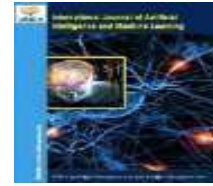




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A Novel Game Theory-Based Adaptive Resource Optimization Algorithm for Efficient Communication in WBSN

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Abstract:

Wireless Body Sensor Networks (WBSNs) have become an important part of putting continuous health monitors into operation and are affected by the shortage of energy, latency and dependable conveyance of information. This paper suggests a Game Theory-Based Adaptive Resource Optimization (GTARO) solution that aims to improve energy efficiency, radio communication stability and Quality of Service (QoS) within WBSNs. The approach combines node state sensing, utility-based coalitions and adaptive resource allocations to Nash Adaptive Equilibrium Routing (NAER) nodes next hop selection stability. A Dynamic Multi-Factor Optimization (DMFO) mechanism is applied by using firefly optimization and genetic operators to optimize end-to-end routing paths in terms of energy, reliability and latency compromises. The adaptive framework modifies the weights energy, load, priority and link quality. The results indicate that GTARO performs substantially better than the existing protocols. In particular, it generated the highest network lifespan, lower consumption of energy per round and it greatly minimized the latency. Further, GTARO performed best in packet delivery ratio and throughput in a dense WBSN, demonstrating its strength in such a scenario. The adaptive re-optimization method guaranteed stable performance in different traffic and topology process. This proves the effectiveness of GTARO in balancing between energy savings and QoS assurances, which makes it a viable tool in real-time healthcare monitoring routines.

Keywords: Energy efficiency, Game theory, Wireless Body Sensor Networks, Quality of Service, Network lifetime, Healthcare monitoring, Reliable data transmission.

I. Introduction

Wireless Body Sensor Networks (WBSNs) have seen significant coverage over the last few years because these enable a composite outcome related to uninterrupted health, prompt diagnosis and live support. Such networks allow bio-sensors to be implanted and wearable that record physiological data and pass it efficiently to healthcare professionals, optimizing the quality of medical care and delivering better patient outcomes. Nevertheless, there is a non-trivial issue of limited resources, specifically energy, bandwidth and processing capabilities on WBSNs. This presents a challenge in making the communication energy-efficient, secure and reliable.

Routing energy optimization in WBSNs has been solved by several studies. Reinforcement learning-based clustering techniques have also been proposed to enhance the efficiency of routing, extend network lifetime [1] and dynamic adaptive routing techniques have been proposed to reduce power consumption under variable network conditions [2]. In order to increase data transmission security and efficiency further, models of identity-based group signature systems with a secure encryption have been proposed [3]. This is related to content-based adaptive scheduling schemes presenting greater energy efficiency in large-scale deployment of wireless sensors [4] and threshold-based routing schemes offering the balanced use of energy in WBSNs [5]. The emerging applications in which, energy-efficient methods of synchronization have been developed including health care in metaverse [6].

Serve cooperative and reliable routing is a field of action that has been pursued actively. The advantages of cooperative energy-efficient protocols are that these improve the end-to-end reliability of intra-body communications [7] and prolong the network lifetime. The proposed enhanced Bennett-Brassard 1984 Protocol (BB84) effortlessly solves the problem of high practicality requirement of quantum-cryptography scheme and effectively achieves a high level of quantum of security guarantee [8]. Along with this, machine learning has also been used to develop the secure and safe disease detection frameworks in medical WBSNs [9]. Cluster based aggregation mechanisms have also been introduced to minimize redundant transmissions and increase scalability [10].

The other studies have been on multi-criteria route decisions. Specifically, delay-aware mechanisms, link quality and temperature have been proposed to guarantee good throughput with physiological limits [11]. Energy-efficient routing protocols have been suggested that consider distance and links so as to maximize the performance [12]. Other than healthcare applications, weighted geographical routing applies to diverging application areas such as vehicular health monitoring applications [13]. Moreover, the studies demonstrate the real-life effect of WBSN-enabled systems that measure such crucial health parameters as heart rate [14]. In an effort to solve security issues, the use of Elliptic Curve Cryptography (ECC) key exchange mechanisms has been suggested to allow lightweight and efficient security protection to WBSNs [15].

These areas help in increasing energy efficiency, security and reliability. Most of the current methods address each aspect separately, without providing a united approach in optimizing dynamic resources. There has been a lack of integrated solution that focus on energy consumption, resource allocation, routing efficiency and Quality of Service (QoS) at the same time as changes in the real-time network.

To deal with these shortcomings, this paper presents a Game Theory-Based Adaptive Resource Optimization (GTARO) that integrates Cooperative Game theory with a Dynamic Multi-Factor Optimization (DMFO) strategy. A new Nash Adaptive Equilibrium Routing (NAER) paradigm is proposed within GTARO to find energy-efficient paths that strike a balance between resources consumed by the nodes. Also, DMFO has incorporated bio-inspired methods through firefly optimization methods to dynamically adjust the routing paths, lower latency and improve reliability. The GTARO framework enhances the reliability of communication, maximizes network life span and guarantees QoS in WBSNs.

Contribution: This paper makes a key contribution in the form of: The cooperative game-theoretic framework to adaptive resource allocation in WBSNs. A Nash adaptive Equilibrium Routing (NAER) mechanism to obtain energy efficient balanced routing. Dynamic Multi-Factor Optimization (DMFO) algorithm is combined with bio-inspired algorithms. In order to show the enhancement of energy efficiency, latency, reliability and QoS, the real-time changes in networks are addressed.

Organization: The rest of the work is organized in section 2, which describes the related work. Section 3 describes the system model and approach. In section 4, results of simulation set-ups and performance studies are presented. In section 5, discussions and research directions in future are discussed. Lastly, the conclusion of the paper is in section 6.

II. Background Study

In Hosseinzadeh et al. (2023), a secure routing protocol of WBSNs was proposed by implementing an algorithm, League Championship Algorithm (LCA). This had been a population-based metaheuristic approach. The solution also optimized on routing path considering energy cost, reliability of links and security. Simulation findings indicated great energy efficiency, network lifeward and secured datum distribution at better levels compared to the use of traditional protocols. However, the methodology exhibited shortcomings regarding easiness. It involved parameter tuning that compromised the scalability in highly dynamic WBSN environment. Mehmood et al. (2020) have developed an Energy-Efficient and Reliable Communication Scheme (ERCS) in WBANs with remote patient monitoring. It seemed trust based. The algorithm took into consideration the energy-aware routing algorithm attributed to trust criteria to ensure that no unreliable data was delivered and the malicious node behaviour was minimized. The result indicated very high delivery of packets, less energy consumption and security. However, the scheme carried an additional overhead of constant trust evaluation. Angelucci et al. (2024) validated a Body Sensor Network (BSN) device to record the cardio-respiratory parameters in a continuous manner. The study applied wearable devices to record respiration and cardiac activity. The results were compared with the outcomes recorded by gold-standard laboratory equipment. The findings provided reasonable precision and validity of BSN in the detection of activity in life situations. However, there were shortages of this system and these were instability of signal in high-motion conditions and reduced system precision of measurements.

The proposed routing framework by Memon et al. (2021) enabled to mitigate the temperature and reliability of WBANs. It happened when, on-body sensors are at the risk of overheating and there is a risk of failure in data delivery. The technique automatically optimized routes according to temperature restrictions, traffic link quality and other reliability considerations. Experimental tests demonstrated a decreased node heating of sensors, improved dependability and enhanced node lifespan. Since sacrificing nodes led to greater delay in transmission, the drawback was a trade off with latency.

Mavinkattimath and Khanai (2022) developed the hardware accelerator architecture of WBSNs in an effort to enhance the processing performance and lessen energy consumption. The technique was Field-Programmable Gate Array (FPGA)-based simulation in order to speed up the computation heavy tasks in WBSN nodes. As compared with conventional schemes, the results indicated increased throughput with lower power use. The drawback was that the hardware design had not been verified in real-world medical equipment that was

limiting its practical use. The below table 1 indicates the comparison of various energy-efficient protocols utilized in WBSNs.

Table 1: Comparison table on Energy-Efficient Protocols and Techniques in Wireless Body Sensor Networks

Authors & Year	Algorithm	Performance Metrics	Results
Thirumoorthy et al. (2020)	TCEM-PQM (Time-Critical Energy Minimization Protocol)	Energy consumption, Latency, Network lifetime	Reduced energy use by ~25%, achieved lower latency in time-critical data and extended network lifetime compared to conventional routing.
Iqbal et al. (2022)	Greedy Algorithm-based Energy-Efficient Protocol Stack	Energy efficiency, Packet Delivery Ratio (PDR), Scalability	Improved energy efficiency by ~18%, maintained higher PDR under nano-scale conditions; scalable but less adaptive in high mobility scenarios.
Mehdi et al. (2020)	Self-Adaptive Sampling Rate with Watchdog Sensor	Sampling rate adaptation, Network lifetime, Energy savings	Increased lifetime by ~20% via adaptive sampling, reduced redundant transmissions; effectiveness depended on context recognition accuracy.
Zhang et al. (2022)	Electromyography (EMG) Signal Compression Sampling	Compression ratio, Reconstruction accuracy, Bandwidth utilization	Achieved high compression up to 40–50% with minimal signal distortion of <5% error, reducing transmission load and improving bandwidth efficiency.
Kaleem & Devarajan (2024)	Energy-Efficient Classification for Malicious Node Detection	Detection accuracy, Energy consumption, Reliability	Achieved >90% malicious node detection accuracy with energy savings of ~15%; improved security but required extra computational cost.

In Iqbal et al. (2021), a multi-fuzzy criteria based network selection scheme on confidential data transmission in WBSNs is suggested. The technique used fuzzy logic to optimize the selection of an optimal network as a result of considering multiple parameters such as energy, security and channel quality. Experiments revealed that there was higher confidentiality, better resource utilization and more reliability in transmission. The drawback was that fuzzy decision-making required a greater computation cost in real-time applications.

Bangash et al. (2021) proposed the use of multi-constraint aware routing mechanism in WBSNs where, the factors of consideration were energy, delay and temperature, link quality in routing. The strategy maximized path selection with utility that equaled the ratio of energy required to make the path selection to energy that the path selection prevented the motor control to use. As compared to baseline protocols, simulation results reported an increase in network lifetime and packet delivery. Nonetheless, the model incurred increased routing costs because of the multi-parameter computations.

The impact of intellectual tools of health monitoring applied with Flower Pollination Algorithm and Bee Colony Optimization was investigated by Teekaraman et al. (2023). The bio-inspired combined method had the minimal number of sensors positions and data transmission effectiveness. The results showed that it reduced energy savings and the accuracy of monitoring was increased. The drawback was that the method was tested only in simulated conditions without applying it to the real life of health care.

Kaba et al. (2021) have proposed a channel modeling framework of Optical Wireless Body Sensor Networks (OWBSNs) that targeted monitoring the elderly people during walks. The approach defined channel behavior on the effects of body movement and changes in surrounding area. The results proved that OWBSNs were feasible with reasonable precision to be used in health monitoring. However, the study had been limited by testing in real world and the sensitivity caused by movement.

Another recent contribution was proposed by Al-Barazanchi et al. (2022). The authors presented a multi-sensor body area network system that was used to perform the remote monitoring of patients. The system connected wearable sensors to a cloud-based monitoring system in order to monitor the vital signs in real time. The outcomes were quite positive as it worked well due to remote monitoring and health notifications in time needed to address the pandemic medical needs. The disadvantage was that it had limited availability to the

places with constant connections and data protection that had been not hindering to the reliability in fluctuating networks.

III. Material and Methods

The section presents the methodology of the proposed GTARO framework of WBSNs. The specific strategy is the combination of node state sensing, utility based coalition evolution and adaptive resource allocation with a Nash Adaptive Equilibrium Routing (NAER) algorithm that offers a stable next hop list. The end to end routing paths are further optimized according to energy, latency and reliability by a Dynamic Multi objective Firefly Optimization (DMFO) algorithm. This multi-stage process allows adaptive, energy-efficient and QoS-aware communication with changing network conditions.

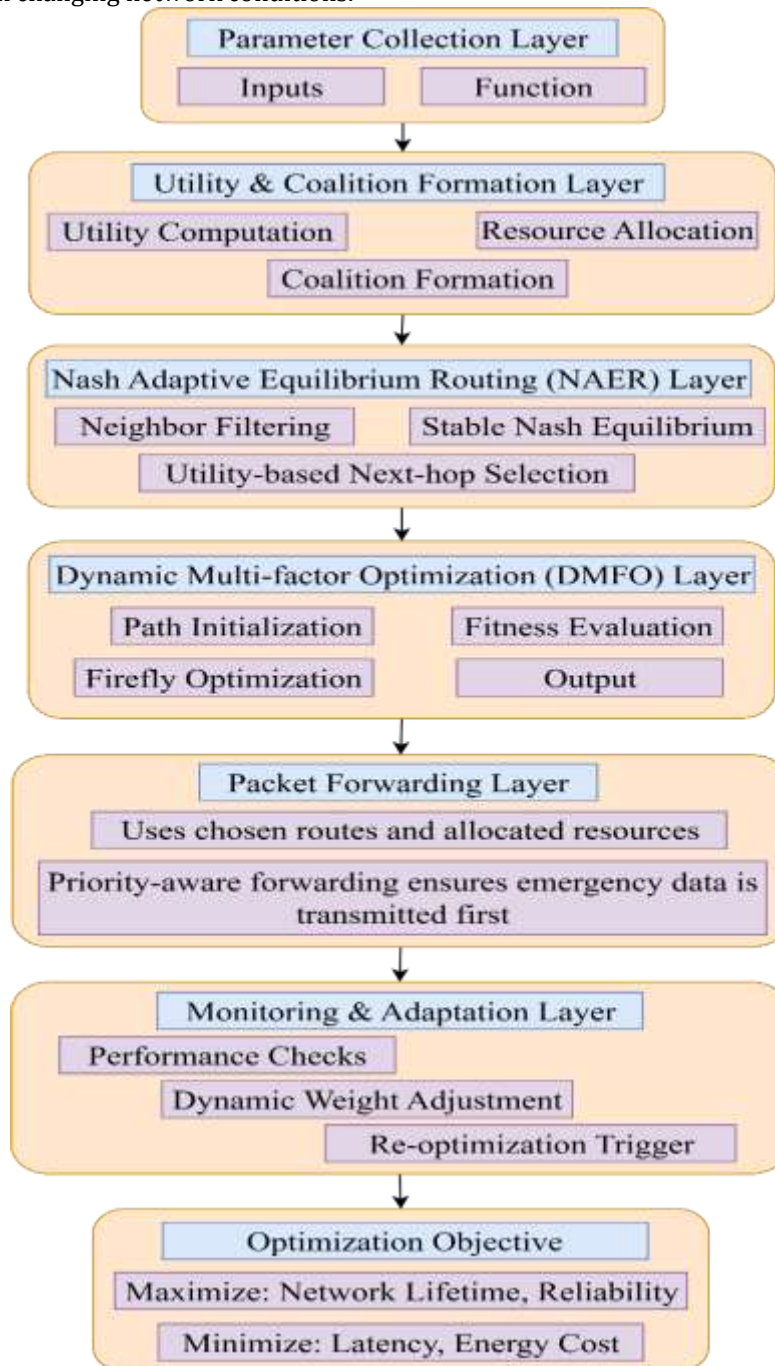


Figure 1: Overall Work Flow Architecture

Figure 1 of GTARO algorithm uses a layered structure; the first layer is the parameter collection layer that collects the input and determines the functions of system. The utility & coalition formation layer then calculates utility, allocates resources and forms coalitions with the participants to enable efficient collaboration. The Nash

Adaptive Equilibrium Routing (NAER) Layer makes sure that stable route selections are made based on the use of neighbor filtering and the Nash equilibrating strategies. Then, this is followed by the Dynamic Multi-factor Optimization (DMFO) Layer that implements optimized procedures using the methods such as the firefly based search to aid in the efficient initialization of path along with the fitness evaluation. The packet forwarding layer implements the selection of routes and prioritizes the transmission of emergency data. Lastly, the monitoring & adaptation layer periodically monitors and rebalances the weights and re-activates the optimization, so that the performance is maintained to optimize the overall goal of maximizing network lifetime, reliability, minimize latency and energy cost.

3.1 Parameter Collection

In this step, the key parameters monitored by each bio-sensor continuously are residual energy, data load, link quality, data priority. The network developed these parameters as its basis to adaptive decision-making. The system kept track of the status of nodes in real time. Hence, communication channels are constructed out of stable and energy efficient nodes. This monitoring is critical in the reduction of packet loss and extension of network life.

3.2 Utility & Coalition Formation

Utility values of each node are generated in a subsequent procedure to reflect the contribution potential of each node in network. On the basis of these utilities, nodes are in cooperative coalitions that allowed a balance in the distribution of workloads. Formation of coalition allowed the equitable distribution of resources and limited the possibility of overloading high-energy nodes. This game-theory cooperation made communication more stable and it has augmented the robustness of communication links.

3.3 Resource Allocation

The proportionate allocation of available resources such as transmission slots, bandwidth and forwarding capacity was carried out based on the coalition information utility scores. Data and nodes of higher priority with a higher quality link are preferred, so critical health information is able to travel with reliability. The resultant allocation of resources in response to adaptive distribution avoided congestion and maximized the consumption of limited network energy. Due to this, communication efficiency and general Quality of Service (QoS) are enhanced greatly.

3.4 Nash Adaptive Equilibrium Routing (NAER)

Then, a sensor node obtains the status messages of directly adjacent nodes regarding residual energy, integrity of links, overflow situations in buffers at the present data load. These guarantee that the routing procedures are performed using actual network status. It prevents the choice of energy-drained or overloaded nodes.

$$\hat{E}_j = \frac{E_j}{E_{\max}} \text{-----} (1)$$

Equation (1) normalizes the residual energy $\hat{E}_j$ of node j by dividing its current energy E_j with the maximum possible energy $E_{\max}$. This ensures the value $\hat{E}_j$ lies between 0 and 1, making it comparable with other performance factors.

Based on the neighbor information collected, the node discards unstable or inefficient candidates, such as the nodes with poor link efficiency or high congestion. The others compose the possible next-hop candidates. This move minimizes packet loss and forces only the strong links to be utilized in routing.

$$N_i = \{j \in N(i): \hat{Q}_{ij} \geq Q_{\min}, \hat{L}_j \leq L_{\max}^{(thr)}, T_j \leq T_{\max}\} \text{-----} (2)$$

Equation (2) defines the set of eligible neighbor nodes N_i for node i . A node j is included only if its normalized link quality $\hat{Q}_{ij}$ is above the minimum threshold $Q_{\min}$, its load $\hat{L}_j$ is within the maximum limit $L_{\max}^{(thr)}$ and its delay T_j has not exceeded the allowed maximum $T_{\max}$.

To measure each candidate next-hop, game-theoretic utility is used. It combines various considerations that include residue energy, foreseen transmission delay, data priority and reliability. This guarantees that the routing decisions are made to achieve the level of energy efficiency considering QoS control.

$$x_j = \frac{c_j}{B_j + \epsilon b} \text{-----} (3)$$

Equation (3) calculates the normalized cost factor x_j of node j . Here, c_j represents the communication cost, while B_j is the available bandwidth. A small constant ϵb avoids division by zero, ensuring stable computation.

Nodes follow an iterative approach and update the routing-based choice to use the next-hop that yields the higher payout these computed. This step simulates the competitive and complementary aspect of routing because in every node, each makes decisions based on the choice of neighbors. The process repeats until one of the responses is the best possible.

$$j_i^* = \arg \max_{j \in N_i} \pi_i(j) \text{-----} (4)$$

Equation (4) selects the optimal next-hop node j_i^* for node i . It chooses the neighbor $j \in N_i$ that maximizes the utility function $\pi_i(j)$, ensuring the best trade-off between energy, link quality and priority during routing. The routing takes a stable condition at Nash equilibrium, where no node is able to obtain any improvement by the unilateral change of next-hop. When a stable state is reached, the network performs energy-balance, reduced feasible latency and reliable data delivery. This guarantees efficiency and long-time sustainability of communication in WBSN.

$$\pi_i(j_i^*) \geq \pi_i(j) \text{ ----- (5)}$$

Equation (5) ensures the Nash equilibrium condition in routing. It states that the utility of the selected next-hop node $\pi_i(j_i^*)$ has to be greater than or equal to the utility of any other neighbor $\pi_i(j)$. This guarantees that no node has an incentive to deviate from the chosen optimal strategy.

3.5 Dynamic Multi-Factor Optimization (DMFO)

The optimization starts by creating the feasible routing paths traditionally either randomly or based on known paths. Each path is taken as a candidate solution which is to be optimized. This secures varied options to be assessed and optimized.

$$\{x_i\}_{i=1}^N \leftarrow \text{randomly generate ----- (6)}$$

Equation (6) represents the initialization step of optimization process. It means that the positions $\{x_i\}_{i=1}^N$ are randomly generated for all N bio-sensor nodes. This provides diverse starting points for the bio-inspired optimization algorithm, ensuring the effective exploration of solution space.

Each path is evaluated by means of a fitness function, which gauges the performance aspects of path including energy consumption, latency and reliability. Those with few energy demands and better speed of transmission have better assigned fitness. This step enables the system to prioritize the routes in terms of overall efficiency of communication.

$$f(x_i) = w_E \cdot (1 - \text{EnergyCost}(x_i)) + w_R \cdot \text{Reliability}(x_i) - w_D \cdot \text{Latency}(x_i) \text{ ----- (7)}$$

Equation (7) defines the fitness function $f(x_i)$ used in optimization. It evaluates each candidate solution x_i by combining the weighted factors (w_E, w_R, w_D) such as minimizing energy cost, maximizing reliability and minimizing latency with controlling the relative importance.

More fit paths serve as attractive solutions and influence lower fitness paths. The intensity of attraction diminishes as the route disparity lowers, so that only the comparable paths have an impact on one another. This is done to facilitate the convergence in stronger solutions whilst retaining the diversity in routing options.

$$\beta_{ij} = \beta_0 \exp(-\gamma r_{ij}^2) \text{ ----- (8)}$$

Equation (8) defines the attractiveness function in Firefly algorithm. Here, β_{ij} represents the way in which firefly i is attracted strongly to firefly j . This decreases exponentially with the square of distance r_{ij}^2 . Where, β_0 indicates the base attractiveness and γ is the light absorption coefficient.

Weaker routes update the topology by imitating that of stronger routes, including by selecting more energy efficient nodes. To investigate the further possibilities and not to be trapped in local optima, a slight degree of randomness is injected. This update process enhances the overall path quality during this continuous update.

$$x_i \leftarrow x_i + \beta_{ij}(x_j - x_i) + \alpha \text{rand}() \text{ ----- (9)}$$

Equation (9) represents the position update rule in Firefly algorithm. The new position of firefly x_i is updated by moving towards a brighter firefly x_j , scaled by attractiveness β_{ij} along with a randomization term $\alpha \text{rand}()$ to maintain the exploration diversity.

At the end of a succession of optimizations, the algorithm best identifies the most favorable routing path having the greatest optimizing value. The adopted path prevents high latencies and energy approaches to balance and offers the excellent communication throughout in WBSN. It constitutes the optimum solution to the existing network conditions.

$$t \geq T_{\max} \Rightarrow \text{terminate ----- (10)}$$

Equation (10) defines the termination condition of optimization. It states that if the iteration count t reaches or exceeds the maximum allowed threshold $T_{\max}$, the algorithm stops execution.

3.6 Monitoring & Adaptation

The Wireless Body Sensor Networks is set up to observe the network performance parameters: QoS, residual energy, latency and PDR on an on-going basis. Each project-threshold such as minimum residual energy or maximum delay is checked. In case of any exceeding, the system initiated a re-optimization procedure with DMFO and NAER mechanisms. The use of this adaptive monitoring is able to provide energy-efficient routing, reliable and responsive to the dynamic changes due to network conditions.

3.7 Game Theory-Based Adaptive Resource Optimization (GTARO)

Adaptive Resource Optimization (ARO) is an adaptive optimization algorithm. It is used to optimize the competing parameters in body sensor networks such as energy, latency, reliability and load. In GTARO, as

opposed to single-objective methods, multiple parameters are assessed in a coordinated way and the decisions are adapted dynamically when the conditions in network change.

The optimization action took into account major parameters, namely, residual energy, data priority, link stability and network load. These elements allowed gaining the comprehensive knowledge related to network health and steered the selection of most expedient communication channels in WBSN.

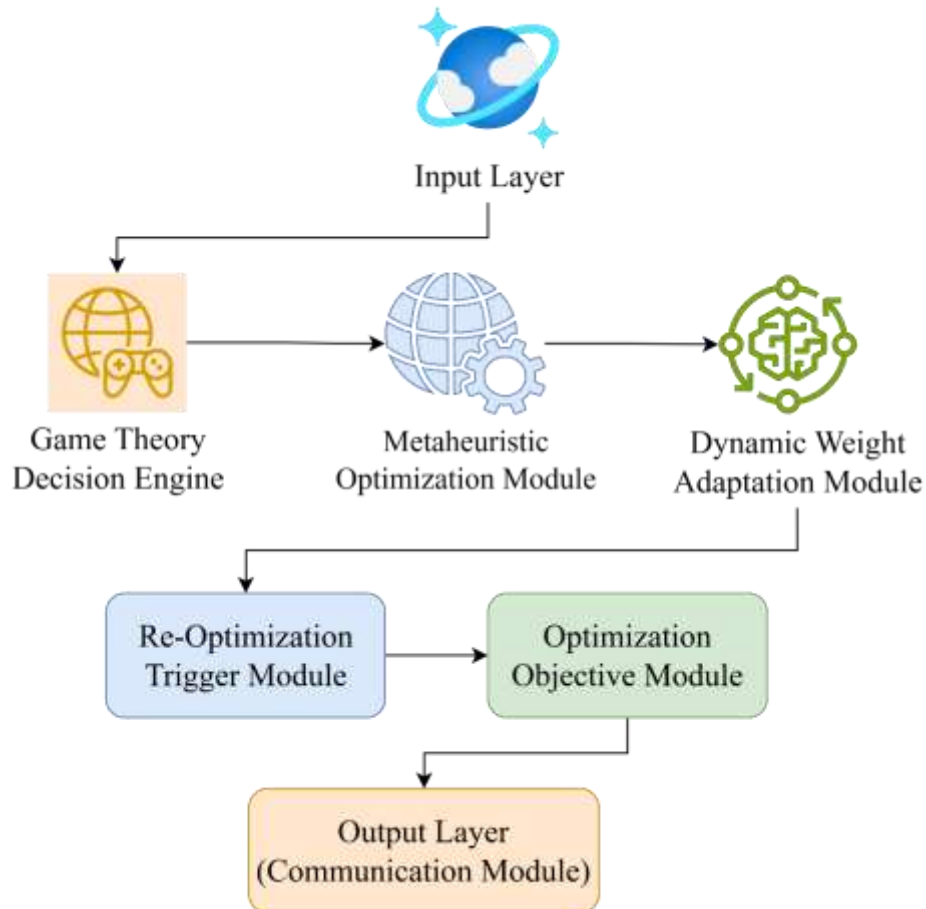


Figure 2: Game Theory-Based Adaptive Resource Optimization Architecture

This figure 2 is described as intelligent routing optimization framework. The input layer gathers information about data and parameters in the network. The game theory decision engine approaches the balancing of guaranteed fair and stable distribution of routing and resource allocation, metaheuristic optimization module aims at improving the path selection with global optimization techniques. The dynamic weight adaptation module also readjusts routing weights in the course of real-time conditions. When performance falls below expectations, the re-optimization trigger module restarts the process of optimization, and the optimization objective module keeps energy efficiency, reliability and latency goals in mind. Lastly, the output layer (Communication Module) performs the optimum routing in order to transfer the data successfully.

$$F_i = [\hat{E}_i, \hat{P}_i, \hat{Q}_i, 1 - \hat{L}_i]^T \text{ ----- (11)}$$

Equation (11) defines the factor vector F_i for node i , which is transformed by the transpose vector T . It combines the normalized residual energy $\hat{E}_i$, priority $\hat{P}_i$, link quality $\hat{Q}_i$ and inverse load $1 - \hat{L}_i$ into a single vector, representing the node's overall suitability for routing and resource allocation.

Firefly optimization and genetic operators are used as metaheuristic techniques to investigate the solution space in an efficient manner. These algorithms simulated the nature to find optimal near-routes as well as minimize latency and maximize reliability.

$$f(x) = w_E \cdot \bar{E}(x) + w_P \cdot \bar{P}(x) + w_Q \cdot \bar{Q}(x) + w_L \cdot \overline{(1 - L)}(x) \text{ ----- (12)}$$

Equation (12) defines the multi-factor fitness function $f(x)$. It computes the weighted sum of normalized energy $\bar{E}(x)$, priority $\bar{P}(x)$, link quality $\bar{Q}(x)$, and inverse load $\overline{(1 - L)}(x)$. Each weight (w_E, w_P, w_Q, w_L) reflects the relative importance of that factor in optimizing routing and resource allocation.

The algorithm is dynamic in that, the weight of various factors is altered based on the context. As an example, in an emergency medical transmission of data, the urgency of data is taken over energy limitations. Thus, the data is delivered in time.

$$w_k(c) = \frac{\exp(\tau[w_k^{(0)} + \alpha_k c])}{\sum_m \exp(\tau[w_m^{(0)} + \alpha_m c])} \text{-----} (13)$$

Equation (13) represents the dynamic weight adaptation rule. Here, the weight of factor $w_k(c)$ is updated using a softmax function. Where, τ controls sensitivity, $w_k^{(0)}$ is the initial weight and $\alpha_k c$ adjusts the weight based on context. The denominator ensures all weights are normalized and sum to 1. The denominator is the normalization term in which, $\sum_m \exp$ adds the every nodes, the baseline weight is $w_m^{(0)}$, α_m indicate the sensitivity factor, c as the context variable, and $\exp(\cdot)$ assures the normalized scores in the positive manner.

Depending on service activation or deactivation, node failures or changing traffic burdens, the system is expected to monitor the topology changes, internode failures or changing traffic loads and re-optimize the routing decisions. This behavioral adaptability ensured that there is stable communication amidst the changing WBSN conditions

$$(\hat{E}_i < \theta_E) \vee (\text{Latency}(x) > \theta_D) \vee (\text{PDR}(x) < \theta_R) \text{-----} (14)$$

Equation (14) defines the re-optimization trigger condition. It states that if a node's normalized energy $\hat{E}_i$ drops below the energy threshold θ_E or the latency exceeds the delay threshold θ_D or the Packet Delivery Ratio (PDR) falls below the reliability threshold θ_R , the system activates re-optimization to maintain QoS and network stability. Latency(x) refers to the transmission delay of data packet x that denotes the communication timeline, PDR(x) is its packet delivery ratio means communication reliability.

The solution is to address the conflicting aims of maximizing the total network lifetime via energy conservation and ensuring QoS of the reliable delivery of healthcare information. This trade off optimization guarantees both performance and strength.

$$\max_x [\lambda_{\text{life}} \cdot \text{Lifetime}(x) - \lambda_{\text{delay}} \cdot \text{Latency}(x) + \lambda_{\text{rel}} \cdot \text{Reliability}(x)] \text{-----} (15)$$

Equation (15) represents the overall optimization objective $\max_x$. It seeks to maximize a weighted utility function where the network lifetime is rewarded ($\lambda_{\text{life}} \cdot \text{Lifetime}(x)$), latency is penalized ($\lambda_{\text{delay}} \cdot \text{Latency}(x)$) and reliability is promoted ($\lambda_{\text{rel}} \cdot \text{Reliability}(x)$). The algorithm adjusts these weights (λ) to balance the trade-offs between energy efficiency, delay and communication reliability.

Algorithm 1: Game Theory-Based Adaptive Resource Optimization

Input:

$G = (V, E)$ # Wireless Body Sensor Network graph with nodes V and edges E
 params = {IT_MAX, T_max, β_0 , γ , α , cost_x, priority, thresholds}
 State metrics per node: Energy ($\hat{E}$), Latency ($\hat{L}$), Queue ($\hat{Q}$), Priority ($\hat{P}$), Trust (T)

Output:s

Optimized QoS-aware routing paths for all flows
 Resource allocation strategy ensuring energy efficiency, reliability, and low delay

Begin

initialize_status_for_all_nodes()

while run_active:

Step 1: Node State Sensing

for each node $i \in V$ do

sense_and_normalize_state(i) # Collect $\hat{E}$, $\hat{L}$, $\hat{Q}$, $\hat{P}$, T

Step 2-3: Utility & Coalition Formation

$U \leftarrow \text{compute_node_utilities}(V)$

Coalitions $\leftarrow \text{form_coalitions}(V, U)$

Allocation $\leftarrow \text{allocate_resources}(\text{Coalitions}, U, \text{priority}, \text{cost_x})$

Step 4: Next-hop Adaptive Energy-aware Routing (NAER)

changed $\leftarrow \text{True}$; it $\leftarrow 0$

while changed and it < IT_MAX do

changed $\leftarrow \text{False}$; it $\leftarrow \text{it} + 1$

for each node $i \in V$ do

$N_i \leftarrow \{j \in N(i) \mid \text{pass_thresholds}(j)\}$ # Eligible neighbors

for each $j \in N_i$ do

$\pi[i][j] \leftarrow \text{utility}(i, j)$ # QoS utility value

$j^* \leftarrow \text{argmax}_j \pi[i][j]$

```

        changed ← changed OR update_next_hop(i, j*)
    routes_NAER ← extract_routes()
    # Step 5: Dynamic Multi-objective Firefly Optimization (DMFO)
    for each active flow (s → d) do
        Pop ← init_paths(routes_NAER[s→d], N)
        w ← softmax_context_weights()
        best ← None
        for t = 1 to T_max do
            fitness ← evaluate_fitness(Pop, w)      # QoS multi-objective fitness
            best ← select_best(Pop, fitness, best)
            if converged then break
            Pop ← firefly_update(Pop, β0, γ, α)
            Pop ← genetic_operators(Pop)           # Selection, crossover, mutation
        route[s→d] ← best
    # Step 6: Packet Forwarding
    forward_packets(route, Allocation, priority)
    # Step 7: Trigger-based Re-optimization
    if trigger_violation( $\hat{E}$ , latency, PDR) then
        adjust_context_weights()
        continue # re-run NAER/DMFO with updated state
    # Step 8: Termination
    if time_exceeded() or all_dead() then
        break
    End while
    Return route, Allocation
End Algorithm
    
```

The pseudocode in algorithm 1 provided by GTARO gives a multi-stage routing framework in the case of WBSNs. It starts by sensing node state and cooperation-based resource allocation, then constructing route by NAER mechanism to adjust neighbor-selection. The DMFO algorithm provides the best end-to-end path using firefly updates and genetic operations to improve reliability and energy efficiency. Lastly, the packets are forwarded and dynamic re-optimization is activated when a performance threshold is breached and performance is robust and adaptive routing.

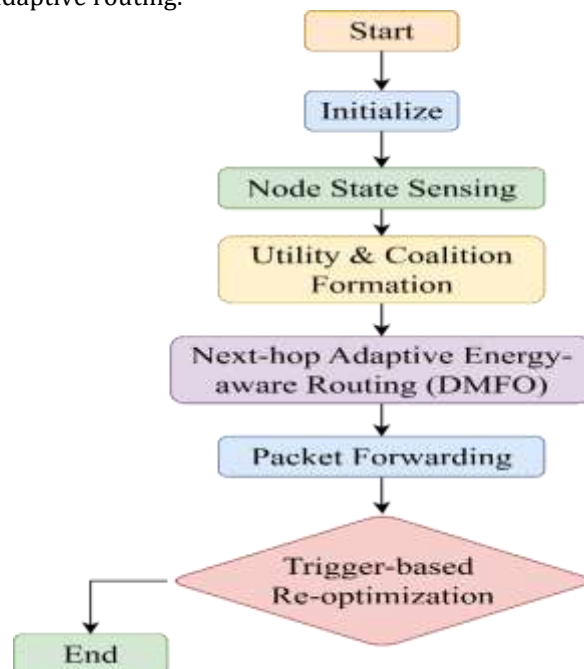


Figure 3: Flow Chart of Game Theory-Based Adaptive Resource Optimization

Figure 3 shows energy-aware routing in WBSNs. This begins with initialization and followed by the detection of nodes states, so as to determine the nodes status. Through this, utility and coalition formation is

performed to maximize cooperation amongst the nodes. The Next-hop Adaptive Energy-aware Routing (DMFO) internally selects the most efficient path to send packets and when monitored, performance anomalies or energy stress arise it and triggers an offline reconfiguration to stabilize the performance.

IV. Results and Discussion

The general outcomes of simulation are the strong evidence of the better performance of suggested GTARO protocol than the QELAR, DUCS and QTAR in relation to QoS parameters. The proposed recorded the longest network lifetime, least power consumption and also the least latency in all cases. It also demonstrated the most packet delivery ratio and throughput which depicts its efficiency in resource allocation, guaranteed existence of data transfer and real-time communication of WBSNs in variable network sizes.

Table 2: Simulation Parameters for WBSN Performance Evaluation

Category	Parameter	Value
Network	Area	50 m × 50 m
	Node counts	50, 100, 150, 200, 250
	Deployment	Random uniform
Radio	Standard	IEEE 802.15.4, 2.4 GHz
	Data rate	250 kbps
	Transmission range	10–15 m (body sensors)
Traffic	Packet size	32 bytes
	Packet generation	Constant bit rate (CBR), 1 pkt/sec
	Priority	Emergency > Normal
Energy Model	Initial energy per node	0.5 J
	Transmission energy	50 nJ/bit
	Reception energy	50 nJ/bit
Routing / Protocol	Methods evaluated	QELAR, DUCS, QTAR, GTARO
	Simulation time	5000 sec
QoS Metrics	Monitored	Lifetime, Energy, Latency, PDR, Throughput

As per table 2, WBSN simulation scenarios are with 50 m x 50 m area with 50-250 placed nodes randomly. The nodes each used 2.4 GHz IEEE 802.15.4 radios at 250 kbps data rate and 1015 m range, transmitted at a constant bit rate of 32-byte packets. Nodes are initialized to 0.5 J and 50 nJ of energy per bit which is used to transmit and receive the data. The comparison is done between QELAR, DUCS, QTAR, and GTARO, whereas monitoring the lifetime, energy, latency, PDR and throughput of each of these took place in the course of 5000 seconds.

Table 3: Comparison Table on Network Lifetime (Rounds)

Method	50	100	150	200	250
Q-learning-based Energy-efficient and Lifetime-Aware Routing (QELAR) [31]	3136	1796	1304	1030	863
Distributed Underwater Clustering Scheme (DUCS) [32]	2959	1694	1226	976	816
Q-learning-based Topology-Aware Routing (QTAR) [33]	3301	1900	1377	1094	912
GTARO (Proposed)	4365	2498	1802	1437	1200

Network lifetime comparison in table 3 shows that GTARO is always faster than QELAR, DUCS and QTAR regardless of the number of nodes. In 50 nodes, GTARO produced 4365 rounds as compared to the pearly 3301 rounds generated by QTAR. When the nodes are added to 250, GTARO achieved the longest lifetime of 1200 rounds demonstrating that it is efficient in balancing energy consumption and prolonging network operation. This implies that the adaptive resource allocation and Nash Adaptive Equilibrium Routing on a game-theory-based approach needs extended network lifetime relative to the current approaches.

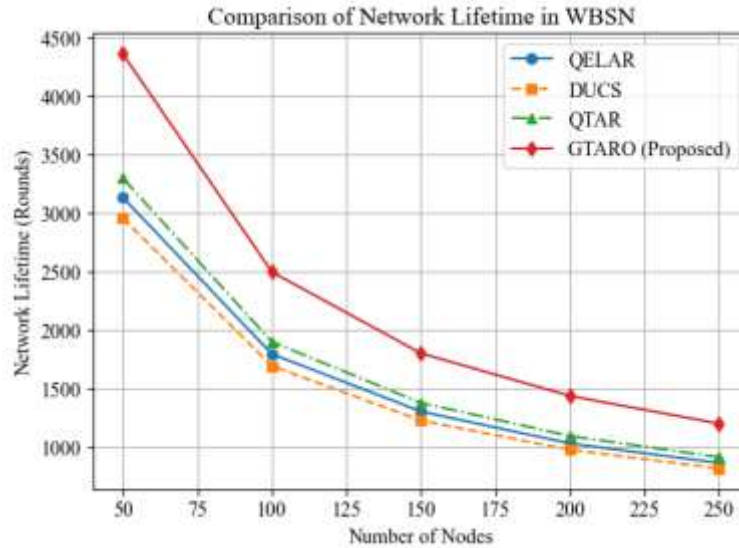


Figure 4: Networks Lifetime Comparison Chart

Figure 4 shows the relative network lifetime of four protocols in WBSNs as a function of the number of nodes. The Proposed GTARO outperforms QELAR, DUCS and QTAR; its lifetime at 50 nodes is 4365 rounds, holding up to 1200 rounds at 250 nodes. This proves efficient energy management and adaptive routing of GTARO that optimally manage resource consumption and prolong the network operation of different network sizes.

Table 4: Comparison Table on Energy Consumption per Round (mJ)

Method	50	100	150	200	250
QELAR	3.945	6.876	7.923	8.651	9.169
DUCS	6.563	7.324	8.032	8.744	9.424
QTAR	3.916	6.626	7.572	8.322	8.913
GTARO (Proposed)	3.147	5.035	6.103	6.761	7.853

In table 4, energy needed by each method per round indicates that GTARO is the least energy-intensive protocol of all the methods under comparison. At 50 nodes, GTARO used a 3.147 mJ per round which is less than the value of QTAR that is 3.916 mJ, and QELAR that is 3.945 mJ. The proposed remained the least consuming of 7.853 mJ per round as the network grew to 250 nodes indicating that it allocates resources and performs routing in a manner that minimizes energy usage.

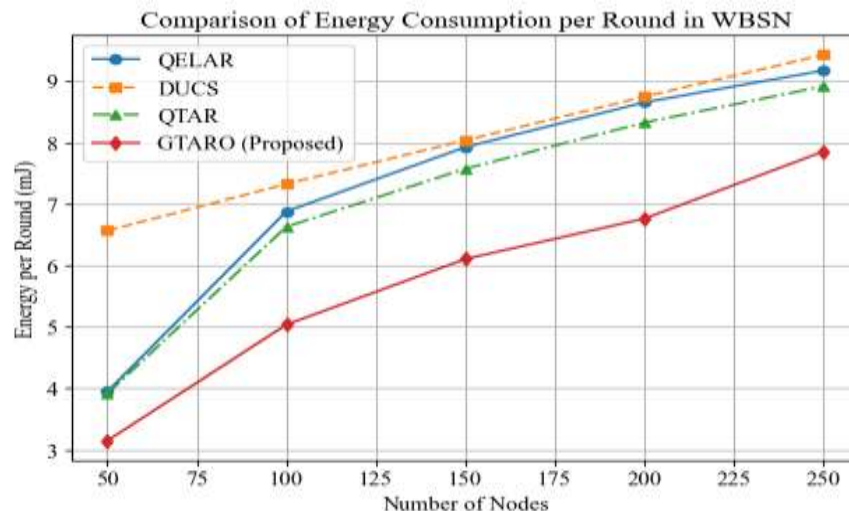


Figure 5: Energy Consumption Comparison Chart

Figure 5 has compared the number of energy consumption per round in WBSN using various protocols as the number of nodes is added. It reveals that QELAR and DUCS in addition to QTAR requires far more energy as the node number increases, whereas the proposed GTARO protocol uses the least amount of energy. It is an indication that GTARO is more energy-efficient, which makes it suitable in prolonging the network lifetime of WBSNs on larger scales.

Table 5: Comparison Table on Latency (ms)

Method	50	100	150	200	250
QELAR	67.07	120.00	145.64	176.84	205.39
DUCS	72.17	134.38	160.20	194.25	226.00
QTAR	62.43	109.67	133.59	164.64	193.98
GTARO (Proposed)	48.96	75.00	94.96	113.33	132.62

Table 5 latency scores reveal that GTARO minimizes the communication delay than other protocols. Fewer than 50 nodes scenario, the latency of GTARO is 48.96 ms, this is significantly lower than that of QTAR (62.43 ms) and QELAR (67.07 ms). As the network scale further expanded to 250 nodes, GTARO consistently recorded the shortest latency of 132.62 ms, proving the ideal effectiveness of dynamic multi-factor optimization and adaptive routing strategies to reduce delays and achieve better real time data transmission in WBSNs.

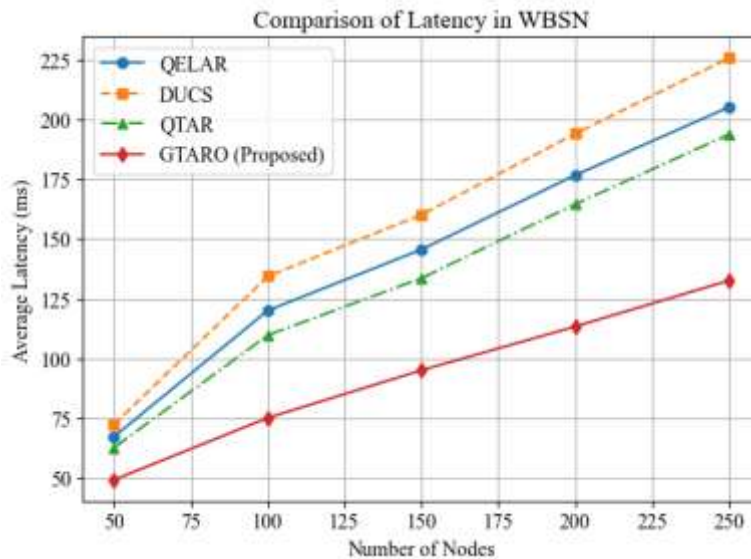


Figure 6: Latency Comparison Chart

Figure 6 demonstrates the comparison of average latency across different protocols when the number of nodes in WBSN grows. It is evident that DUCS and QELAR are the highest growing with latency followed by QTAR but the proposed GTARO protocol always exhibits the least latency. This serves to indicate the speed of communication using GTARO. It is more efficient with less delay, thus more reliable in the time-sensitive applications in WBSNs.

Table 6: Comparison Table on Packet Delivery Ratio (PDR, %)

Method	50	100	150	200	250
QELAR	96.75	93.82	91.26	88.21	85.35
DUCS	94.18	91.40	88.56	85.96	83.04
QTAR	97.70	94.97	92.40	89.34	86.39
GTARO (Proposed)	99.52	96.94	94.14	91.41	88.38

Table 6 results in Packet Delivery Ratio (PDR) comparison indicate the highest reliability of GTARO as compared to all the protocols. At 50 nodes, GTARO achieved a probability of detection rate (PDR) of 99.52% which is better than QTAR (97.70%) and QELAR (96.75%). In 250 nodes, GTARO performed the best with PDR (88.38%) illustrating its high capability to guarantee the successful transmission of packets and ensure network reliability under different node densities.

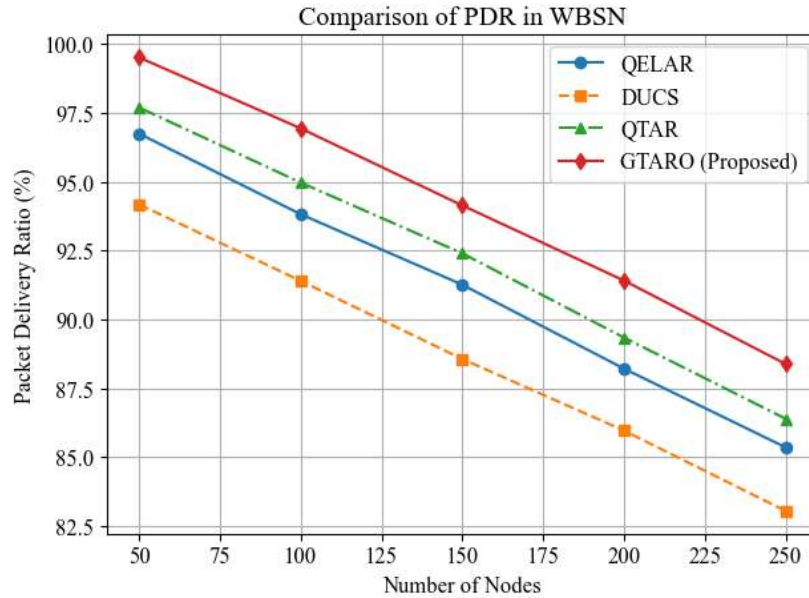

Figure 7: Latency Comparison Chart

Figure 7 indicates the comparison of Packet Delivery Ratio (PDR) in WBSN with different protocols as the number of nodes increase. It is also clear that PDR declines as the node grows in all the methods; the proposed GTARO, QTAR, QELAR and DUCS. This means that GTARO is characterized by high data relaying integrity. It delivers data packets in higher integrity even in abundant network situations.

Table 7: Comparison Table on Throughput (kbps)

Method	50	100	150	200	250
QELAR	220	198	180	162	145
DUCS	210	185	170	155	138
QTAR	230	210	190	172	155
GTARO (Proposed)	265	240	215	190	170

The throughput analysis in table 7 indicates that the highest number of data is transferred during the operation of all nodes in GTARO. At 50 nodes, GTARO outperformed QTAR and QELAR. As the network is scaled up to 250 nodes, GTARO kept delivering the maximum throughput rate of 170kbps, a characteristic that depicts lowest latency and effective route capability, efficient resource distribution and allocation dynamics of GTARO, parameters that improve network performance in WBSNs.

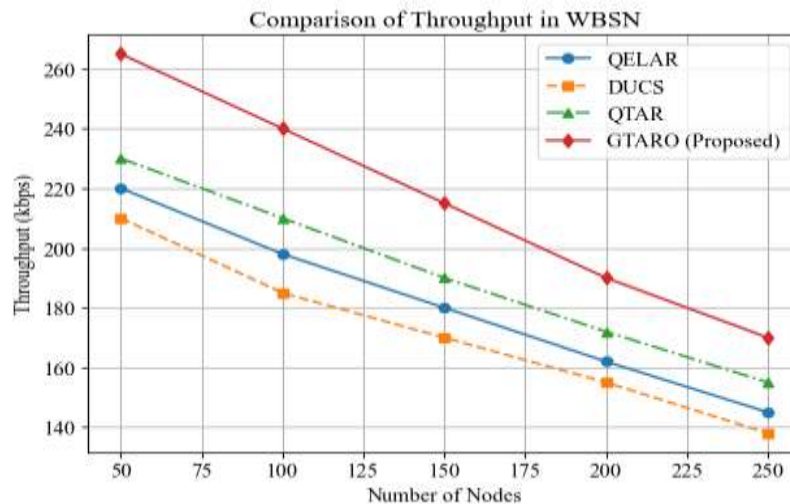

Figure 8: Throughput Comparison Chart

Figure 8 gives a comparison of the throughput of WBSNs using different protocols as the number of nodes increases. The throughput reduces monotonically through all the methods with node growth, though the proposed GTARO protocol gives the maximum throughput among the other protocols available namely QELAR, QTAR and DUCS. This shows the effectiveness of GTARO in supporting faster data transmission rates, which guarantees a better improvement in the overall performance of network, especially in a dense WBSN.

V. Conclusion

This proposed GTARO framework has been shown to be an effective and adaptive scheme of solving routing and optimization problems in terms of resource usage in WBSNs. Incorporating parameter monitoring, coalition formation and proportional resource allocation with Nash Adaptive Equilibrium Routing (NAER) and Dynamic Multi-objective Firefly Optimization (DMFO), GTARO achieves a good balance of energy consumption, latency, reliability and throughput. The simulation results revealed that GTARO already performs significantly better than other existing methods which include QELAR, DUCS and QTAR in all the Quality of Service (QoS) metrics. In particular, it had long network lifetime, low per-round energy expenditure, low latency, high packet delivery ratios and increased throughput in different network sizes. These enhancements demonstrate that GTARO has potential to guarantee consistent data transmission against achieving energy efficiency that is critical to WBSNs in healthcare monitoring usage cases. Also, its actual design allows the real-time modification of the changing network conditions, which makes it advantageous to use in emergency and priority-based communication. Game-theoretic cooperation was satisfactory to guarantee stability in routing and metaheuristic optimization achieved the robust path selection even in dense networks. In the end, GTARO is a fully scalable, practical and comprehensive solution to increase the working life of WBSNs and the effectiveness of patient monitoring. Novel and significant contributions of the proposed research are not only the advancement of energy-aware and QoS-driven routing but also the creation of precedent to the establishment of a future intelligent healthcare communication system where, high reliability and efficiency are required.

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