing architect solutions and applying blockchain technologies for a secure and scalable system. His multidisciplinary work bridges theoretical innovation with practical applications, and makes pragmatic contributions toward the advancement of intelligent and interconnected network systems.

Dr. Lina Mohamed Shaker, PhD, is one of the most prominent names in research within the fields of optoelectronics and advanced contact lens technologies. She obtained her Ph.D. in Optoelectronics from Universiti Kebangsaan Malaysia (UKM), which is a foremost research-oriented university in Malaysia known for its specialty in scientific and engineering disciplines. At present, Dr. Shaker is working as a lecturer in Al-al-Bayt University of Jordan, and contributes quite effectively to curricular and scientific orientation, teaching, and supervision. Her grounds are based upon nanophotonics, functional polymer optics, and biomedical device engineering with a clear interest in the design, fabrication, and characterization of smart contact lenses. Across the years, Dr. Shaker has developed a substantial body of work, as witnessed by 80+ research articles published in high-impact, Scopus-indexed journals. Her scholarly influence can be gauged by her Scopus h-index of 26, which is a clear reflection of the depth, quality, and impact of her various researches in terms of multidisciplinary context. A recognized innovator, Dr. Shaker holds many national (Iraqi) and international patents that highlight the design and promotion of ophthalmic lenses, particularly those related to UV filtration, blue-blocking, and therapeutic drug delivery systems. Her patented work attempts to bridge the gap between biomedical engineering and real-world health applications, for the purpose of recreating user comfort and safety with vision protection. With a reasonable profound body of work, she seems to be respected as "heavy-duty researcher" in the academic community not only by the volume but also for the strategic relevance and technological novelty of her work. Throughout her career, her work is frequently cited in optical biosensing, nanomaterials for ocular use, as well as eco-safe polymer engineering areas.