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

[1]A Dinesh and [2]J Rangaraj
[1]Department of ECE, Annamalai University, Chidambaram, Tamil Nadu, India.
[2]Department of ECE, (Deputed to GCT Coimbatore), Annamalai University, Chidambaram, Tamil Nadu, India.
[1]dineshcolours@gmail.com, [2]srd_jsrd@yahoo.co.in

Correspondence should be addressed to A Dinesh : dineshcolours@gmail.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202303016
Received 21 October 2022; Revised form 28 January 2023; Accepted 27 February 2023.
Available online 05 April 2023.

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 life time, 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].

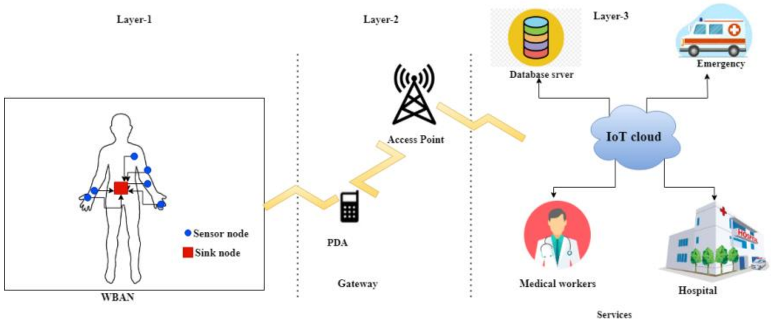

Fig 1. General WBAN Architecture.

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 tod^2. The overall energy consumption of each node to transmit the n-bit data packet is specified by the following equations:

$$E_{tx}(n,d)=\left(\frac{n \times Eelec + n \times \varepsilon fs \times d2, if\ d<do}{n \times Eelec + n \times \varepsilon mp \times d4, if\ d \geq do}\right) \tag{1}$$

$E_{tx}$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, *ε*fs is the energy used for amplification in the free space model, and *ε*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.

$$E_{rx}\ (\mathrm{l})=\mathrm{n*Eel} \tag{2}$$

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.

$$E_{total}=E_{tx}+E_{rx} \tag{3}$$

Where E_{total} is the total energy loss for the system.

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 Ei be the node's initial energy. After t periods, the energy consumed by node E(t) is given by

$$\mathrm{E\ (t)} = (n_{tpkts} *\alpha) + (n_{rpkts} *\beta), \tag{4}$$

Where *ntpkts*and *nrpkts*are the number of transmitted and received data packets, respectively. *α* and *β* are constants in the range of (0,1).The *E*res of a node at time *t* is computed by using following equation.

$$E\mathrm{res} = Ei - E(t) \tag{5}$$

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

$$\mathrm{NC}=\frac{\sqrt{\frac{\sum d^{2(c_{i,j})}}{T}}}{D} \tag{6}$$

where *d*(*Ci*, *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.

$$\mathrm{NOVER}\ (u-v) = \frac{2*|N(u) \cap N(v)|}{|N(u)|+|N(v)|-2} \tag{7}$$

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.

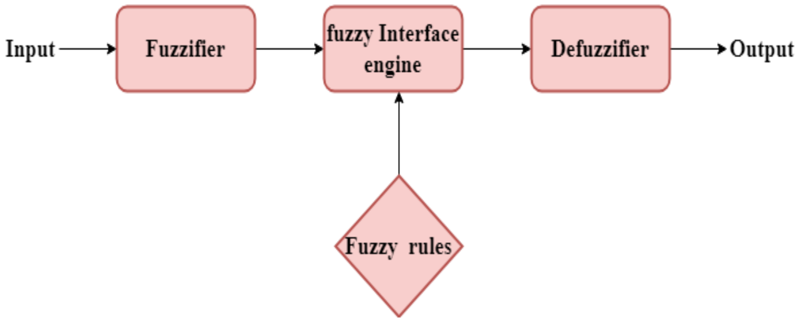

Fig 2. Fuzzy Systems for Cluster Head Selection

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.

$$\text{F1}=\sum_{j=1}^{m}(\frac{1}{lj}\sum_{k=1}^{lj} dis(s_{k,CHj})) \tag{8}$$

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

$$\text{F2}=\sum_{j=1}^{m}(\frac{1}{lj} dis(CHj, BS)) \tag{9}$$

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.

$$\text{F3}=\frac{1}{\sum_{j=1}^{m}(E_{CHj})} \tag{10}$$

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.

$$\text{F4}=\sum_{j=1}^{m}\frac{n}{m} - l_j \tag{11}$$

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:

$$\text{Fitness function}=a*f1 +b*f2 +c*f3 +(1-a+b+c)*f4 \tag{12}$$

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 Mti(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].

$$M^{ti} = \{M^{ti}\ (\mathrm{a, b})\};\ 1\leq \mathrm{a} \leq \mathrm{C};\ 1\leq \mathrm{b} \leq \mathrm{D}. \tag{13}$$

Letθ_a,$(T_i)^{t_i+1}_{(a,b)}$ and τ 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 $ei_a$the brakebr_a, and the gear positionEi_a.

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**.

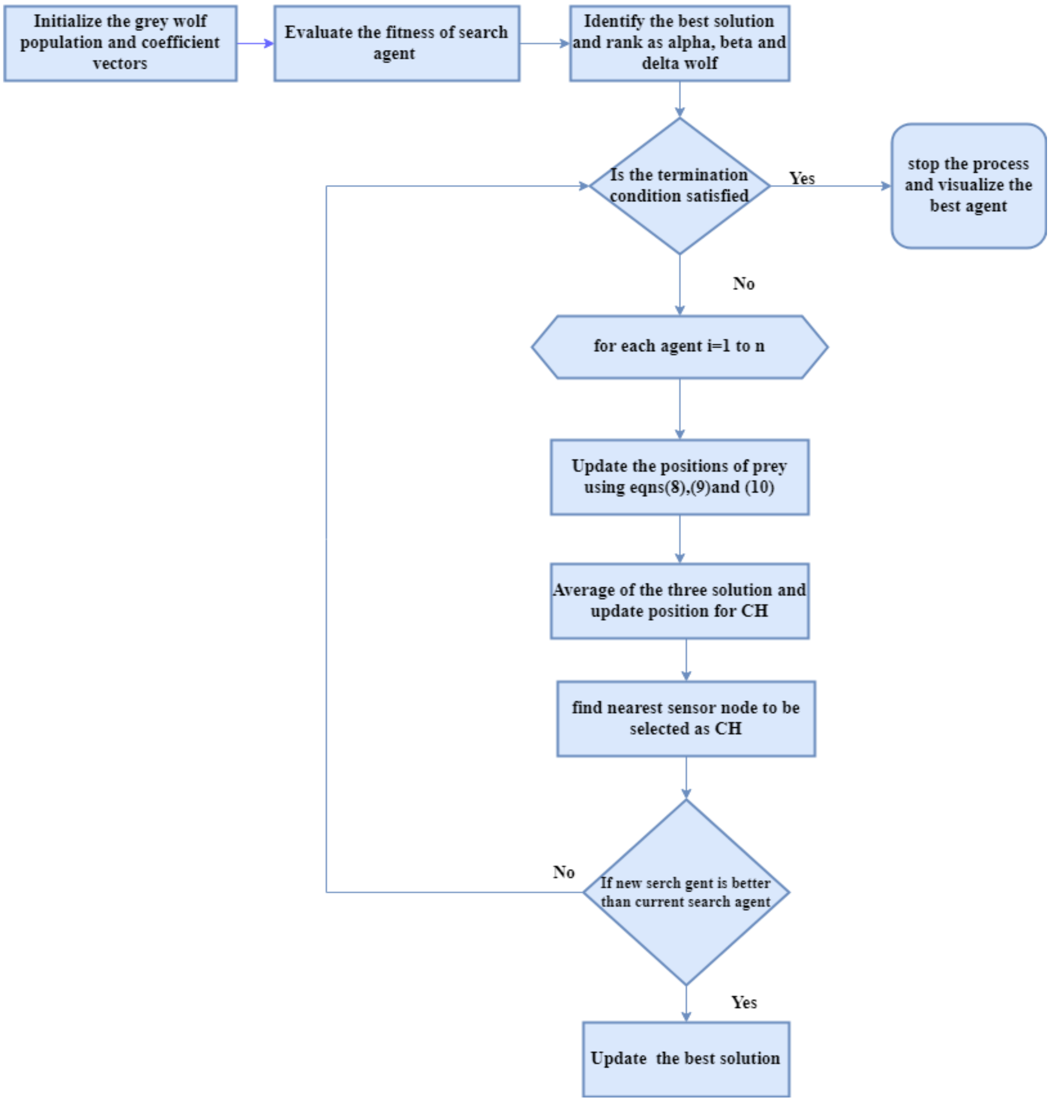

Fig 3. Flowchart of the Proposed Algorithm

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 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 γ is a value spanning one and [1], v is any number between 0 and 1, is any number between 1 and C, and μ is any value between 0 and 1 of size 1 x D.

$$X_{ti+1}^{B_i} = \gamma[M^{ti}(t,b) * \mu(b) + M^{ti}(v,b) * [1 - \mu(b)]] \tag{14}$$

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, $T{i_{a,b}}^{ti+1}$denotes the steering angle of the a^{th}rider in the c^{th}coordinate, and d_a^{ti}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.

$$X_{ti+1}^{Fi}(a,c) = X^{Li}(Li,c) + [cos\ cos\left(Ti_{a,b}^{ti+1}\right) * X^{Li}\left(L_{i,}c\right) * di_a^{ti}] \tag{15}$$

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

$$X_{ti+1}^{Oi}(a,c) = X_{ti}(a,c) + [Di_{ti}^{li}(a) * X^{Li}\left(L_{i,}c\right)] \tag{16}$$

The generalized distance vector is calculated by subtracting the location of 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).

$$Xi_{ti+1}^{Ai}(a,c) = X^{Li}(Li,b) + [cos\ cos\left(Ti_{a,b}^{ti+1}\right) * X^{Li}\left(L_{i,}b\right) * di_a^{ti}] \tag{17}$$

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).

$$Ai_m^{ti+1}(a)=\{1; \quad if \quad r_{TI+1}(a) > r_{ti}(a)\ 0; \quad otherwise \tag{18}$$

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

$$Ti_{a,b}^{ti+1}=\{Ti_{a+1,b}^{ti} \quad if Ai_m^{ti+1}(a) = 1, \quad Ti_{a-1,b}^{ti} \quad if\ Ai_m^{ti+1}(a)0 \tag{19}$$

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

$$Ei_a^{ti+1} = \{E_a^{ti} + 1 \quad if\ Ai_m^{ti+1}(a) = 1, E_a^{ti}\ \neq \left|Ei\right| E_a^{ti} - 1\ if\ Ai_m^{ti+1}(a) = 0, E_a^{ti}\ 0 \quad Ei_a^{ti}, \quad otherwise \tag{20}$$

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
Return
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).

$$X_{ti+1} = \frac{X_{ti+1}^{B_i} + X_{ti+1}^{F_i}}{2} \tag{21}$$

$$X_{ti+1} = \frac{X_{ti+1}^{O_i} + X_{ti+1}^{A_i}}{2} \tag{22}$$

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
Return
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 bx 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 1. Parameter Setup

Parameters	Values
Simulator	MATLAB
Initial energy	0.5 joule
Number of nodes	100
Area	100*100 meters
Channel Access protocol	MAC
Antenna type	Omi-directional
Medium	Wireless

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 2. Network Throughput (Kbit/s)

Simulation time (s)	LEACH	ECCRA	EERP	SEAR	F-MROA
20	4	4.5	5.2	5.4	6.6
40	2.2	2.5	2.9	3.5	3.8
60	1.5	1.8	2	2.8	3.0
80	0.8	1.5	1.5	1.8	2.8
100	0.2	0.8	1	1.4	2

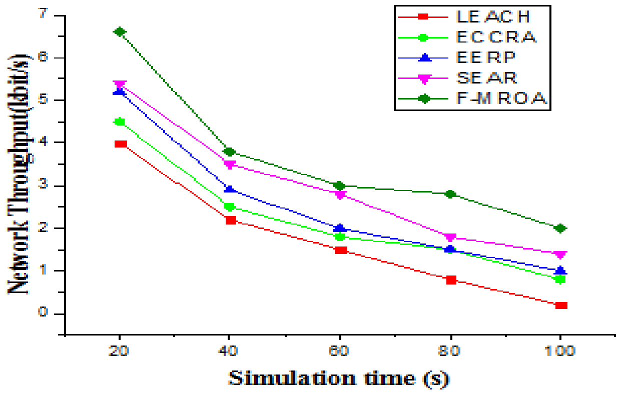

Fig 4. Network Throughput of Different Routing Algorithms

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 3. Residual Energy (J)

Simulation time (s)	LEACH	ECCRA	EERP	SEAR	F-MROA
20	12	14	15.8	18	22.4
40	10.4	12.5	13.4	15.5	19
60	7	10	12	13.6	17
80	6.5	8.6	9.8	12	16
100	4.2	6	7	10.4	14

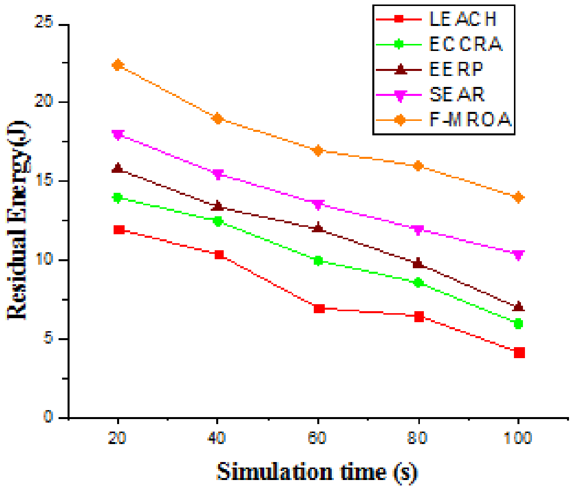

Fig 5. Residual Energy of Different Routing Algorithms

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

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

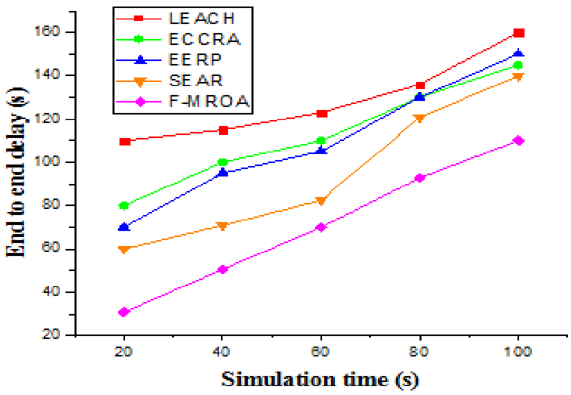

Fig 6. End-to-End Delay of Different Routing Algorithms

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.

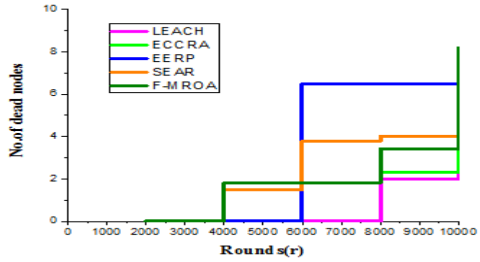

Fig 7. Analysis of Network Lifetime

Table 5. Network Life Time

Rounds(r)	LEACH	ECCRA	EERP	SEAR	F-MROA
2000	0	0	0	0	0
4000	0	0	0	1.5237	1.8701
6000	0	1.8312	6.521	3.876	1.8701
8000	2.394	2.347	6.521	4.321	3.4233
10000	4.3661	6.212	6.521	4.321	8.489

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 3800 epochs, and the LEACH 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

Table 6. Path Loss

Rounds(r)	LEACH	ECCRA	EERP	SEAR	F-MROA
2000	512	470	425	372	375
4000	455	312	270	120	375
6000	455	312	270	120	375
8000	420	306	220	120	106.4
10000	0	0	0	0	0

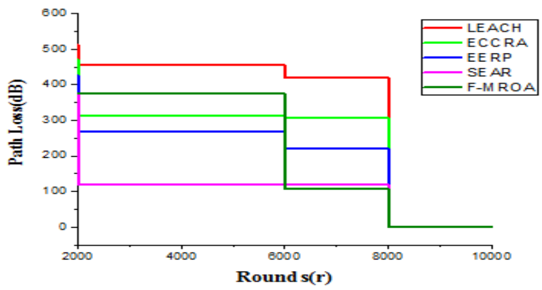

Fig 8. Analysis of Path Loss

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
[1]. A. Mushtaq, M. Nadeem Majeed, F. Aadil, M. Fahad Khan, and S. Lim, "An Intelligent Cluster Optimization Algorithm for Smart Body Area Networks," Computers, Materials & Continua, vol. 67, no. 3, pp. 3795–3814, 2021, doi: 10.32604/cmc.2021.015369.

[2]. Y. Qu, G. Zheng, H. Ma, X. Wang, B. Ji, and H. Wu, "A Survey of Routing Protocols in WBAN for Healthcare Applications," Sensors, vol. 19, no. 7, p. 1638, Apr. 2019, doi: 10.3390/s19071638.

[3]. W. A. N. W. Abdullah, N. Yaakob, M. E. Elobaid, M. N. M. Warip, and S. A. Yah, "Energy-Efficient Remote Healthcare Monitoring Using IoT," Proceedings of the International Conference on Internet of things and Cloud Computing, Mar. 2016, doi: 10.1145/2896387.2896414.

[4]. A. Zeb, S. Wakeel, T. Rahman, I. Khan, M. I. Uddin, and B. Niazi, "Energy-Efficient Cluster Formation in IoT-Enabled Wireless Body Area Network," Computational Intelligence and Neuroscience, vol. 2022, pp. 1–11, Apr. 2022, doi: 10.1155/2022/2558590.

[5]. F. Aadil, O. Song, M. Mushtaq, M. Maqsood, S. Ejaz Sheikh, and J. Baber, "An efficient cluster optimization framework for internet of things (IoT) based Wireless Body Area Networks," Journal of Enterprise Information Management, Nov. 2020, doi: 10.1108/jeim-02-2020-0075.

[6]. M. Verma and R. Rai, "Energy-efficient Cluster-based Mechanism for WBAN Communications for Healthcare Applications," International Journal of Computer Applications, vol. 120, no. 19, pp. 24–31, Jun. 2015, doi: 10.5120/21337-4338.

[7]. D. P, S. P, and V. J, "Energy Efficient and Secured Cluster Based Routing Protocol for Wireless Sensor Networks," Wireless Sensor Networks, Jun. 2011, doi: 10.5772/38729.

[8]. J. B. S. L. J. B. Shajilin Loret and T. G. K. J. B. Shajilin Loret, "An Improved Trust based Energy Efficient Routing Protocol for Wireless Sensor Networks," Sensors, vol. 22, no. 7, pp. 1509–1516, Dec. 2021, doi: 10.53106/160792642021122207005.

[9]. W. Li et al., "A Comprehensive Survey on Machine Learning-Based Big Data Analytics for IoT-Enabled Smart Healthcare System," Mobile Networks and Applications, vol. 26, no. 1, pp. 234–252, Jan. 2021, doi: 10.1007/s11036-020-01700-6.

[10]. A. H. Sodhro et al., "Decentralized Energy Efficient Model for Data Transmission in IoT-based Healthcare System," 2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring), Apr. 2021, doi: 10.1109/vtc2021-spring51267.2021.9448886.

[11]. H. Sharma, A. Haque, and F. Blaabjerg, "Machine Learning in Wireless Sensor Networks for Smart Cities: A Survey," Electronics, vol. 10, no. 9, p. 1012, Apr. 2021, doi: 10.3390/electronics10091012.

[12]. M. Mamun-Ibn-Abdullah and M. H. Kabir, "A Healthcare System for Internet of Things (IoT) Application: Machine Learning Based Approach," Journal of Computer and Communications, vol. 09, no. 07, pp. 21–30, 2021, doi: 10.4236/jcc.2021.97003.

[13]. I. H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," SN Computer Science, vol. 2, no. 3, Mar. 2021, doi: 10.1007/s42979-021-00592-x.

[14]. L. J., "Power Aware Energy Efficient Cluster Based Network Coding Algorithm for Dynamic Source Routing (PA-EECSNC DSR)," International Journal of Psychosocial Rehabilitation, vol. 24, no. 5, pp. 1742–1750, Mar. 2020, doi: 10.37200/ijpr/v24i5/pr201845.

[15]. E. Refaee et al., "Secure and Scalable Healthcare Data Transmission in IoT Based on Optimized Routing Protocols for Mobile Computing Applications," Wireless Communications and Mobile Computing, vol. 2022, pp. 1–12, Jun. 2022, doi: 10.1155/2022/5665408.

[16]. Ivan Leonid, "Review of Algorithms, Frameworks and Implementation of Deep Machine Learning Algorithms", vol.2, no.4, pp. 132-142, October 2022. doi: 10.53759/181X/JCNS202202016.

[17]. T. Han, L. Zhang, S. Pirbhulal, W. Wu, and V. H. C. de Albuquerque, "A novel cluster head selection technique for edge-computing based IoMT systems," Computer Networks, vol. 158, pp. 114–122, Jul. 2019, doi: 10.1016/j.comnet.2019.04.021.

[18]. S. Murugan and M. Jeyakarthic, "An Energy Efficient Security Aware Clustering approach using Fuzzy Logic for Mobile Adhoc Networks," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), Mar. 2020, doi: 10.1109/iccmc48092.2020.iccmc-000102.

[19]. S. Pattnaik and P. K. Sahu, "Assimilation of fuzzy clustering approach and EHO-Greedy algorithm for efficient routing in WSN," International Journal of Communication Systems, vol. 33, no. 8, p. e4354, Feb. 2020, doi: 10.1002/dac.4354.

[20]. Anandakumar Haldorai, "Deep Space Communications Current Trends, Technologies and Opportunities", Advances in Intelligent Systems and Technologies, pp. 087-096. 2022. doi:10.53759/aist/978-9914-9946-0-5_10

[21]. Xinhe HOU and Donglai LU, "Security Evaluation of Side Channel Attacks on CPS Architectures", vol.2, no.4, pp. 153-163, October 2022. doi: 10.53759/181X/JCNS202202018.

[22]. M. Alazab, K. Lakshmanna, T. R. G, Q.-V. Pham, and P. K. Reddy Maddikunta, “Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities,” Sustainable Energy Technologies and Assessments, vol. 43, p. 100973, Feb. 2021, doi: 10.1016/j.seta.2020.100973.

[23]. V. Cherappa, T. Thangarajan, S. S. Meenakshi Sundaram, F. Hajjej, A. K. Munusamy, and R. Shanmugam, “Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks,” Sensors, vol. 23, no. 5, p. 2788, Mar. 2023, doi: 10.3390/s23052788.

[24]. D. Binu and B. S. Kariyappa, “Multi-Rider Optimization-Based Neural Network for Fault Isolation in Analog Circuits,” Journal of Circuits, Systems and Computers, vol. 30, no. 03, p. 2150048, Aug. 2020, doi: 10.1142/s0218126621500481.

[25]. Zhonghe Zuyan, “An Review of Medical Cyber Physical System Architecture and STP Issues", vol.2, no.4, pp. 164-174, October 2022. doi: 10.53759/181X/JCNS202202019.