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A new routing protocol for wireless body area networks based on Q learning and grey wolf optimization

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ABSTRACT

Click here and insert your abstract text. In this paper, a new routing protocol is proposed based on the Q-learning and Grey Wolf Optimization, applicable to Wireless Body Area Networks. The new protocol is designed to improve the routing proficiency with the help of the variables of the adaptive learning approach and metaheuristic optimization. We provide simulations that show the effectiveness of our approach to enhance reasonable network performance in terms of energy usage, end-to-end delay, networks' lifespan, and many others, The Gray Wolf Optimization (GWO) algorithm was used. For several reasons, including less consumption in ensuring the delivery of complete power data, and the network's longevity is comparable to previously used algorithms such as Particle Swarm Optimization (pso) and Ant Lion Optimizer (ALO), in which more energy is spent, approximately twice what is spent in (GWO). 7.5 is spent on the rest of the algorithms used, and 4.2 is spent on the algorithm used in the article, as the algorithms start from the first round at a rate of 2100 and the GWO starts at a rate of 1200 and produces 4050 rounds, as we will explain later in the practical part.

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1. Introduction

Wireless Body Area Networks (WBANs) have appealed a lot of people due to the possibilities that are perceived in revolutionizing the whole health industry. Hence, such networks are wearables/implantable designed to monitor the human body parameters and signs, passing the collected info to a central device, such as a smartphone or server, for analysis. WBANs present actual-time and nature of health info with a purpose to facilitate the clinicians for starting the remedy of disease of their affected person at a preliminary stage [1]. Nevertheless, WBANs' promised features still make design of secure and efficient communication channel problematic. Power is one of the significant issues in wearable and implantable devices as most of them are low power devices that use non-rechargeable batteries with low energy backup. Additionally, in WBANs not only the change of a routing path but also changing channel status and nodes' mobility is possible (e. g. due to a body movements).

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As a result, this paper proposes the GWO-Q hybrid routing as a remedy to tackle the aforementioned challenges in order to enhance the network performance and the reliability of the network. This strategy relates to how the modification of the GWO algorithm and Q-leanning makes it certain that the routing system is intelligent. It also automatically integrates the methods to schedule a network path, conserve or minimize power usage, and further improve the steadiness and dependability of the operated network [2].

2. Related work

2.1 Routing Protocols in WBANs

Contemporary advancements in wireless sensor networks have enabled the measurement of various physical entities in both industrial and civil domains, such as military operations, energy management, healthcare, and environmental monitoring. A significant proportion of these applications need the deployment of large Wireless Sensor Networks (WSNs). Because the sensors nodes are computed with a reduced quantity, only a small number of them with a user interface could be equipped. Hence, the sensor nodes of a Wireless Sensor Network (WSN) present significant obstacles for managers in effectively managing and monitoring their operations. In certain instances, the number of sensors can reach values as high as thousands [2].

2.2. Grey Wolf Optimization

An evolutionary paradigm refers to a group of computing methods that combine evolutionary principles with genetic-specific algorithms, drawing inspiration from nature. These algorithms employ a range of approaches like as selection, crossover, and mutation to operate on populations of candidate solutions in order to obtain the optimal solution. In the process of routing optimization in Wireless Body Sensor Networks (WBSNs), evolutionary algorithms can be used to investigate and develop routing strategies. This allows for fitness evaluation and genetic operations to be performed each time, leading to the optimization of the techniques [3].

2.3. Q-learning

The Q-learning algorithm is a commonly employed reinforcement learning technique in the fields of robotics, artificial intelligence, and machine learning. The proposed model-free and off-policy learning technique enables an agent to acquire optimal decision-making strategies even in the presence of unknown environmental conditions. Q-learning is founded upon the framework of iterative experimentation. An agent interacts with a tangible or virtual environment by performing actions and subsequently obtains feedback in the form of rewards or punishments. An initial objective of the agent is to acquire a policy that produces a greater discounted or cumulative reward. This component is executed by utilizing a Q-table, which serves as a storage for the anticipated reward of every state-action combination in the environment. Indeed, the Q-values represent the projected future total reward in relation to the action performed under the specified condition [4].
The agent undergoes a process of education guided by the objective of identifying effective strategies by experimenting with various actions and observing the resulting rewards. The revised Q-values are calculated using the Bellman equation, which expresses the expected cumulative reward in a state-action combination as the sum of the immediate reward and the anticipated maximum cumulative benefit from the next state. Throughout the process, the agent's selection Q-table is continuously enhanced, leading to the optimization of its policy and strengthening its robustness.
The Q-learning algorithm is highly efficient in addressing scenarios that involve discrete states in state and action spaces, and is capable of handling stochastic dynamics. It finds extensive and widespread application in several domains including as robotics, gaming, resource management, and autonomy systems [5].

2.4. Optimization algorithm

An optimization algorithm is a computational method used to determine the fundamental optimal value or the most optimal solution for a predefined problem. The challenges associated with this include primarily determining the maximum or minimum value of a given function and solving it within specified constraints. Approximate algorithms are crucial components in several disciplines like engineering, finance, data science, and operations [6].

2.5. Application of GWO and Q-Learning in Wireless Communication

The GWO and Q-Plus Learning algorithms are two distinct nature-based optimization techniques that have been used for wireless communication in order to address challenges and enhance network performance. Such methods are designed to offer a diverse range of possibilities, either individually or together, for various facilities in contemporary wireless communication networks. Application of Grey Wolf Optimization (GWO) and Quantum Learning (Q-Learning) in wireless communication includes the following: The uses of Grey Wolf Optimization (GWO) and Quantum Learning (Q-Learning) in wireless communication are as follows: Application of Grey Wolf Optimization (GWO) in Wireless Communication: A Comprehensive Analysis Application of Grey Wolf Optimization (GWO) in Wireless Communication: A Comprehensive Analysis

1. Resource Allocation: Grey Wolf Optimization (GWO) can be employed to address the problem of resource allocation in wireless communication systems, such as power, bandwidth, and time slots, to designated users or channels. In the context of GWO, the ability to find resource allocations and equilibrium, thereby enhancing overall system performance and capacity, is contingent upon achieving a balance between exploration and exploitation.
2. Channel Assignment: GWO may optimize the assignment of channels in multi-channel communication schemes to ensure successful routing to various nodes or consumers. By considering variables such as channel quality and interference, GWO can suggest channel assignments that minimize the interference of these transmissions and promote higher data transfer rates [7].

3. Beamforming: GWO can also be used in beamforming to quantify the orientation and intensity of the beam signals, taking into account variables such as directionality and radio communication. By optimizing beamforming, the GWO system may enhance power intensity and reduce interference noise, leading to consistent and excellent communication performance.

4. Handover Optimization: Grey Wolf Optimization (GWO) can be employed to generate improved handover decisions in a cellular network, where mobile devices will actively switch between several base stations. In order to minimize signal blackouts caused by switching from one base station to another, the handover procedures of the GWO can establish optimal thresholds and policies without any gaps throughout the handover process [8].

2. 6. Metaheuristic Optimization

Many optimization algorithms have been reported in literature, out of them one of the most successful metaheuristic algorithms, known as Grey Wolf Optimization (GWO), has been proposed by Mirjalili and Lewis [9], which has been used for network optimization, since it is known to have the good balance between exploration and exploitation. Research by Xu and Zeng, based on the works of [10] show that GWO can be used in optimizing that aspect of the routing protocols by offering enhanced energy consumption and route stability.

2. 7. Hybrid Approaches

As a result of integrating Q-learning with GWO, this paper proposes a more suitable strategy to improve routing for WBANs. The integration of Q-learning which has the flexibility aspect combined with the optimization factor of GWO to fine-tune the choice of routing and hence enhance the network performance [10]. This combination is intended to solve the difficulties of dynamic routing, as well as the energy deficit.

2.8. Gaps in Existing Literature

My most recent update, which is from September 2021, indicates that the subject of study is always evolving and being published intermittently. After the latest update, I will be unable to identify any gaps in the most recent literature. Furthermore, my proposed gaps may be derived from the information that was accessible and pertinent at that time, as previously referenced. When investigating the new routing protocol for Wireless Body Area Networks (WBANs) based on Grey Wolf Optimization (GWO) and Q-Learning, researchers should take into account the following gaps:

1. Restricted Integration of GWO and Q-Learning: Despite the exceptional optimization capabilities of GWO and Q-Learning, there is a little of uncertainty regarding their combined application in routing of WBAN due to insufficient study. To ascertain the significance of these two methodologies and their potential integration for yielding enhanced outcomes in Wireless Body Area Networks (WBANs), it would be prudent to do study on this subject matter.

2. Real-World Implementation and Validation: Most research publications tend to prioritize theoretical concepts, abstract considerations, or evaluation through computer simulations rather than real-world experimentation. Related articles may not include comprehensive coverage of the live deployment and testing of the GWO-Q protocol for WBANs. Thorough evaluation of the protocol in real-world scenarios can provide insights into its feasibility, efficiency, and the challenges it may encounter.

3. The dynamic nature of Wireless Body Area Networks (WBANs) is characterized by a high degree of volatility in factors such as topology, network status, and sensor motions located on the human body. The existing literature may lack comprehensive research that specifically examines the intricacies and difficulties arising from the dynamic nature of Wireless Body Area Networks (WBANs) and how the anticipated routing protocol may effectively adjust to these evolving conditions.

4. Energy efficiency and node lifespan: The prevention of energy wastage and the optimization of energy usage are important concerns for the power resources of Wireless Body Area Networks (WBANs) adopted by wearable and implanted devices. A comprehensive analysis of the protocol solution's impact on energy consumption and the potential for node lifetime extension will be absent in the exam (paragraph 40).

5. Considerations for Quality of Service: A significant number of contemporary medical applications belong to the Wireless Body Area Network (WBAN) category and necessitate a sophisticated Quality of Service (QoS) mechanism to address conflicts and reliability concerns associated with data transmission. An advantageous inclusion would be the examination of how the given protocol meets Quality of Service (QoS) criteria, therefore giving early precedence to the critical health data and ensuring its seamless and prompt transmission.

6. Scalability: While both GWO and Q-Learning appear to be effective optimization techniques, it is important to assess their scalability in the context of large-scale WBAN deployment. Thorough investigation is necessary to understand how the suggested protocol may adapt to the increasing number of nodes and the resulting challenges.
7. Given the data sensitivity of such WBANs, it is imperative to highly value and protect their security and privacy. The undertaking of such research requires the formulation of security standards and the implementation of further scrutiny on the possible vulnerabilities and privacy concerns that may arise [11].

8. comparison Analysis of Existing Protocols: The literature may benefit from comparison studies that standardize the GWO-Q routing protocol and present it in competition with traditional protocols and other cutting-edge techniques. Studies of this nature facilitate the comparison between the proposed procedure and the real-world situation, therefore revealing both its strengths and faults within a wider framework.

In healthcare applications, these gaps provide working-level researchers with the chance to introduce new routing protocols and tackle any arising problems.

3. Research Methodology

3.1. System architecture

In the first stage within the system architecture, we incorporate and implement the general framework of Wireless Body Area Network (WBAN). It is formed by nodes that are intended to gather and disseminate information and that can also have the objective of researching good energy practices. In the system, sensor nodes and the cluster heads are some of the most important facets. Another is the process of elections that is made customer oriented to give overall control of selections among the community. Also, it is necessary to inform about the most effective paths for transferring data and methods determining such paths for proper data transmission while mapping pathways.

Numerous low-capability sensor nodes are available in the system and are located at the front and the back of the body as indicated in the Figure 1. These nodes are perfect for being localized and tracked. It also covers the sink nodes predesignated as H = {N, L}, with 'N' symbolizing the sink node and 'L' symbolizing the link between network components. network components.

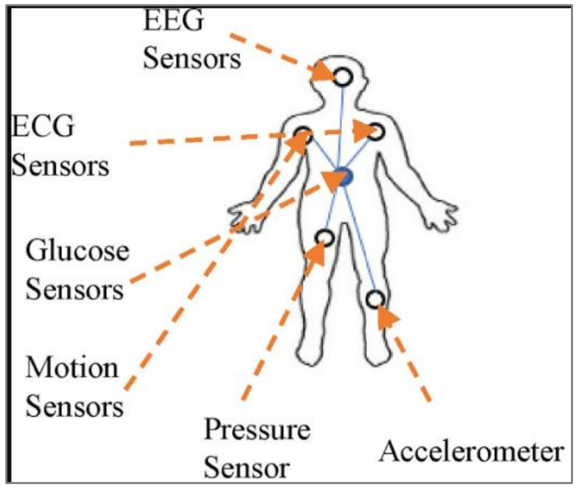

Fig. 1- Sensor nodes are placed on the human body

Several key principles define this system:Several key principles define this system:

a. This system employs a 2-D Cartesian coordinate system hence the location of a particular sensor node is not pre-specified.

b. Every device is provided with a non-rechargeable source of energy to enable it to work round the clock.

c. Sensors are mounted, that means that the position and angle of the sensors do not change.

d. Depending on the type of functions and the protocols they implement, there is a difference in computational capabilities and memory of the sensor nodes.

e. All sensors begin at the same energy status of a new battery.

f. Data transmission is also bidirectional, this made sure that the connection between the sensors and the network managers is perfect when it comes to feedback and changes.

Table 1- Description of Sensor Nodes in WBAN

Node	Description	Location
1	EEG Sensor	Head
2	EEG Sensor	Head
3	EEG Sensor	Head
4	EEG Sensor	Head
5	ECG Sensor	Chest
6	ECG Sensor	Chest
7	Glucose Sensor	Stomach
8	Motion Sensor	Right Shoulder
9	EMG Sensor	Right Wrist
10	BP Sensor	Left hand
11	Oximeter Sensor	Left hand
12	Lactic Acid Sensor	Right side thigh
13	Accelerometer	Right side knee
14	Respiration Sensor	Left side thigh
15	Pressure Sensor	Left leg
16	Pressure Sensor	Right leg
Sink_1	Central Coordinator	Right Side

3.2. System initialization

Table 1 presents a theoretical model of the distribution of sensor and sink nodes for a certain body component. Once the nodes have been successfully configured, the "Hello" and "Reply" message packets are sent, and the alternative nodes reflect. These signals give quantitative information about each node, such as its location, energy consumption, proximity to the sink node, and proximity to other nodes. Furthermore, we will examine the transmitter strength, as shown in Figure 2.

This abundance of data facilitates numerous essential network operations:

1. Cluster Formation: This data facilitates the establishment of a single cluster consisting only of specified nodes. This group engaged in networking activities to achieve more than simply improved team communication and resource management.

2. Cluster Head Selection: Nodes are selected for this purpose by evaluating sensor data. The primary responsibility of cluster heads is to facilitate effective communication among clusters.

3. Data Routing: These parameters provide cost functions for the implementation of data routing. Cost functions provide network operators the ability to select the most optimal data traffic paths. The channels should transfer messages with high efficiency and minimal energy consumption.

Therefore, the interchange of information and its use enhance the performance of lighting systems and networks. An alternative approach is to encase energy collecting material within each sensor node to guarantee energy provision and accommodate the limited power characteristics of a Wireless Body Area Network. An alternative approach is to include energy collecting material in every sensor node to guarantee energy provision and accommodate the limited power characteristics of a Wireless Body Area Network. Wireless Body Area Networks address power efficiency concerns by incorporating energy harvesting into every sensor node (SYNC). Given that energy is the primary challenge for WBANs, each SN would have an energy collecting capability to acquire and temporarily store electricity.

Every individual sensor node (SN) inside Wireless Body Area Networks (WBANs) has the capability to absorb and handle temporarily available electricity. Each SN incorporates power harvesting to comply with the energy constraints of WBAN models. Machine learning algorithms employ EGatheri(t; Psetup) to estimate the energy data collected at each node. Equation 1 characterizes the future behavior of the network, enabling the achievement of optimal energy consumption [12].

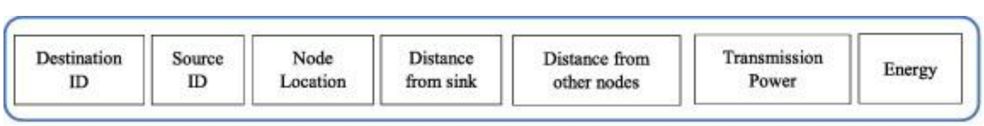

Fig. 2- Data packet information format

The energy harvesting capacity of each sensor node (SN) enables it to gather and utilize electricity in order to overcome the power limitations that are inherent in Wireless Body Area Networks (WBANs). The energy collected, represented as EGatheri(t; Psetup), for each node is predicted using machine learning methods. The forecast expressed in Equation (1) facilitates the effective management of the energy resources inside the network [13].

$$E_{Gatheri}(t; P_{setup}) = \int_{t}^{t+P_{setup}} \lambda_{i(T)}\, dT$$

EGatheri represents the energy collected by node i during the specified time period (T). Let λi (T) represent the charging rate of node i during the set time (T).

3.3. Selection of CH and cluster formation

Selection of cluster heads depending on the priority of the first zone group is a component of this procedure. With the assistance of a receiving controller or cluster head, these nodes manage their clusters and restrict network bandwidth. Information is exclusively exchanged among identified nodes within the cluster. Created clusters enable the optimization of system convergence and improvement of communication.

Utilise system initialisation data for cluster creation and head election. Automatically, every few transmission cycles, the cluster head position is chosen among sensor nodes that satisfy the predetermined eligibility criteria for each cluster.
Figure 3 depicts the methodology outlined below. An eminent characteristic of this approach is the unequal composition of groups. The network is resilient among specific branches, may be expanded, uniformly distributes the load, and offers supplementary advantages. Formation of clusters and selection of leaders are undertaken to ensure optimal network operation and efficient communication.
The following pseudocode outlines the process of data transmission and optimization utilizing a network of sensors (sensor nodes), sink nodes, and cluster heads. Python syntax and libraries for machine learning and optimization are required for this task. The Python code provided herein reflects the pseudocode.

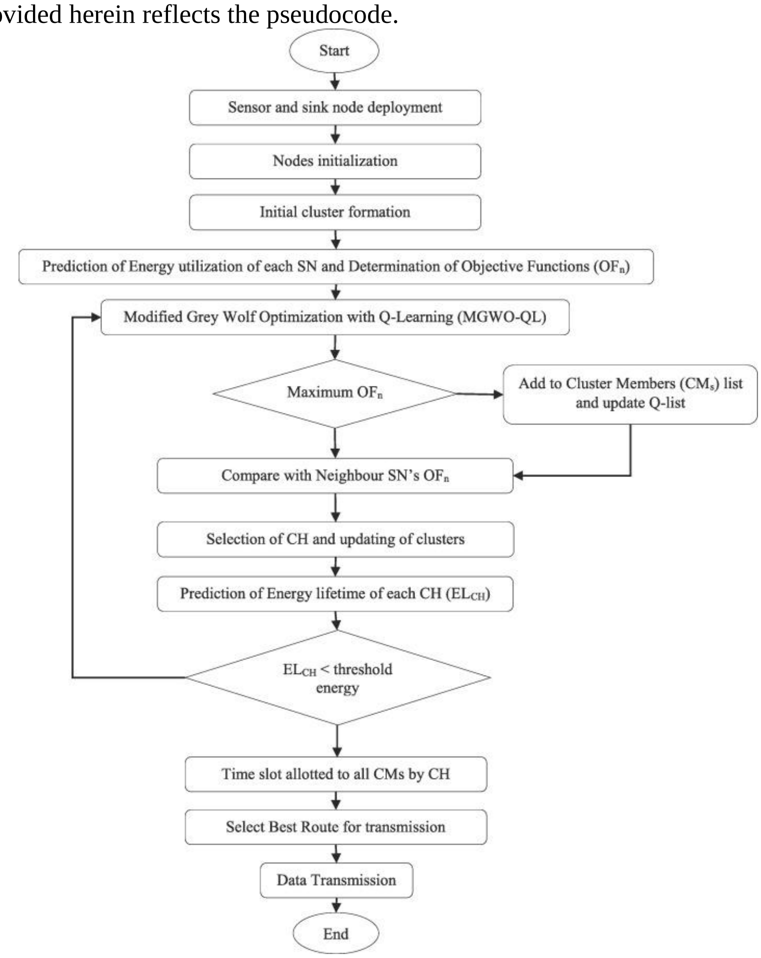

Fig. 3- Flowchart of the proposed methodology

Selection of a Cluster Head (CH) in the network is a crucial decision, influenced by several factors. Key characteristics are node proximity, computational complexity, battery life, and signal strength. Power consumption impacts all wireless networks, especially Wireless Body Area Networks (WBANs), so the Community Head prioritizes a higher-energy consumption directive.

This paper presents a new approach for tackling several issues. In our proposed multi-objective optimization approach, each objective is optimized independently. This technology concurrently develops energy-efficient, non-congestive CH selection techniques that satisfy other crucial criteria. Incorporating many judgment criteria and employing the multi-objective approach will enhance the performance and efficacy of the selection process. The objective of developing more sustainable and efficient Wireless Body Area Networks (WBANs) that optimize energy utilization may contradict this. Furthermore, this leads to an enhancement in network longevity and service excellence. The present implementation approach employs a Q-learning model with off-policy control. This update model use Q-learning to select the cluster Head (CH) according to the prevailing environmental conditions. Iterative model updates are determined by these criteria. Equation (2) demonstrates the approximation of the Q-learning model (see to [14] for further information) and how the selection of CH adapts to variations in network performance as the network environment evolves.

$$Q_{i+1}^{x}\left(st_{i}^{x}, ac_{i}^{x}\right)=(1-\gamma) Q_{i}^{x}\left(st_{i}^{x}, ac_{i}^{x}\right)+\gamma\left[r_{i+1}^{x}\left(st_{i+1}^{x}\right)\right]+\delta \max_{x \in X} Q_{i}^{x}\left(st_{i+1}^{x}, st_{i}^{x}\right)]$$

Where,

st_i^x =Agent's state at time instance t.

ac_i^x =Respective action to.st_i^x

γ=learning rate $(0 < \gamma < 1)$.

$r_{i+1}^x\left(st_{i+1}^x\right)$ =Respective reward for action.

The modified Grey Wolf Optimization (MGOW-QL) strategy, which is based on the Q learning algorithm, is used to find the cluster head (CH) and update formula 2. Achieving optimal selection of crucial components using Grey Wolf Optimization (GWO) transforms Q-learning into positive values.

4. Simulation Results

In this section, we discuss and explain the simulation outcomes, with the specific focus on the methodology we introduced earlier. Here the general aim is to assess the desirability and effectiveness of the model by testing it with different conditions and parameters on MATLAB. Key parameters examined are listed below:Key parameters examined are listed below:

4. 1. Simulation scenario

Based on the simulation of WBAN scenarios, one is able to evaluate the performance and effectiveness of routing algorithms and networking protocols. Below is a scenario for WBAN simulation:Below is a scenario for WBAN simulation:

Table 2- Simulation scenario for WBAN

Simulation Scenario	Values
Area	1m*1m
WBAN sensor nodes	8
Initial energy of network	4.8J
Energy Dissipation while transmitting bits	16.7 nJ/bits
Energy Dissipation while receiving bits	36.1 nJ/bits
Energy Dissipation during amplification of power	1.98 nJ/bits
Packet size	4000

Table 3- Simulation scenario for multi-WBAN

Simulation Scenario	Values
Area	30m*30m
WBAN sensor nodes	50
Initial energy of network	30J
Energy Dissipation while transmitting bits	16.7 nJ/bits
Energy Dissipation while receiving bits	36.1 nJ/bits
Energy Dissipation during amplification of power	1.98 nJ/bits
Packet size	4000

4.2. Simulation Results and Discussion

When testing the proposed model in MATLAB, the authors ensured that they performed diverse simulations to determine the model's easy sensitivity and pliability regarding the different conditions. The parameters used in the research were crucial in modeling and testing the model by including the topology of the network, energy consumption and details of the simulator used.

Key Aspects:

•Network Topology: Explained what a sensor node is and its ability of communication, transmission range as well as the scalability of the network. For some of them, specific parameters like the intensity of electromagnetic waves, the speed light and others were incorporated in the model to simulate various operating conditions.

•Energy Parameters: See Table 3 which contains the sensor node's energy level and energy harvesting rate, power level and consumption rate. These factors were most important if the energy efficiency of the given model was to be evaluated.

•Simulation Settings: Such features as simulation time, set of models and parameters of machine learning algorithms that make it possible to estimate long-perspective work of the system in considered conditions.

•Performance Benchmarks: Quantitative measures such as residual energy, throughput, network lifetime and path loss were used in order to measure of the models in terms of energy consumption, data transfer and signal quality.

4.3. Network lifetime

The findings shown in Figure 4 demonstrate significant differences in energy consumption and network lifespan when routing criteria are established using three different optimization algorithms: Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Ant Lion Optimizer (ALO). The performance of the real-world model exceeds that of PSO and ALO, which jointly spend less than 7.5% of the network energy. By comparison, the radiant particle system depletes the power reserves of the starting node after 1200 rounds of gaming, whereas ALO depletes the power reserves of the first node after 2100 rounds of simulation. The Grey Wolf Optimization (GWO) algorithm is quite effective in producing a very energy-efficient perspective. Within the current round of operation, the primary node has the capacity to carry out around 4350 rounds.

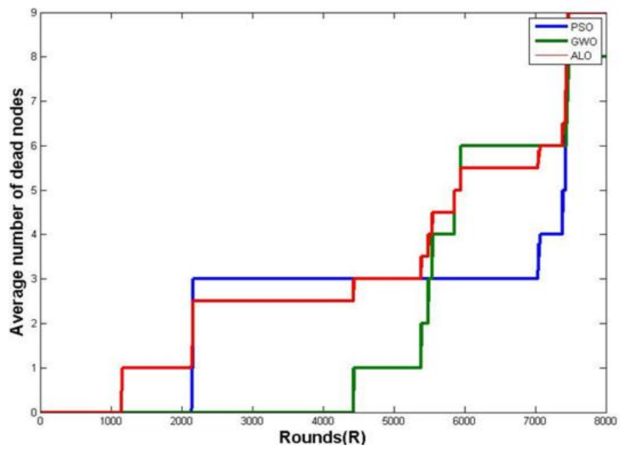

Fig. 4- Network lifetime

Among optimization techniques, Figure 4 illustrates that GWO has the longest network lifespan. Simulation results indicate that the duration of one round of GWO is 7632, PSO is 7600, and ALO is 7550. Therefore, the approach demonstrates superior performance compared to ALO and PSO. This is due to its ability to select the most efficient routes for data transport. In comparison to earlier approaches, GWO exhibits superior performance. GWO focuses on the short, energy-intensive connections between commercial centres. The use of this approach ensures prudent energy consumption and safeguards equipment, therefore prolonging the lifespan of the network. Figure 4 demonstrates that GWO exhibits superior energy efficiency and longer lifespan compared to ALO and PSO. The GWO system optimizes resource use and exceeds customer expectations through meticulous route selection.

4. 3. Throughput

Thus, the results shown in figures 5, and in table 1 regarding the analysis of packet transmission and throughput prove that GWO outperforms PSO and ALO routing protocols in WBANs. In terms of packets transmitted, GWO was able to reach 2754, while for the PSO it was 1750, for ALO it was 2255, which shows that the network lasts longer because energy is conserved well in GWO.

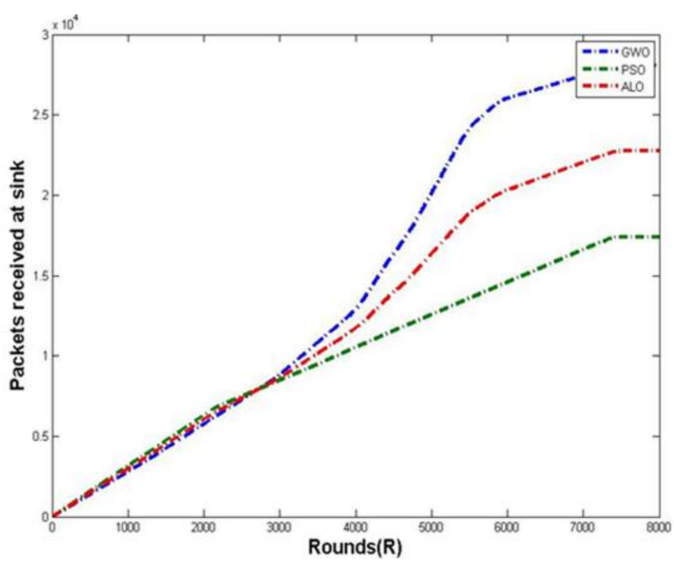

Fig. 5- Throughput

4.4. Residual energy

Table 2 and Figure 6 compare GWO routing protocol power efficiency with PSO and ALO and pinpoint GWO high level of energy efficiency. GWO has minimum energy consumption of 912. 2 kW by lowering energy consumption by 23% compared to PSO and 16% compared to ALO. This a clear sign that GWO is capable of dealing with energy management in a great way.

The energy efficiency in GWO originates from the approach the relay nodes are selected based on a fitness function to enhance the paths' energy consumption. Besides optimizing the network performance, this approach also aids in increasing the years of its functionality.

Figures 3 and Table 3 also depict that the energy efficiency of GWO is higher than ALO and PSO techniques and hence, façade could be a better option in Wireless Body Area Networks (WBANs).

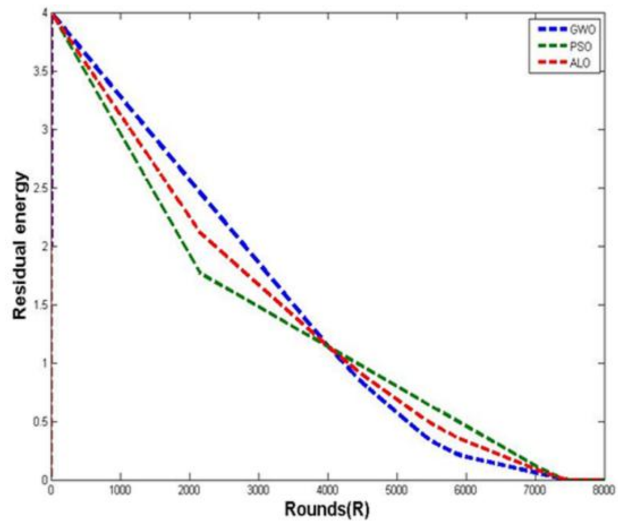

Fig. 6-Residual energy

5. Future Research

1. Energy Harvesting Advancements:

Create enhanced techniques to generate energy for WBANs using solar kinetic, and thermoelectric methods to improve WBANs life expectancy.

2. Machine Learning Enhancements:

Enhance the efficiency of existing machine learning algorithms in forecasting and optimal power consumption in WBANs. Investigate deep learning and reinforcement learning algorithms to improve the results of energy consumption administration.

3. Multi-Objective Optimization:

Lease use techniques like multi-objective optimization to cut power usage, traffic and network lifetime. It is important to note that this approach is useful for actualization of advanced WBAN applications.

4. Interoperability and Standardization:

Set up the WBAN devices guidelines and norms in order to achieve compatibility. This will help in the incorporation of the WBAN technology into the health care facilities.

6. Summary

The study based its conclusions on the implementation of the GWO algorithm in increasing energy performance in WBANs and, therefore, proving to offer better results than PSO and ALO by minimizing energy use in the same networks. Some of the necessary components that can help in prolonging the WBANs' useful life include the development of new methods of energy harvesting technologies like solar and kinetic systems and the enhancement of new energy prediction models say using machine learning models. Also, using multi-objective optimization helps in achieving an optimal trade-off between energy consumption, data traffic, and the network's lifetime. Since the process of implementing these features will allow for the creation of compatible standards for WBANs to be incorporated into healthcare systems, general efficiency and system compatibility will be enhanced.

It has been proven that the algorithm used is relatively better than previous algorithms in terms of energy consumption, extending the network life, and data reliability, with success that reached twice what previous research reached. We mentioned it previously in the fourth chapter of the article, and we proved it practically through the graphs, numbers, and amount of energy waste or consumption for all the algorithms used. As we estimate, we succeeded by 95% in achieving the goals we were aiming for, and we gave future studies that could potentially lead us to higher levels than we expected to obtain in the future.

Acknowledgements

Acknowledgements and Reference heading should be left justified, bold, with the first letter capitalized but have no numbers. Text below continues as normal.

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