Energy Efficient Clustering and Routing Using Hybrid Fuzzy with Modified Rider Optimization Algorithm in IoT-Enabled Wireless Body Area Network

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Abstract – Wireless sensor networks are widely used in various Internet of Things applications, including healthcare, underwater sensor networks, body area networks, and multiple offices. Wireless Body Area Network (WBAN) simplifies medical department tasks and provides a solution that reduces the possibility of errors in the medical diagnostic process. The growing demand for real-time applications in such networks will stimulate significant research activity. Designing scenarios for such critical events while maintaining energy efficiency is difficult due to dynamic changes in network topology, strict power constraints, and limited computing power. The routing protocol design becomes crucial to WBAN and significantly impacts the communication stack and network performance. High node mobility in WBAN results in quick topology changes, affecting network scalability. Node clustering is one of many other mechanisms used in WBANs to address this issue. We consider optimization factors like distance, latency, and power consumption of IoT devices to achieve the desired CH selection. This paper proposes a high-level CH selection and routing approach using a hybrid fuzzy with a modified Rider Optimization Algorithm (MROA). This research work is implemented using MATLAB software. The simulations are carried out under a range of conditions. In terms of energy consumption and network lifetime, the proposed scheme outperforms current state-of-the-art techniques like Low Energy Adaptive Clustering Hierarchy (LEACH), Energy Control Routing Algorithm (ECCRA), Energy Efficient Routing Protocol (EERP), and Simplified Energy Balancing Alternative Aware Routing Algorithm (SEAR).

Keywords – Wireless Body Area Network, Clustering, Routing, Internet of Things, Rider Optimization Algorithm.

I. INTRODUCTION
A body area network (BODYNET) or wireless body area network (WBAN) is a network comprised of programmable wearable sensors that also serve as nodes. These nodes can communicate with other smart sensors and devices like smartphones. In addition to sensing, these sensor nodes can perform some operations. Data can also be sent, received, stored, and calculated. Interconnections between smart devices (such as smartphones), IoT devices, and wireless body area networks (WBANs) have been demonstrated to be built into existing and new networks [1]. It has gotten a lot of attention because of its high potential value. The emergence of WBAN can reduce or eliminate some social issues, such as the prevalence of various chronic diseases, population aging, and the strain on medical staff and facilities. As a result, many people expect WBAN technology to be implemented as soon as possible. [2].

IoT will mainly impact the automotive, transportation, and healthcare industries. In general, the Internet of Things (IoT) integrates a variety of objects with arbitrary sensors to configure and work together without the need for human intervention. The research community is paying close attention to this IoT highlight. These IoT-based heterogeneous WBANs could revolutionize future healthcare implementations. These networks are anticipated to significantly enhance disease prevention and control initiatives and boost purchasing [3, 4].
WBAN sensors have a finite amount of battery life, processing power, and bandwidth. Utilize these resources as effectively as possible shown in Fig 1. It is designed with an energy-saving mechanism with the following characteristics: computationally intensive features, low routing overhead, and maximized throughput. Despite great strides, WBAN still has obstacles, including mobility, network lifetime, transmission range, a heterogeneous environment, and resource limitations [5]. WBAN has advanced due to the rapid development of sensor and communication technology. However, the technology is still in its infancy, and its research and application have many problems and challenges. Given the abovementioned issues, intelligent clustering algorithms can help WBANs become more manageable, optimized, scalable, and have network load balancing.

To address this issue, the field employs several clustering algorithms. However, these algorithms generate many cluster heads (CH), resulting in poor resource utilization and performance [6]. Routing protocol design is also influenced by deployment, power consumption, and security factors. As a result, researchers are focusing on developing energy-efficient nodes and protocols capable of supporting a wide range of operations [7]. As a result, to reduce network energy consumption and extend network life, an effective routing strategy is required. Numerous studies have utilized novel routing techniques to maximize node lifetime, optimize node energy consumption, and enhance network performance. We propose a brand-new hybrid Fuzzy with a modified rider optimization algorithm for wireless body area networks.

The rest of this article is written below: Section II reviews existing research on routing protocols with low energy consumption. The suggested technique is described in Section III. Results and analysis of our work are presented in Section IV. We conclude in Section V by summarizing our findings.

II. LITERATURE REVIEW
In [8] recently released an extensive review of machine learning methods for big data analysis in the medical industry. Additionally, various research challenges are highlighted, along with the strengths and weaknesses of current technology. Our research offers information to prepare government organizations and healthcare professionals for the newest trends in machine learning-based big data analytics for smart healthcare. This gives readers insight into the field and allows them to select a topic of interest from the available techniques to begin their research. Several research questions and challenges are discussed, and researchers are encouraged to pursue them further.

The [9] suggested Adaptive Energy Efficiency (EEA) algorithm is offered to enhance the energy efficiency, battery life, and throughput by taking advantage of this effect. In MATLAB, the outcomes are simulated while considering a lithium-ion battery. Additionally, the proposed adaptive energy saving (EEA) algorithm contrasts the most recent version of the BRLE technique. The proposed algorithm outperforms the BRLE algorithm in terms of performance, battery life, and energy consumption. It uses little power and allows for uninterrupted and continuous device connection.

In [10] for typical WSN-IoT nodes in smart city applications, we recommend using machine learning as an optimization technique. As far as the authors are aware, this is the first thorough analysis of the literature on all ML techniques in low-power WSN-IoT for smart cities. According to the findings of this one-of-a-kind study, supervised learning algorithms (61%) are the most widely used algorithms for smart city applications, followed by reinforcement learning (27%) and unsupervised learning (12%).

The work [11] presented a healthcare system that uses supervised machine learning methods to analyze ECG reports. Experienced doctors can access analysis reports saved on a cloud platform for later use. Six supervised machine learning algorithms were used to analyze ECG data to evaluate performance.

There are two groups in the dataset. 25% of the data are used for testing, and the remaining 75% are used for model training. Decision tree classifiers are the most effective at predicting heart attacks. The grade is 96%. The algorithm scores 95% for sinus tachycardia when nearest neighbors is excluded. With a score of 95%, the decision tree classifier also performed well for sinus bradycardia. Finally, Support Vector Machines (SVM) received the highest overall score of 96%.

The [12] presented a comprehensive overview of these machine learning algorithms, which can be used to improve applications' intelligence and functionality. As a result, the primary contribution of this study is to explain the principles of various machine learning techniques and their applicability to a variety of practical application domains such as cyber
security systems, smart cities, healthcare, e-commerce, and agriculture. The identified challenges thus generate promising research opportunities in areas that require effective solutions for various application areas.

Author [13] using the buffer size parameter is suggested to fix link failure problems. RPL is a routing protocol that creates routes from sources to destinations. The RPL routing protocol has been improved with the SEAR protocol. A problem that affects network performance is a link failure, which takes place on a known path. For source-to-destination link recovery, buffer size-based techniques have been suggested. The node with the most significant buffer size will be used for path recovery in the event of a network link failure. The proposed method performs well regarding throughput, packet loss, and delay.

The [14] proposed a robust routing method for IoT healthcare using a general multi-agent strategy. The two parts of this white paper's contribution are (i) locating nearly optimal paths using multi-objective optimization methods and (ii) locating alternative paths using networked trusted agents. The simulation results demonstrate that the approach is based on multi-objective optimization technology, looking for the best route for information transmission to enhance the network's critical performance indicators. Furthermore, in healthcare environments, security proxies enable the secure transmission of data over networks. According to experimental findings, this method is 99% reliable and has a data transfer rate of 99.9%. The suggested approach reduces latency by 5.6%, increases the delivery rate by 2%, and extends network life by 14%.

In [15] proposed a secure and scalable framework for healthcare data transfer in the Internet of Things based on optimized routing protocols. First, health data from various IoT devices such as wearable and sensors is collected. Data cleaning and data reduction techniques are used to preprocess raw data. Using modified local binary patterns, extract features from preprocessed data (MLBP). The Butter Ant Optimization (BAO) algorithm for the low-power lossy network is combined with the fuzzy dynamic trust-based RPL algorithm in the proposed fuzzy dynamic trust-based RPL (FDT-RPL) protocol to reduce data and enhance the transmission's overall security. The algorithm has been used in an innovative medical system, and its effectiveness is evaluated compared to more established techniques.

Authors [16] provided efficient communication for IoMT-based applications, propose a Cluster Model for Medical Applications (CMMA) for cluster head selection. The experimental analysis demonstrates that in terms of sustainability and energy usage, the proposed CMMA outperforms the comparative methods. Therefore, we can conclude that based on his claim, CMMA can reduce the energy consumption of edge computing-based IoMT systems. One significant disadvantage of current clustering techniques is that the communication model does not consider the probability of packet errors. This ensures that there are no issues with reliable communication and also reduces medical node energy consumption [17].

**Problem Statement**

- When using cluster-based approaches, selecting the correct cluster size is crucial because performance is based on the average cluster size. The workload of the cluster head increases when a larger cluster is selected for communication, whereas a smaller cluster results in more clusters and worse performance [19].

- Some techniques attempt to lower the node's transmission power as an energy-saving strategy, but this result in more packet loss and retransmissions. In the worst scenario, it might result in higher energy consumption. As a result, the trade-off issue between transmission power and the number of transmitted packets needs to be solved.

- Since there are a lot of sensor nodes in a WBAN, there are a lot of sensor readings produced. Due to the abundance of sensors, the WBAN may experience hot spot issues and packet loss.

- This article suggests a routing protocol to address the issues with current methods, which are motivated by the difficulties of existing multi-hop routing technologies.

**Objective**

Cluster formation is a difficult task fraught with difficulties. The selection of CH is critical in optimizing energy consumption [20]. A fuzzy method is proposed to address the disadvantages of reducing energy consumption and extending network life. The proposed method contributes to the following primary characteristics: The model achieves broad coverage with minimal redundancy. To ensure energy efficiency, this method considers CH candidate nodes, energy feasibility, and energy balance. The network environment of WBAN, a technology used on the human body, is highly complex. Wireless body area network routing is crucial because the gathered physiological data significantly impacts people's lives and health. We suggest a new modified rider optimization algorithm in this paper. As motivation for this paper, we consider the problems of existing routing techniques. A routing protocol that attempts to solve the problems of existing methods is proposed.

**Major Contribution**

- Using fuzzy algorithms, an ideal CH selection process is proposed. As a result, WBAN-IoT attributes like energy, load, delay, and temperature are used to boost CH selection's effectiveness.

- The proposed FUZZY-MROA model should be used to reduce optimization parameters like load, temperature, delay, and distance thereby reducing energy consumption to improve performance.
The proposed model provides more excellent coverage with a lower coverage redundancy rate.

To validate the proposed model’s performance in normalized energy and active nodes, we compare it to the most recent model.

III. PROPOSED METHODOLOGY
This section provides a detailed description of the proposed protocol. To minimize power consumption and balance power consumption among nodes, we use Fuzzy and a modified rider-optimized routing algorithm in this work. The terms used in the proposed protocol are defined in the following section, followed by a list of the included fitness functions.

System Model
When the threshold distance \(d_0\) exceeds the propagation distance \(d\), the energy consumption of a node is directly proportional to \(d^2\). The overall energy consumption of each node to transmit the \(n\)-bit data packet is specified by the following equations:

\[
E_{tx}(n,d) = \left( \frac{n \times E_{elec} + n \times \epsilon_{fs} \times d \times (d \leq d_0)}{n \times E_{elec} + n \times \epsilon_{mp} \times d \times (d > d_0)} \right)
\]  

\(E_{tx}\) is the total amount of energy needed to transmit, \(E_{elec}\) is the amount of energy used to operate a circuit, such as a transmitter or a receiver per bit, \(\epsilon_{fs}\) is the energy used for amplification in the free space model, and \(\epsilon_{mp}\) is used in the multipath model; both of these models heavily rely on the transmitter amplifier model, and \(d_0\) is the minimum transmission distance. Similarly, the power consumption of the receiving circuit when receiving \(n\)-bit data is given by the following equation.

\[
E_{rx} = n \times E_{elec}
\]  

Where \(E_{rx}\) is the energy consumed to receive data and \(E_{elec}\) is the energy dissipation per bit to run the circuit, i.e., transmitter or receiver, and is affected by several factors such as modulation, digital coding, signal spreading, and filtering. In general, radio wave propagation is highly variable and difficult to model.

\[
E_{total} = E_{tx} + E_{rx}
\]  

Cluster Head Selection using Fuzzy Approach
The fundamental challenge of cluster construction in WBAN is optimal CH selection. In recent years, fuzzy logic has become increasingly helpful for WSN researchers in selecting the best CH [18][19]. When using fuzzy logic to select CH, three factors were considered. The NC, NOVER, and residual energy of sensor networks are used in a fuzzy concept to reduce energy consumption and extend the lifetime of sensor networks. The following are the input parameters:

Residual Energy: The nodes with the highest energy are chosen as CH. Let \(E_i\) be the node’s initial energy. After \(t\) periods, the energy consumed by node \(E(t)\) is given by

\[
E(t) = (n_{tpkts} \times \alpha) + (n_{rpkts} \times \beta),
\]  

Where \(n_{tpkts}\) and \(n_{rpkts}\) are the number of transmitted and received data packets, respectively. \(\alpha\) and \(\beta\) are constants in the range of \((0,1)\). The \(E_{res}\) of a node at time \(t\) is computed by using following equation.

\[
E_{res} = E_i - E(t)
\]  

NC: It specifies how centered the chosen CH concerns nearby channels throughout the network.

\[
C = \frac{\sum_{i,j} d^2(\text{CH}_i, \text{CH}_j)}{D}\n\]  

where \(d(\text{CH}_i, \text{CH}_j)\) is the distance among the CH node and its member nodes, \(D\) is the dimension of sensing field area, and \(T\) is the number of neighbors

NOVER: The NOVER method is used to compute mutual adjacencies between link end nodes. A link that has a small NOVER is to connect two unique networks, and a link that has a high NOVER is bound to be among nodes in the same network. The sets of neighbors of nodes \(u\) and \(v\) are defined by \(N(u)\) and \(N(v)\) individually.

\[
\text{NOVER}(u-v) = \frac{2 \times |N(u) \cap N(v)|}{|N(u)| + |N(v)| - 2}
\]
Fuzzy logic contains the steps of fuzzy rules, fuzzifier, defuzzifier, and fuzzy inference engine. Fig 2 illustrates the fuzzy approach.

**Fuzzifier:** All input values are translated into equivalent fuzzy groups by this process. A membership or truth value is given to each fuzzy set.

**Fuzzy Inference Engine:** Fuzzifies input values into appropriate linguistic variables using membership functions.

**Fuzzy Rule:** This section uses an IF-THEN condition that combines input and output fuzzy linguistic variables.

**Defuzzifier:** This procedure produces a single unique input value.

Fig 2. Fuzzy Systems for Cluster Head Selection

### Nascent of the Fitness Function

#### Average Intra-Cluster Distance (F1)

The intra-cluster distance is calculated by adding the distances between all sensor nodes and their corresponding CHs. The length within this cluster should be minimized to reduce network energy consumption. Sensor nodes consume energy when communicating with their respective CHs.

\[
F_1 = \sum_{j=1}^{m} \left( \frac{1}{l_j} \sum_{k=1}^{l_j} d_{is(k,CH_j)} \right)
\]  

#### Average Sink Distance (F2)

The ratio of the distance between the BS and CH and the distance of every sensor node in the corresponding CH is used to calculate the average sink distance. Therefore, this distance should be minimized to reduce energy consumption. It is given as

\[
F_2 = \sum_{j=1}^{m} \frac{1}{l_j} d_{is(CH_j,BS)}
\]  

#### Residual Energy (F3)

Reducing energy consumption is extremely important because a network’s ability to function depends on how much energy it uses. As a result, this parameter is considered. It is calculated as the sum of all the selected CHs’ current energies.

\[
F_3 = \sum_{j=1}^{m} \frac{1}{l_j} e_{CH_j}
\]  

#### CH Balancing Factor (F4)

The cluster should be evenly distributed. The random arrangement of sensor nodes can result in large and small clusters. As a result, this parameter is thought to balance energy consumption.

\[
F_4 = \sum_{j=1}^{m} \frac{n_j}{m} - l_j
\]  

Instead of minimizing each fitness function individually, Equation shows how to reduce a combination of the above functions (19). The fitness functions described above are highly consistent with one another. The following fitness function is used:

\[
\text{Fitness function} = a \times f_1 + b \times f_2 + c \times f_3 + (1-a-b+c) \times f_4
\]

where a, b, and c are constants and a + b + c = 1. The flowchart of the proposed algorithm is given as follows:
Rider Optimization Algorithm

Conventional ROA

ROA [22, 23] generally is based on the concept of a group of riders riding to a goal/target position. The algorithm also includes riders with different work methods, such as Bypass, outperformer, follower, and attacker. The ROA mathematical model is written as follows: Initialization: First, the group is initialized using the expression (1). Eq.(1) denotes the number of riders in the reference group or the number or dimension of coordinates, and $M_{ti}(a,b)$ the position of the rider at time $T$. $Bi$, $Fi$, $Oi$, and $Ai$ are the sums of Bypass, Follower, overtaken, and attacker [24].

$$M_{ti} = \{M_{ti}(a, b)\}; 1 \leq a \leq C; 1 \leq b \leq D.$$  

(13)

Let $\theta_{ai}(T_{i}), (a, b)^{t+1}$ and $r$ be the angles corresponding to at rider's position, steering, and vehicle coordinates. In addition, the main parameters of $a^{th}$ rider $a$'s vehicle are the accelerator $e_{ia}$, the brake $b_{ia}$, and the gear position $E_{ia}$.

Determining Success Rate

All riders’ performance levels are evaluated after initializing their respective rider sets and specifications. The leader, or the rider with the highest value among all riders, is then determined by updating the success rates for each rider. Furthermore, the attacker impacts local convergence, whereas the overtaker controls global convergence. Typically, riders conduct random searches and deftly arrive at their destination. Followers use the multidirectional search space of the leader. Overtaker selects the optimal dimensional space in the final convergence step based on the success rate and directional indicators in Fig 3.

![Flowchart of the Proposed Algorithm](image)

Fig 3. Flowchart of the Proposed Algorithm
Leader Rider Location Update
The leading rider is regarded as the one who is close to the target and has a high success rate. The lead rider may also alter over time based on the success rate. Typically, all riders’ performance rates are assessed, and the leader is selected based on the most recent iteration.

Model of Riders’ Location
A typical ROA consists of four riders:

- A bypass rider who takes the main route to the target position.
- A follower who attempts to follow the lead rider.
- A rider who focuses on a specific path to reach the target.
- The attacker who has surpassed the target.

Furthermore, each driver has predefined rules for precisely using gears, the gas pedal, steering, and brakes to achieve the goal. As defined in Equation, the position update for this group is arbitrary if the overtaking driver disregards the leader’s path and stays in the regular lane. where \( \gamma \) is a value spanning one and \([1]\), \( \nu \) is any number between 0 and 1, is any number between 1 and \( C \), and \( \mu \) is any value between 0 and 1 of size \( 1 \times D \).

\[
X_{ti+1}^{bl} = \gamma [M_{ti}(t, b) * \mu(b) + M_{ti}(v, b) * [1 - \mu(b)]]
\]  

Using the coordinate selector specified in the formula, followers adjust their positions based on the position of the leading rider in order to reach the target. (3), where \( X_{Li} \) designates the location of the leaders, \( Li \) denotes the leader’s index, \( T_{ti}^{i+1} \) denotes the steering angle of the \( a^{th} \) rider in the \( c^{th} \) coordinate, and \( d_{ti}^{li} \) denotes the distance that the \( a^{th} \) rider must cover, which is determined by multiplying the rider’s velocity by the rate at which it falls off.

\[
X_{ti+1}^{fi}(a, c) = X_{ti}^{Li}(Li, c) + [\cos \cos(T_{ti+1}^{i}) * X_{ti}^{Li}(L_i, c) * d_{ti}^{li}]
\]

As shown in Eq. (15), overtaking riders adjust their position using three criteria, including the coordinate selector, relative success rate, and direction indicator. Here, \( X_{ti}^{Li}(a, c) \) specifies the location of the \( a^{th} \) rider in the \( c^{th} \) coordinate, and \( D_{ti}^{il}(a) \) indicates the direction indicator of the rider on.

\[
X_{ti+1}^{0i}(a, c) = X_{ti}^{Li}(a, c) + [D_{ti}^{il}(a) * X_{ti}^{Li}(L_i, c)]
\]

The generalized distance vector is calculated by subtracting the location of a \( a^{th} \) rider from the leader to determine the coordinate selector. Similarly, the attacker rider uses the same update procedure as the follower to try to take the leader’s position. Furthermore, the attacker updates all coordinates rather than specific coordinates, as stated in Eq (17).

\[
X_{ti+1}^{Al}(a, c) = X_{ti}^{Li}(Li, b) + [\cos \cos(T_{ti}^{i+1}) * X_{ti}^{Li}(L_i, b) * d_{ti}^{li}]
\]

Activity Counter: When a rider’s success rate exceeds the rate established, the activity counter uses 1, otherwise 0 for lagging, as shown in Eq (18).

\[
A_{it}^{li+1}(a)=\begin{cases} 1; & \text{if } r_{ti+1}(a) > r_{ti}(a) \ 0; & \text{otherwise} \end{cases}
\]

Steering Angle: The equation-defined steering angle is updated using an activity counter in Eq.(19).

\[
T_{ti+1}^{a} = T_{ti}^{a+1,b} \text{ if } A_{it}^{li+1}(a) = 1, \ T_{ti}^{a-1,b} \text{ if } A_{it}^{li+1}(a)=0
\]

Gear: This is updated as the activity counter is turned on and the higher gear value given by equation (20).

\[
E_{ti}^{i+1} = \begin{cases} E_{ti}^{i} + 1 & \text{if } A_{it}^{li+1}(a) = 1, E_{ti}^{i} \neq 1 \ E_{ti}^{i} - 1 & \text{if } A_{it}^{li+1}(a)=0 \ 0, E_{ti}^{i} & \text{otherwise} \end{cases}
\]

Success Rate Re-Determination: Reassess rider performance ratings to identify the most effective leaders. Parameters update at the end of location update:
To find the best solution, modify the rider parameters after the iteration. After the iteration, the driver must adjust the gears, brakes, downtime, throttle, and steering angle. Termination: The optimization procedure is carried out thoroughly. By maximizing a few parameters, the best solution is eventually discovered. Algorithm 1’s pseudocode represents the traditional ROA model [21].
Algorithm 1. Conventional ROA Model

Data: Arbitrary location of riders,
Result: Leading rider
Allocate the population
Allocate the rider parameters
Evaluate the success rate
While while condition do
    For a=1 to C do
        Upgrade bypass rider location using Eq.2
        Upgrade flower location using Eq.3
        Upgrade overtaker location using Eq.4
        Upgrade attacker location using Eq.5
    Rate riders using their rate of success
    Select a rider with a better success rate as leader.
    Upgrade the rider parameters
End
End

Proposed Model

ROA has many advantages for solving complex problems, but it still requires further development to improve its performance. The way group updates are handled has been enhanced. The proposed ROA algorithm is as follows: When the fitness score is complete, it will be sorted by your best fitness. Because there are ten solutions, there are ten possible fitness values [25]. Furthermore, the corresponding solutions for the first five fitness values are updated by equation (17) is the average of the bypass and subsequent rider updates given in Eq (21) and (22), respectively.

In contrast, the remaining five fitness solutions are also updated by averaging passing and offensive rider updates (based on Eq (14) and (15)) in Eq (20).

\[
X_{\text{fit+1}} = \frac{x_{\text{fit+1}}^{b} + x_{\text{fit+1}}^{f}}{2} \quad (21)
\]

\[
X_{\text{fit+1}} = \frac{x_{\text{fit+1}}^{o} + x_{\text{fit+1}}^{s}}{2} \quad (22)
\]

Algorithm 2. Modified ROA Model Pseudo-Code

Data: Arbitrary location of riders,
Result: Leading rider
Allocate the population
Allocate the rider parameters
Evaluate the success rate
While while condition do
    Evaluate Fitness
    Sort
    For a=1 to 5 do
        Update the solution as per using Eq.9
    End
    For remaining fitness do
        Update the solution as per using Eq.10
    End
    Rate riders using their rate of success.
    Select a rider with a better success rate as leader.
    Upgrade the rider parameters
End

IV. RESULTS AND DISCUSSION

The simulation setup is built around the WBAN application scenario, which continuously tracks the patient's physiological parameters. A biomedical wireless sensor network environment made up of 100 randomly placed and
roaming biomedical wireless sensor nodes is created during the simulation, which lasts for 600 seconds and takes place in a flat space simulation area measuring 1000 m x 1000 m. The network environment is split into ten 100m x 100m areas. The nodes in this simulated environment are distributed randomly and have a transmission range of 100 meters is described in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulator</td>
<td>MATLAB</td>
</tr>
<tr>
<td>Initial energy</td>
<td>0.5 joule</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>100</td>
</tr>
<tr>
<td>Area</td>
<td>100*100 meters</td>
</tr>
<tr>
<td>Channel Access protocol</td>
<td>MAC</td>
</tr>
<tr>
<td>Antenna type</td>
<td>Omi-directional</td>
</tr>
<tr>
<td>Medium</td>
<td>Wireless</td>
</tr>
</tbody>
</table>

**Throughput**

Throughput is the number of packets received by a receiver. The throughput is determined by the number of nodes running or active in the network. The active node count determines the total amount of packets sent to the receiver. Patient data is essential in WBAN. As a result, it is critical to minimize packet loss while increasing throughput. This protocol has a higher throughput than the LEACH, ECCRA, EERP, and SEAR protocols, as shown in Fig 4 and Table 2.

<table>
<thead>
<tr>
<th>Simulation time (s)</th>
<th>LEACH</th>
<th>ECCRA</th>
<th>EERP</th>
<th>SEAR</th>
<th>F-MROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>4</td>
<td>4.5</td>
<td>5.2</td>
<td>5.4</td>
<td>6.6</td>
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<tr>
<td>40</td>
<td>2.2</td>
<td>2.5</td>
<td>2.9</td>
<td>3.5</td>
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<td>60</td>
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<td>80</td>
<td>0.8</td>
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<td>1.5</td>
<td>1.8</td>
<td>2.8</td>
</tr>
<tr>
<td>100</td>
<td>0.2</td>
<td>0.8</td>
<td>1</td>
<td>1.4</td>
<td>2</td>
</tr>
</tbody>
</table>

**Residual Energy**

The average residual energy that all nodes have left is used to compare our protocol's performance in this experiment to that of four other protocols. Keeping the residual energy high is critical for extending the network's lifetime. Table 3 and Fig 5 shows that the average residual energy is more excellent than existing protocols.

<table>
<thead>
<tr>
<th>Simulation time (s)</th>
<th>LEACH</th>
<th>ECCRA</th>
<th>EERP</th>
<th>SEAR</th>
<th>F-MROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>12</td>
<td>14</td>
<td>15.8</td>
<td>18</td>
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</tr>
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<td>40</td>
<td>10.4</td>
<td>12.5</td>
<td>13.4</td>
<td>15.5</td>
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<td>8.6</td>
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<td>6</td>
<td>7</td>
<td>10.4</td>
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</tr>
</tbody>
</table>
**End to End delay**

Table 4 and Fig 5 and Fig 6 compare the end-to-end latency of different routing algorithms. The graph clearly shows that F-MROA outperforms all other routing schemes in terms of performance. While the end-to-end latency of existing methods such as SEAR, ECCRA, LEACH, and EERP increases with simulation time, the end-to-end latency of F-MROA is significantly lower. With changes in human pose and communication errors on the network's links, the end-to-end latency of the four routing algorithms rises, lengthening the time it takes for data to be transmitted.

Table 4. End to End Delay

<table>
<thead>
<tr>
<th>Simulation time (s)</th>
<th>LEACH</th>
<th>ECCRA</th>
<th>EERP</th>
<th>SEAR</th>
<th>F-MROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>120</td>
<td>80</td>
<td>70</td>
<td>60</td>
<td>30.8</td>
</tr>
<tr>
<td>40</td>
<td>115</td>
<td>100</td>
<td>95</td>
<td>70.8</td>
<td>50.5</td>
</tr>
<tr>
<td>60</td>
<td>123</td>
<td>110</td>
<td>105</td>
<td>82.5</td>
<td>78</td>
</tr>
<tr>
<td>80</td>
<td>136</td>
<td>145</td>
<td>130</td>
<td>120.7</td>
<td>92.8</td>
</tr>
<tr>
<td>100</td>
<td>150</td>
<td>160</td>
<td>150</td>
<td>140</td>
<td>110</td>
</tr>
</tbody>
</table>

**Network Life Time**

In this simulation, four different routing protocols are used to determine the average network lifetime of a wireless body network. In this case, the forwarding node is the node with the most remaining energy at the end of each round. As shown in Fig 7 and Table 5, the proposed routing protocol has a longer network life expectancy than the other four protocols when sending data from nodes to receivers. In other words, in terms of network life expectancy, the proposed scheme outperforms the existing four techniques.
Fig. 7. Analysis of Network Lifetime

Table 5. Network Life Time

<table>
<thead>
<tr>
<th>Rounds(r)</th>
<th>LEACH</th>
<th>ECCRA</th>
<th>EERP</th>
<th>SEAR</th>
<th>F-MROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4000</td>
<td>0</td>
<td>0</td>
<td>1.8312</td>
<td>6.521</td>
<td>3.876</td>
</tr>
<tr>
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<td>0</td>
<td>1.8312</td>
<td>6.521</td>
<td>4.321</td>
<td>3.4233</td>
</tr>
<tr>
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<td>2.347</td>
<td>6.521</td>
<td>4.321</td>
<td>8.489</td>
</tr>
<tr>
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<td>4.3661</td>
<td>6.212</td>
<td>6.521</td>
<td>4.321</td>
<td>106.4</td>
</tr>
</tbody>
</table>

Table 6. Path Loss

<table>
<thead>
<tr>
<th>Rounds(r)</th>
<th>LEACH</th>
<th>ECCRA</th>
<th>EERP</th>
<th>SEAR</th>
<th>F-MROA</th>
</tr>
</thead>
<tbody>
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<td>425</td>
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<tr>
<td>6000</td>
<td>455</td>
<td>312</td>
<td>270</td>
<td>120</td>
<td>375</td>
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<tr>
<td>8000</td>
<td>420</td>
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<td>120</td>
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<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Path Loss

Path loss is critical in link design and analysis. Path loss is proportional to frequency and distance. It is calculated as the distance from the receiver to the node at 2.4 GHz. Let the path loss factor be 3.38 for practical implementation. Because the path loss is too dependent on the communication distance, the proposed protocol employs a multi-hop technique. As shown in Fig 8 and Table 6, the communication distance is significantly reduced, and the path loss is reduced compared to the traditional method.

The multihop transmission reduces path loss and shortens transmission distances. The proposed F-MROA, SEAR, EERP, ECCRA, and LEACH protocols function well in the initial stages. The random topology runs out of energy after about 2000 rounds. In contrast, the proposed protocol does not exhibit this behavior until 6100 epochs. Because there are more active nodes in the proposed protocol, F-MROA, there is a more extended stabilization period and less cumulative path loss.

Fig. 8. Analysis of Path Loss

V. CONCLUSION

Wireless Body Area Networks (WBANs) are critical in health monitoring systems for continuous real-time patient health monitoring. It also makes remote monitoring of patients’ essential health conditions easier for healthcare workers. However, real-time use of these systems is severely limited because it is difficult to maintain the sensor nodes’ limited residual energy. This paper uses fuzzy logic with a modified rider optimization algorithm to increase sensor node network lifetime. The selected transponder/parent node sends the patient’s vital sensory data to the sink node. Simulations were run under a variety of conditions. When the proposed protocol, namely the F-MROA protocol, is compared to
LEACH, ECCRA, EERP, and SEAR, the results show that the proposed protocol has significant advantages in network lifetime, residual energy, end-to-end delay, path loss, and throughput. The suggested technique is implemented using MATLAB software. The simulations are carried out under a range of conditions. Compared to the LEACH, ECCRA, EERP, and SEAR protocols, the proposed protocol F-MROA enhanced network lifespan by 94.42%, 36.65%, 30.17%, and 96.45%, respectively.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

Funding
No funding was received to assist with the preparation of this manuscript.

Ethics Approval and Consent to Participate
The research has consent for Ethical Approval and Consent to participate.

Competing Interests
There are no competing interests.

References

