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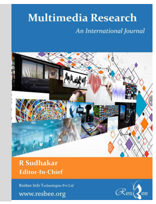

A Bio-Inspired Adaptive-Aphid Optimization Algorithm for Routing in the Internet of Underwater Wireless Sensor Network

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Abstract: Routing in Internet of Things (IoT)-enabled Underwater Wireless Sensor Network (IoT-UWSN) allows energy-efficient and reliable communication among sensor nodes that are deployed underwater for various applications, like military surveillance, disaster prevention, and ocean monitoring. These applications demand high reliability and adaptability since underwater nodes are often deployed in harsh and unpredictable environments. Meanwhile, underwater environments present unique challenges because of their constrained energy resources, node mobility, limited bandwidth, and high propagation delays. Further, the prevailing routing protocols employed in IoT-UWSN mostly failed to adjust to the dynamic underwater environment, which leads to decreased packet loss and shorter network lifetime. This limitation directly affects the sustainability of underwater monitoring systems, as frequent node failures result in data loss and higher maintenance costs. Optimization algorithms are commonly utilized for the routing process, but the prevailing baseline approaches struggled with low residual energy, leading to reduced network coverage, which reduced the overall efficacy of the network. Hence, the new technique known Adaptive Aphid Optimization Algorithm (AdAOA) is devised for routing process in IoT-UWSN. Firstly, the IoUT network is simulated, and then the routing process is carried out utilizing the AdAOA with multi-objectives, namely Packet Delivery Ratio (PDR), delay, distance, and energy. Here, the AdAOA technique is developed by the amalgamation of the Aphid Optimization Algorithm (AOA) and the Adaptive concept. This hybridization enables the algorithm to overcome the limitations of static optimization methods, thereby enhancing robustness against network dynamics. Furthermore, the AdAOA technique attained the maximum residual energy of 93.307 J, and minimum distance and delay of 28.521 m and 0.231 sec.

Keywords: Internet of Underwater Things, Underwater Wireless Sensor Networks, Routing, Adaptive Concept, Aphid Optimization Algorithm

Nomenclature

Abbreviation	Description
IoUT	Internet of Underwater Things
UWSN	Underwater Wireless Sensor Network
IoT-UWSN	IoT-enabled Underwater Wireless Sensor Network
AdAOA	Adaptive Aphid Optimization Algorithm
AOA	Aphid Optimization Algorithm
CH	Cluster Head
SBS	Surface Base Station
PDR	Packet Delivery Ratio
ETC	Expected Transmission Count
CSMA	Carrier Sense Multiple Access
SEP	Stable Election Protocol
DQN-EQSR	Double Deep Q-Network based Efficient QoS Routing
GSA	Gravitational Search Algorithm
Co-DRAR	Cooperative Delay and Reliability Aware Routing
DRAPC	Distributed Routing-Aware Power Control
GA	Genetic Algorithms
UN	Underwater Nodes
DL	Deep Learning
ACO	Ant Colony Optimization
PSO	Particle Swarm Optimization

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1. Introduction

Large water bodies on Earth are typically classified into huge oceans and smaller seas, which together cover around 71% of the surface of Earth. Most regions in the ocean remain mainly unexplored, making it essential to continue exploring these regions. With the growing dependence on marine resources, sustainable monitoring systems are becoming indispensable to support scientific research, security, and industrial applications. In this context, the IoUT is regarded as a promising technique to advance underwater exploration and discovery. The IoUT is contemplated as an exceptional revolution in computing and communication [1]. Owing to its minimal cost, scalability, and flexibility, the IoUT has obtained considerable attention over the last decades. Its diverse applications involve pollution reduction, navigation assistance, oceanic surveillance, disaster prevention, monitoring offshore gas and oil, and so on [2]. Recent developments in wireless communications technology and low-power digital circuits have been a major factor behind the huge success of IoUT. In addition, advancements in miniaturized sensors and energy-harvesting devices have further accelerated IoUT deployments. Since UNs have limited energy supplies, energy-efficient operation is crucial for the IoUT. In the IoUT, the UNs are commonly placed in hard-to-reach underwater environments, which makes recharging and battery replacement challenging. As a result, energy efficiency is vital to ensure the longevity of underwater networks [3]. UWSNs encompass both heterogeneous and homogeneous nodes to collect underwater environmental data and send information to data centers or surface gateways [4]. These networks play a crucial role in protecting and monitoring aquatic ecosystems, offering early warnings for oceanic disasters and pollution, and supporting marine resource exploitation, exploration, and so on [5]. Such capabilities highlight their importance not only in scientific monitoring but also in defense, climate change assessment, and disaster management. UWSNs depend on acoustic modems for communications, which includes different link quality compared to the terrestrial wireless sensor networks. UWSNs encounter numerous difficulties, such as Doppler spread, delay, multipath fading, noise, geometric spreading, attenuation, and path loss [6].

Researchers from multiple fields are progressively exploiting modern routing approaches in the IoUT to enhance energy efficiency by improving data transmission paths, minimizing energy consumption, and extending the lifespan of underwater sensor networks. Swarm intelligence and bio-inspired methods have gained momentum due to their adaptability and ability to solve complex routing problems in dynamic environments. Routing protocols utilize clustering methods to group UNs into different clusters or regions. Within every cluster, one node is selected as the CH, whereas the remnant nodes act as cluster members [7]. These members forward the data gathered from their sensors to the adjacent CH, which groups the information and transmits it to a SBS. Based on the distance between the CH and the SBS, data transmission from CHs to the SBS can arise through multi-hop or single-hop communication [3]. Wireless networks employ numerous protocols, such as reactive, proactive, and hybrid techniques for routing. Proactive routing generates routes before packet transmission; by handling modern routing tables results in higher control overhead. On the other hand, the routes are created by the reactive routing when the packet is transmitted, but this can cause higher delays due to the time essential for path discovery. Hybrid routing strikes a balance among reactive and proactive methods by assimilating the proactive routing's low delay with the minimized control overhead of reactive routing [8]. However, when applied in underwater environments, these traditional approaches often degrade due to long propagation delays and frequent link disruptions. Moreover, meta-heuristics algorithms can manage additional constraints effectually and offer optimum or near-ideal solutions within a reasonable computational time, whether in large- or small-scale networks. Meta-heuristics, namely ACO, PSO, and GAs have been extensively employed to solve shortest path issues across numerous research fields [9]. Nevertheless, they face limitations in handling the dynamic topology and energy constraints of UWSNs, motivating the design of hybrid and adaptive models.

The purpose of this work is to introduce a novel architecture termed AdAOA for routing in IoT-UWSN. At first, the IoUT network is simulated, and further, the routing is performed to recognize the finest path. Here, routing is performed exploiting the AdAOA model by contemplating several multi-objectives, such as PDR, delay, distance, and energy. Furthermore, the AdAOA technique is devised by integrating the Adaptive concept and AOA. This combination enables better trade-offs among conflicting objectives and enhances the robustness of routing decisions in unpredictable underwater scenarios.

The key contribution of this work is,

- ***Proposed AdAOA for routing in*** IoT-UWSN***:*** A new approach called AdAOA is developed for routing in IoT-UWSN. Here, routing is performed to identify the finest path, and is done employing the AdAOA with several multi-objectives. Here, the AdAOA method is formulated merging the Adaptive concept and AOA. This ensures a significant improvement in terms of energy efficiency, reduced delay, and increased packet delivery ratio compared with existing routing protocols.

The remnant sections are organized as: Section 2 illustrates the literature review and difficulties in other baseline models, Section 3 explains the system model of IoUT, Section 4 portrays the explanation of AdAOA, Section 5 explicates the outcomes of AdAOA, and Section 6 portrays the conclusion.

2. Motivation

Routing in IoT-UWSN plays a vital role in ensuring effective data communication across underwater nodes. The success of such networks largely depends on the ability to balance reliability, energy efficiency, and adaptability under constantly changing aquatic conditions. Designing efficient routing protocols is difficult because of the complexities in the underwater environment. Moreover, several optimization approaches employed for routing often encountered many challenges, like high transmission delay and energy consumption, which lead to decreased performance and network lifespan. In particular, most existing metaheuristic and heuristic approaches struggle to adapt quickly to node mobility and resource constraints, resulting in unstable network performance. Hence, a new model called AdAOA has been proposed to identify the best path for data transmission in IoT-UWSN. Further, the limitations of the existing methods are elucidated beneath.

2.1 Literature Review

Ali, E.S., *et al.* [3] formulated the depth-based SEP for heterogeneous routing in IoUT. This model resulted in a better network lifespan because of the balanced energy usage and less interference. However, because it does not incorporate adaptive or learning-based strategies, its performance may deteriorate under highly dynamic underwater environments where node distribution frequently changes. Still, this technique failed to employ swarm intelligence approaches for dynamically altering the CHs on the basis of environmental circumstances and energy levels. A DQN-EQSR was presented by Zhang, M., *et al.* [2] for routing in IoUT. This approach attained robust generalizability, avoided resource wastage, and optimized the entire system performance. The use of deep reinforcement learning enabled the protocol to handle complex decision-making, but the computational demand was relatively high for resource-constrained underwater nodes. However, this method failed to implement model compression technology for lessening the computational cost in the IoUT. Shyamsundar, R. and Harshavarthan, M., [6] formulated the GSA method to optimize UWSN's lifetime. This model improved the clustering efficacy in UWSN by improving the network lifetime and decreasing energy consumption. In addition, the gravitational search concept allowed efficient exploration of the solution space; however, the algorithm's high complexity limited its practical deployment. Still, this method suffered from high time complexity and computation load, which affected its scalability in large-scale environments. Co-DRAR was devised by Ullah, S., *et al.* [10] for routing in UWSN. This approach effectually reduced the information loss and delay rate, while increasing the reliability and minimizing the power consumption of the network. Despite these advantages, Co-DRAR primarily focused on reliability and delay but did not fully address energy balancing among nodes. But this model failed to exploit energy harvesting approaches for decreasing the energy consumption by enhancing the network lifespan. Shen, Z., *et al.* [5] introduced DRAPC for routing in UWSNs. This technique attained low complexity, efficiently decreased the end-to-end delay, and increased the network lifetime. Nevertheless, this approach had low scalability and required high computational overhead.

2.2 Challenges

The limitations faced by the traditional approaches during the routing process is given below,

- In [3], the Depth-based SEP technique obtained better performance on the basis of energy consumption, efficacy, and network lifetime. This made it suitable for small-scale or moderately stable underwater environments. However, this technique failed to minimize the delay rate, and thus it consumed more time for finding the optimum path.
- In [2], the DQN-EQSR approach demonstrated more satisfactory consequences by attaining low PDR with high reliability. Its reinforcement learning design allowed it to adapt to varying conditions, but the added complexity made real-time deployment challenging. Still, this method failed to consider optimization algorithms for decreasing the latency and packet loss with high network performance.
- In [6], the GSA model lessened the computational load with high convergence speed. Its gravity-based search improved cluster head selection, thereby enhancing network lifetime. Nevertheless, this technique failed to utilize multi-objective parameters, like distance and residual energy, for improving the convergence rate.
- In IoT-UWSN, routing protocols are utilized for improving data transmission among the sensor nodes. However, most of these protocols are designed with assumptions of relatively stable

topologies, which rarely hold true in underwater networks. The various approaches employed for this process failed to lessen the energy consumption, which led to improved communication delays in detecting the optimal path.

3. System Model of IoUT

The system model of IoUT [11] comprises of UWSNs that are randomly deployed on the bottom of the ocean to transmit, sense, and sample the data. Such random deployment reflects real-world conditions, where controlled placement of nodes is often impractical due to water currents, tides, and terrain constraints. Acoustic transceivers are used by these nodes for communication, and these nodes are energy-constrained and requires multi-hop transmission. Multi-hop transmission not only extends communication range but also helps distribute energy consumption across nodes, thereby preventing early depletion of individual sensors. Furthermore, the sensed data is transformed and it performs as an intermediate collection points. Here, every sink node is equipped with radio transceivers, acoustic modems and GPS for allowing the communication among surface networks and underwater nodes. The aggregated information is transmitted by the sink nodes to the base stations, which acts as the central controller. This stable communication technology is exploited for monitoring, configuring, and controlling the acoustic sensor nodes. It ensures that even in dynamic environments, network administrators can remotely adjust system parameters without the need for physical intervention. Besides, the CSMA is employed for avoiding the data collision. Hence, reliable end-to-end communication from the underwater sensors to remote users is ensured by this model. Fig. 1 represents the system model of IoUT.

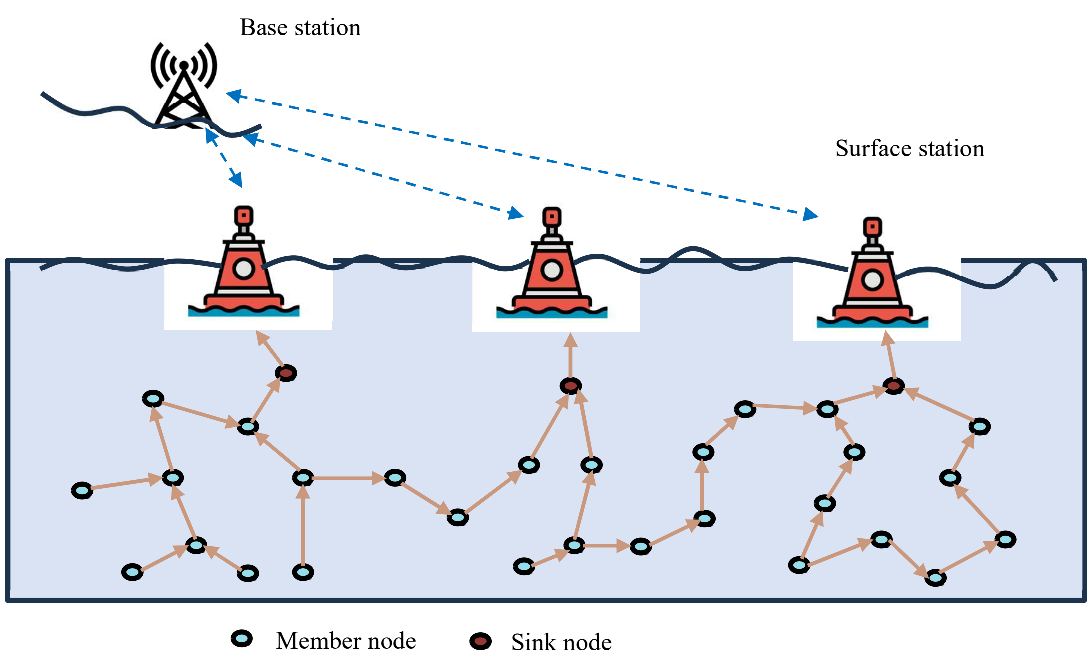


Fig. 1. *System model of IoUT*

3.1 Energy Model

In the IoUT network [12], every node has an initial energy M_0, further, when the data from the β^{th} node is transmitted to the μ^{th} CH, the multi path fading and free space approach leads to energy loss based on the distance amongst the transmitter and receiver. This highlights the fact that communication cost in underwater networks grows nonlinearly with distance, making short-range and multi-hop routing strategies more energy-efficient. Here, the radio electronics and power amplifier are included in the transmitter for significant energy dissipation. For every data packet, the energy has size of κ, which relies on the distance and nature of the node. Further, the energy dissipated by an underwater sensor node while forwarding the κ bytes of data is written by,

$$M_{dis}\left(\gamma^{\beta}\right) = M_{elc} * \kappa + M_{amp} * \kappa * \left\|\gamma^{\beta} - \zeta^{\mu}\right\|^{4}, \text{ if } \left\|\gamma^{\beta} - \zeta^{\mu}\right\| \geq g_0 \tag{1}$$

$$M_{dis}\left(\gamma^{\beta}\right) = M_{elc} * \kappa + M_{e} * \kappa * \left\|\gamma^{\beta} - \zeta^{\mu}\right\|^{2}, \text{ if } \left\|\gamma^{\beta} - \zeta^{\mu}\right\| < g_0 \tag{2}$$

$$g_0 = \sqrt{\frac{M_e}{M_{amp}}} \tag{3}$$

Here, electronic energy which is formulated by contemplating the factors, namely digital coding, modulation, amplifier, filtering, and spreading are signified by M_{ele}, and is modeled as,

$$M_{ele} = M_{tran} + M_{agg} \tag{4}$$

This formulation allows the model to capture the realistic processing overheads that are often overlooked in simplistic energy models.

wherein, ζ^{μ} implies the corresponding CH, M_e stipulates an energy of free space, γ^{β} exemplifies the normal node, energy parameter exploited for power amplifier is implied by M_{amp}, energy required for data aggregation is denoted as M_{agg}, distance amongst the CH and sensor node is characterized by $\left\|\gamma^{\beta} - \zeta^{\mu}\right\|$, and transmitter energy is designated by M_{tran}. On receiving the data of size κ bytes from the CH, the energy dissipated is expressed by,

$$M_{dis}\left(\zeta^{\mu}\right) = M_{ele} * \kappa \tag{5}$$

Data aggregation energy is especially significant in clustered architectures, as it reduces redundant transmissions and helps conserve network-wide energy.

In addition, every node's residual energy (M_i) is modified after sending/receiving κ bytes of data and is specified as,

$$M_{i+1}\left(\gamma^{\beta}\right) = M_i\left(\gamma^{\beta}\right) - M_{dis}\left(\gamma^{\beta}\right) \tag{6}$$

$$M_{i+1}\left(\zeta^{\mu}\right) = M_i\left(\zeta^{\mu}\right) - M_{dis}\left(\zeta^{\mu}\right) \tag{7}$$

Besides, the afore mentioned process is continued till every node in the IoUT-based underwater network are contemplated as dead node. Here, the node is regarded as dead when the remaining energy is less than zero. Once a significant portion of nodes are depleted, the network's sensing coverage and connectivity degrade rapidly, marking the end of network lifetime.

4. Proposed Adaptive Aphid Optimization Algorithm for Routing in IoT-UWSN

In IoUT, the routing is regarded as a critical aspect for the transmission of data packets from underwater sensor nodes to a BS or surface station by finding the finest optimum path. Since underwater nodes are highly energy-constrained and subject to frequent mobility, identifying stable and energy-aware paths is essential for maintaining long-term connectivity. However, underwater environment possesses various challenges characterized by low data rates, high latency, and limited bandwidth because of the use of acoustic communication. Numerous traditional optimization approaches for routing encountered significant difficulties in ensuring optimum distance paths, reducing transmission delays and energy consumption. Most of these methods either focus only on a single objective, such as minimizing energy or delay, without effectively balancing multiple conflicting factors at the same time. Thus, a new approach called AdAOA has been formulated for routing in IoT-UWSN. Initially, the IoUT network is simulated, and then the routing process is carried out by exploiting the AdAOA considering several multi-objectives, namely PDR [13], delay [14], distance [14], and energy [14]. Here, the AdAOA technique is developed by the amalgamation of AOA [15] and Adaptive concept. The pictorial view of AdAOA for routing is portrayed in Fig. 2. As illustrated, the framework integrates the IoUT model with optimization objectives, highlighting how AdAOA manages trade-offs between performance metrics to achieve optimal routing paths.

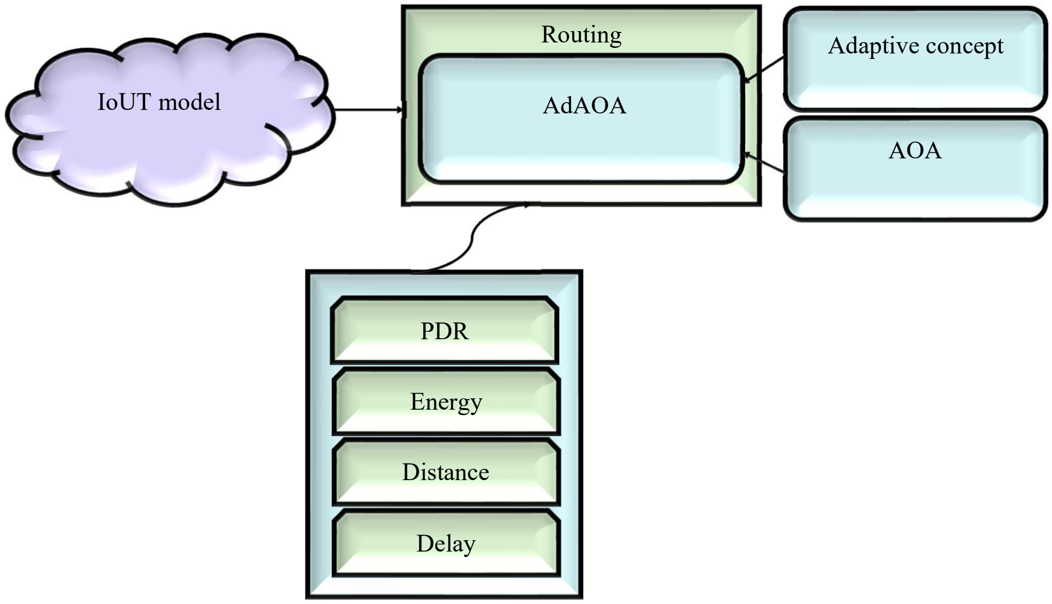


Fig. 2. P*ictorial view of AdAOA for routing*

4.1 Routing using AdAOA

Routing is referred to the process of choosing the best path for data transmission amongst the sensor nodes. In the underwater environment, this task becomes even more complex due to node mobility, variable channel quality, and energy constraints. Moreover, routing is typically carried out using acoustic signals in underwater communication. Although acoustic signals allow long-distance transmission, they suffer from high latency and limited bandwidth, which necessitates intelligent optimization of routing strategies. Effective routing in IoUT involves improved network lifetime because of the less energy consumption, increased data delivery reliability in complex underwater environments, and better network performance. Thus, routing protocols must be designed to balance multiple conflicting objectives simultaneously rather than optimizing for a single metric. Here, the routing is performed by exploiting the AdAOA approach based on multi-objectives, such as PDR [13], delay [14], distance [14], and energy [14]. Moreover, the AdAOA method is devised by the integration of Adaptive concept and AOA [15]. While the AOA provides strong global search capabilities inspired by aphid behavior, the adaptive mechanism introduces flexibility to dynamically adjust to changing network conditions. Further, the fitness function, solution encoding, and detailed explanation of AdAOA is elucidated beneath.

4.1.1 Solution Encoding

Solution encoding is utilized for characterizing the possible paths or routes in a structured format. Each encoded solution represents a candidate route from source to destination, where the path is defined by the sequence of nodes involved in forwarding data. Furthermore, the encoding process enables the AdAOA technique for effectually evaluating different routing solutions. The solution encoding involves simplifying complex routing issues, which allows faster computation in finding the near-optimum solutions. This also reduces computational overhead, which is particularly important for energy-constrained underwater sensor nodes. Moreover, the effective encoding increases the flexibility and convergence for adapting to various routing scenarios. Fig. 3 displays the solution encoding of routing using AdAOA.

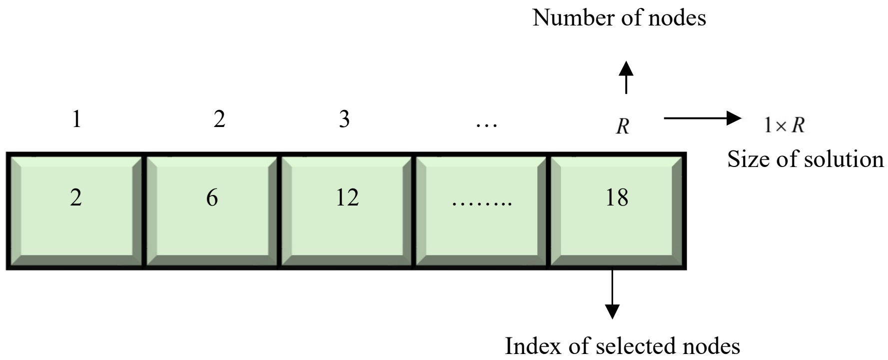


Fig. 3. *Solution encoding of routing using AdAOA*

4.1.2 Fitness Function

The fitness function is considered as a major parameter utilized for assessing and optimizing the routing paths on the basis of many multi-objectives. It acts as the evaluation criterion that guides the optimization process toward the most efficient and reliable solutions. Fitness function is modeled considering multi-objectives, like PDR, delay, distance, and energy for evaluating the entire quality of a route. Further, this process enables the routing algorithm to improve the network performance with high reliability. Hence, the fitness function becomes the key driver for selecting routes that extend network lifetime while maintaining consistent data delivery. By minimizing the function, the IoUT can identify the most effective path which optimizes the network performance. Besides, the description of the multi-objectives is explained below.

(i) Delay

The overall time required for a data packet to travel from the source node to the base station via the underwater communication is referred as delay [14], and it is modelled as,

$$Z(h) = \sum_{q=1}^{v} A_q(h)\left(F + W_q\right) \tag{8}$$

where, propagation delay of q^{th} node is epitomized by W_q, v specifies the entire amount of nodes, $Z(h)$ signifies the delay, transmission delay is embodied as F, ETC at h^{th} time is implied as $A_q(h)$. Minimizing delay is critical for real-time and safety-related applications, such as tsunami detection or military surveillance.

(ii) Distance

Distance [14] is defined as the space amongst the nodes, which should be kept minimum for ensuring effectual communication and effective energy usage. Moreover, distance is specified as,

$$\eta(h) = \sum_{\ell=1}^{P} \sum_{q=1}^{v} \left\| I_q - U_\ell \right\| \tag{9}$$

Here, Euclidean distance among the sensor nodes q and ℓ is characterized by $\left\| I_q - U_\ell \right\|$, overall amount of underwater sink is denoted as P, and distance is exemplified by $\eta(h)$. Shorter distances generally translate into lower energy requirements and more stable links, which in turn enhance the robustness of the routing path.

(iii) PDR

The proportion among the amount of packet effectively received by the sink nodes to the entire amount of packet transmitted is referred as PDR [13], and is expressed by,

$$PDR = \frac{N_\delta}{N_\omega} \tag{10}$$

where, N_ω specifies the overall amount of packet transmitted and N_δ symbolizes the amount of packet received. A higher PDR reflects reliable communication and reduced data loss, which is essential for mission-critical IoUT applications.

(iv) Energy

The power consumed by underwater devices for computation, sensing, and communication is referred as energy, and its expression is specified in Equation (6) and (7). Energy efficiency directly impacts network lifetime, and therefore plays a dominant role in determining the sustainability of IoUT deployments.

Additionally, the fitness function for selecting the best routing path is designated by the below equation.

$$Fitness = \frac{1}{4}\left[M + Z(h) + \eta(h) + (1 - PDR)\right] \tag{11}$$

This aggregated formulation ensures that the optimization algorithm evaluates all routing paths holistically, rewarding those that achieve balanced performance across multiple objectives.

4.1.3 Proposed AdAOA for Routing in IoUT

The novel AdAOA technique, which is devised by combining AOA [15] and Adaptive concept, is exploited to discover the optimum path for effective routing. This hybridization ensures that the strengths of both strategies are utilized—AOA provides exploration and global optimization, while the adaptive concept introduces real-time flexibility to adjust to environmental changes. AOA [15] is a bio-inspired metaheuristic approach and is inspired from the aphid's behavior, especially their unique reproductive strategies. Aphids exhibit complex survival behaviors, such as attack mood, flight mood, and generation of winged aphids. These behaviors are abstracted into mathematical operators that mimic exploration, exploitation, and adaptive decision-making in routing. Moreover, AOA provides robust global search ability, which reduces the possibility of getting trapped in local optima. This is particularly useful in UWSNs, where dynamic topology often increases the risk of sub-optimal route selection. It also exhibits high convergence speed, and attains high flexibility across several complex optimization tasks. Adaptive concept is considered as the most vital approach, and is utilized to maintain reliable and effectual communication. Using this concept, the parameters or behaviors of the network can be altered to change the external and internal conditions. The adaptive concept improves the network flexibility, which allows the system to operate well even in complex conditions. It also achieves better reliability by degrading the congested routes. Therefore, the hybrid AdAOA approach results in a high scalable, robust, and energy-aware routing solution. This makes it suitable not only for small-scale deployments but also for large-scale underwater networks that demand scalability. Moreover, the mathematical procedure of AdAOA is specified below.

(i) Initialization

In this phase, the H individuals in the aphid swarm are initialized arbitrarily, and the process is articulated in Expression (12).

$$Q = \{Q_1, Q_2, ..., Q_n, ..., Q_H\} \tag{12}$$

Here, entire population is signified by Q and Q_n designates the n^{th} aphid. A diverse initialization ensures wide coverage of the solution space, which increases the likelihood of finding globally optimal paths.

(ii) Fitness function

The fitness of the AdAOA technique is represented in Expression (11) and the solution that attains the lowest fitness is regarded to be ideal. This ensures that only those routes which achieve balanced trade-offs among energy, delay, distance, and PDR are selected for data transmission.

(iii) Flight mood

The individuals enter the exploration phase during the flight mood process of aphid. During this process, the energy saved by the individual is progressively decreased when the flight time is increased, and this is formulated by,

$$L = 1 - \frac{\xi}{D} \tag{13}$$

wherein, aphid's energy is characterized by L, D exemplifies the maximal iteration, ξ represents the iteration count. This gradual energy decrease simulates the realistic constraint of limited energy resources in underwater sensor nodes.

Furthermore, the wind is considered as the crucial role since it is beneficial for the aphids to fly. The term J specifies the wind effect, and is considered to be adaptive, and its equation is indicated as,

$$J = 4 \cdot B\left[\hbar\left(\frac{\xi}{D} - D\right)\right] \tag{14}$$

$$B(a) = \frac{1}{1 + e^{-a}} \tag{15}$$

where, $D \in [0,1]$ signifies the position of transition, $\hbar$ embodies the steepness of the sigmoid, ξ designates the present iteration. This adaptive wind factor enhances exploration by guiding the aphids toward promising solution regions without premature convergence. Besides, the passive flight is performed by the aphid, when the energy saved by the individual is low. In this case, the aphids move in a straight line based on the wind direction, which is expressed as,

$$Q_n(\xi + 1) = J * \left[Q_S(\xi) - Q_n(\xi)\right] \tag{16}$$

Here, location of the n^{th} individual in the present population is implied by Q_n, Q_S indicates the arbitrarily chosen individual. Moreover, the aphid flies more actively when the saved energy of the individual is large, and under this condition, the spiral flight is performed by the aphid. This dual-flight mechanism balances global exploration with local exploitation. Further, the crowding distance $Y(Q_n)$ is employed for judging the individual's crowding degree, and is modelled as,

$$Y(Q_n) = \sum_{\lambda=1}^{H} \varpi_{n,\lambda} \tag{17}$$

wherein, ϖ designates the distance, the Euclidean distance from the n^{th} individual to the λ^{th} individual is represented by $Y(Q_n)$. If the individual is in crowded phase, then the individual with large crowding distance is chosen for guiding the present solution. If not, the random individual is selected by the crowd for guiding the flight, and it is simulated by,

$$Q_n(\xi+1) = Q_n(\xi) + J * \left[e^c \cos(2\pi c) * \left[Q_u(\xi) - Q_n(\xi)\right]\right] + J * \left(e^c \sin(2\pi c) * \left[Q_u(\xi) - Q_n(\xi)\right]\right); \text{ if } \; Y(Q_n) < Y(Q_{avg}) \tag{18}$$

where, Y implies the crowding distance, spiral radius representing a random number distributed uniformly among $[-1,1]$ is denoted by c and aphid with large crowding distance is specified as Q_u. This mechanism prevents premature convergence by encouraging diversity in the population.

(iv) Attack mood

In the attack mood, the aphid searches the host, which is done utilizing the sense of smell for determining the landing location. Moreover, the host plant's smell is a crucial role in attracting the aphid and guiding its flight towards the host. Additionally, the vision sense is also considered for searching the host. This dual sensory model allows the algorithm to exploit both global knowledge (smell) and local knowledge (vision) for optimization. The host plant's position is detected via smell V_{smell}, and is considered as the global optimum solution, whereas the host plant's position detected using vision V_{vision} is contemplated as personal best position, and it is represented by,

$$Q_n(\xi+1) = V_{smell}(\xi) + \alpha * \left[\left(V_{smell}(\xi) - Q_n(\xi)\right) + \left(V_{vision}(\xi) - Q_n(\xi)\right)\right] \tag{19}$$

Here, arbitrary number amongst $[0, 0.1]$ is indicated by α.

(v) Transition

During flight, the aphids are attracted to yellow waves, and thus the yellow wave's stimulation intensity N is modelled by,

$$N = \frac{1}{1 + e^{-\frac{1}{\tau+1}}} \tag{20}$$

wherein, the Euclidean distance amongst the average location of the host plant and population is implied as τ. Furthermore, the below equation is utilized for expressing the individual's tendence to long-wave flight, and is specified by,

$$K = N * \left[1 - \frac{\xi}{D}\right] \tag{21}$$

Assume $rand$ as the random variable distributed uniformly among $(0,1)$, which is employed for determining if the attack mood or flight mood is executed as : if $K < rand$ then the flight mood is carried out, else the attack mood is initiated. This probabilistic decision-making introduces a balance between exploration and exploitation at each iteration.

(vi) Reevaluation

The fitness value of a solution is assessed to find the optimal path, and it is formulated using Equation (11). By continuously reevaluating fitness, the algorithm dynamically adapts its search towards the most promising solutions.

(vii) Termination

The above steps of the AdAOA approach are repeated till the best solution is accomplished. Termination is typically reached when a predefined maximum iteration is achieved or when no further significant improvement is observed in the fitness value.

5. Results and Discussion

The performance of the newly developed AdAOA technique is correlated with other baseline approaches for verifying the effectiveness of the AdAOA. This comparative analysis is crucial to demonstrate not only the theoretical soundness of the algorithm but also its practical superiority in real-world underwater scenarios. Moreover, experimental settings and comparative assessment are explicated as follows.

5.1 Experimental Setup

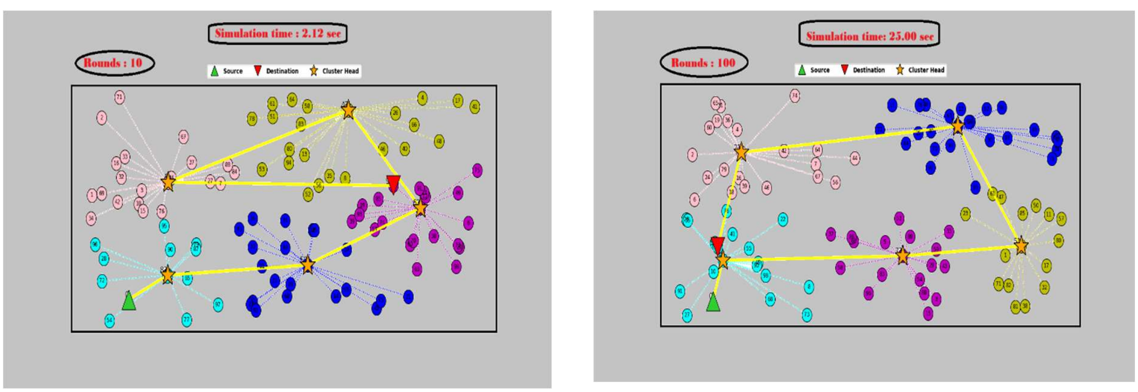
The implementation of the AdAOA exploited for routing in IoT-UWSN is done in Python tool. The experimental settings of IoT-UWSN and AdAOA is specified in the below Table 1. These settings include network size, node distribution, initial energy, and iteration limits, which collectively ensure that the experiments replicate realistic underwater conditions.

Table 1. *Experimental settings of IoT-UWSN and AdAOA*

IoT-UWSN		AdAOA	
Parameter	***Range***	***Parameter***	***Range***
Number of cluster head	5	Lower bound	100
Destination	1	Random variable $rand$	(0,1)
Initial energy	100 J	Population size H	50
Height of simulation area	100 m	Upper bound	100
Source	1	Spiral radius c	(-1, 1)
Total Data packets	1000	Maximum Iteration	500
Width of simulation area	100 m	Decision variable	100
Number of nodes	150	-	-

5.2 Simulation Results

In Fig. 4, the simulation results of the AdAOA for routing process in IoUT are delineated. The visualization helps in understanding how the algorithm organizes clusters and forwards data efficiently over multiple rounds. The figure shows CH, destination, source, and other nodes. Here, CHs are designated in star shape and the nodes are grouped under clusters are signified with different colours. This clustering representation clearly illustrates how AdAOA balances energy consumption by rotating responsibilities among different nodes. Further, the CHs are responsible to forward the data from the source (green triangle) to the destination (red triangle). Moreover, Fig. 4(a) specifies the network topology at round 10 with simulation time of 2.12 sec. At this early stage, the network shows minimal energy depletion, and routes are more uniformly distributed. In Fig. 4(b), the network topology at round 100 with a simulation time of 23.00 sec is specified.



(a) (b)

Fig. 4. *Simulation result of AdAOA for routing at (a) 10 Rounds, and (a) 100 Rounds*

5.3 Performance Measures

The measures, namely distance, delay, and energy are utilized for routing in IoT-UWSN. These metrics were selected because they directly capture the trade-offs between communication efficiency, timeliness, and sustainability of the network. Moreover, the expression of distance is specified in Equation (9), delay is designated in Expression (8), and Energy is expressed in Equation (6) and (7).

5.4 Comparative Methods

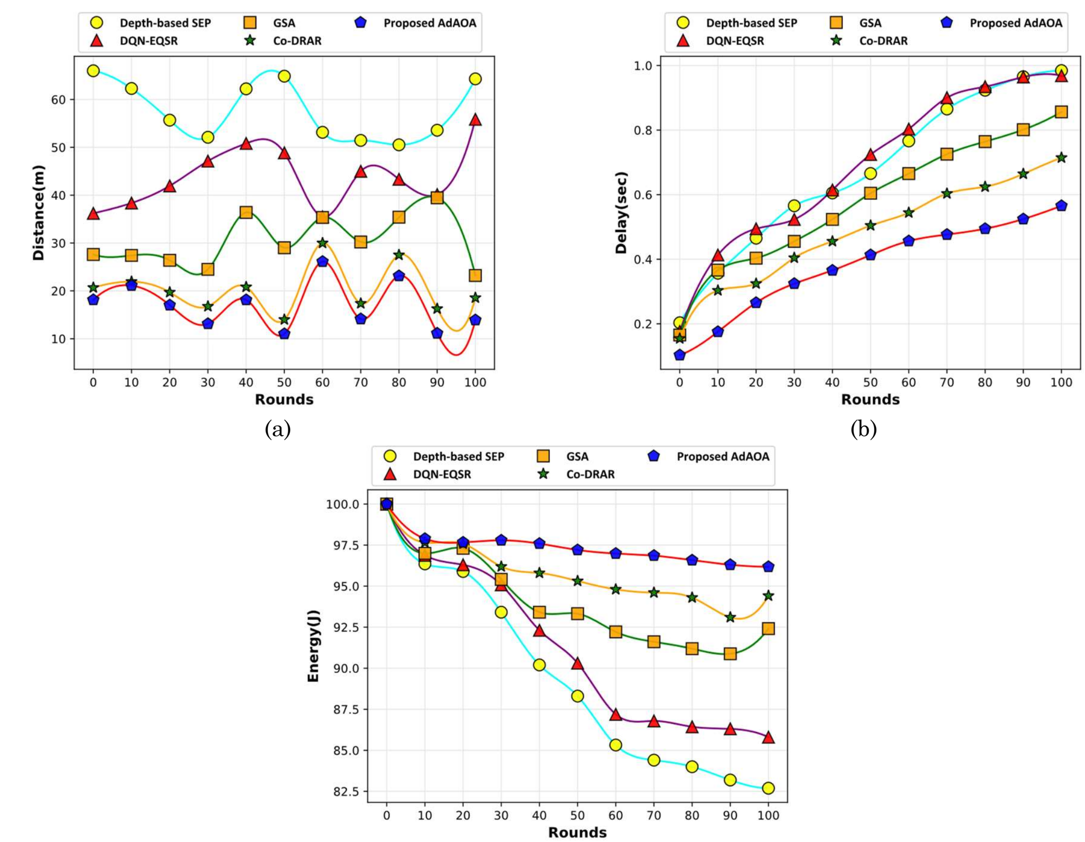
The novel AdAOA technique utilized for the routing process is correlated with numerous conventional approaches, such as Depth-based SEP [3], DQN-EQSR [2], GSA [6], and Co-DRAR [10] to evaluate its superiority. These baseline methods were carefully chosen as they represent different categories of routing strategies, including depth-based clustering, reinforcement learning, heuristic optimization, and cooperative reliability-based approaches.

5.5 Comparative Assessment

The assessment of the newly devised AdAOA approach performed on the basis of two setups, namely 100 and 150 nodes concerning several measures is demonstrated in this section. Testing on two different network sizes highlights the scalability of the algorithm and shows how it performs under varying node densities.

5.5.1 For 100 nodes

Fig. 5 designates the graph plotted amongst the rounds and various evaluation metrics for 100 nodes. This experimental setup reflects a moderately sized underwater network, where balancing energy efficiency and delay is particularly challenging. In Fig. 5(a), the distance-based valuation of the AdAOA model is specified. At 90 rounds, the distance measured by AdAOA is 11.131 m, while the baseline approaches including Depth-based SEP, DQN-EQSR, GSA, and Co-DRAR computed the distance of 53.570 m, 40.131 m, 39.451 m, and 16.271 m. This shows that AdAOA consistently identifies shorter and more efficient paths, minimizing communication overhead. The investigation of the AdAOA regarding delay is exemplified in Fig. 5(b). The delay figured by the Depth-based SEP, DQN-EQSR, GSA, Co-DRAR, and AdAOA for 100 rounds is 0.984 sec, 0.968 sec, 0.856 sec, 0.714 sec, and 0.565 sec. The lower delay achieved by AdAOA confirms its ability to support time-sensitive underwater applications, such as early-warning systems. Fig. 5(c) depicts the assessment of the AdAOA based on energy. For 90 rounds, the value of energy figured by Depth-based SEP is 83.191 J, DQN-EQSR is 86.310 J, GSA is 90.880 J, Co-DRAR is 93.099 J, and AdAOA is 96.301 J. The superior residual energy recorded by AdAOA demonstrates its efficiency in balancing transmission load among nodes, thereby extending the overall network lifetime.



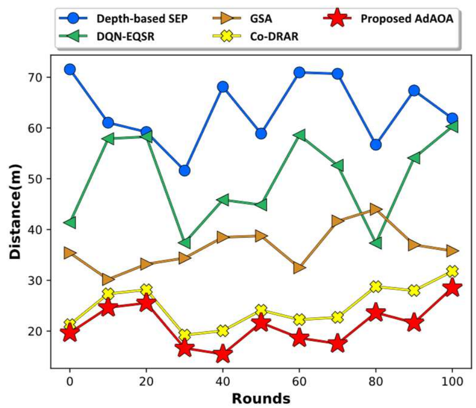
(a) (b)

(c)

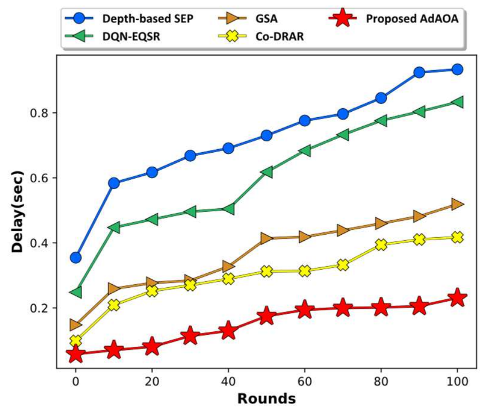
Fig. 5. *Evaluation of AdAOA for nodes 100 (a) Distance, (b) Delay, and (c) Energy*

5.5.2 For 150 nodes

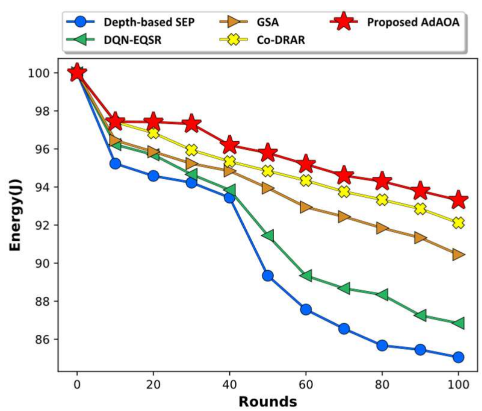
The graph plotted amongst the rounds and various evaluation metrics for nodes 150 is portrayed in Fig. 6. This larger setup represents a denser underwater sensor network, where scalability and load balancing become critical for sustaining performance. Fig. 6(a) depicts the estimation of the AdAOA on the basis of distance. For 90 rounds, the distance figured by Depth-based SEP is 67.385 m, DQN-EQSR is 54.109 m, GSA is 36.987 m, Co-DRAR is 27.985 m, and AdAOA is 21.631 m. The significantly shorter distance achieved by AdAOA demonstrates its capability to optimize path selection even in dense topologies, reducing unnecessary hops and energy waste. In Fig. 6(b), the delay-based estimation of the AdAOA model is specified. At 80 rounds, the delay measured by AdAOA is 0.202 sec, while the baseline approaches including Depth-based SEP, DQN-EQSR, GSA, and Co-DRAR computed the energy of 0.845 sec, 0.776 sec, 0.460 sec, and 0.394 sec. This substantial improvement in delay highlights the robustness of AdAOA in minimizing latency, which is particularly important for real-time underwater monitoring and surveillance applications. The valuation of the AdAOA concerning energy is exemplified in Fig. 6(c). The energy figured by the Depth-based SEP, DQN-EQSR, GSA, Co-DRAR, and AdAOA for 100 rounds is 85.054 J, 86.843 J, 90.452 J, 92.119 J, and 93.307 J. The consistently higher residual energy of AdAOA indicates better energy distribution across nodes, preventing premature failures and prolonging the network lifetime.



(a)



(b)



(c)

Fig. 6. *Evaluation of AdAOA for setups 150 (a) Distance, (b) Delay, and (c) Energy*

5.6 Comparative Discussion

The comparative discussion of the AdAOA concerning various performance measures for 100 rounds is depicted in Table 2. This table provides a consolidated view of how AdAOA consistently outperforms baseline methods across multiple key metrics. Here, for nodes 150, the newly formulated AdAOA technique measured a minimum delay and distance of 0.231 sec and 28.521 m, and a maximum energy of 93.307 J. These values indicate that AdAOA achieves both efficiency and reliability, addressing the dual challenges of energy conservation and latency reduction. Further, the delay recorded by the conventional approaches, like Depth-based SEP, DQN-EQSR, GSA, and Co-DRAR is 0.933 sec, 0.833 sec, 0.519 sec, and 0.417 sec, whereas these prevailing techniques computed the distance of 61.892 m, 60.280 m, 35.797 m, and 31.774 m. Compared to these results, AdAOA demonstrates a clear margin of improvement, proving its adaptability to larger network sizes and complex underwater conditions. Besides, the energy quantified by the Depth-based SEP is 85.054 J, DQN-EQSR is 86.843 J, GSA is 90.452 J, and Co-DRAR is 92.119 J. From the table, it is exhibited that the AdAOA model attained better results than other baseline techniques. This superiority is consistent across all three metrics—distance, delay, and energy—highlighting the robustness of the algorithm. Moreover, the AdAOA developed by combining AOA and Adaptive concept ensured more energy-efficient, reliable, and effective data transmission, which improved the entire performance by finding the most optimal path. This hybrid design allows AdAOA to overcome the shortcomings of existing single-method approaches, making it a strong candidate for real-world IoUT deployments where stability, efficiency, and adaptability are equally important.

Table 2. *Comparative discussion of AdAOA*

Metrics	Depth-based SEP	DQN-EQSR	GSA	Co-DRAR	Proposed AdAOA
For nodes 100					
Distance (m)	64.307	55.859	23.213	18.561	13.909
Delay (sec)	0.984	0.968	0.856	0.714	0.565
Energy (J)	82.691	85.802	92.413	94.413	96.180
For nodes 150					
Distance (m)	61.892	60.280	35.797	31.774	**28.521**
Delay (sec)	0.933	0.833	0.519	0.417	**0.231**
Energy (J)	85.054	86.843	90.452	92.119	**93.307**

6. Conclusion

Routing in IoT-UWSN is a vital aspect that directly influences the reliability and performance of data transmission. Since underwater environments are inherently unpredictable and resource-constrained, efficient routing strategies are essential to maintain stable communication and prolong network lifespan. The major issue in IoT-UWSN routing is effectively delivering the data due to various challenges, namely high propagation delay, limited energy resources. These challenges become more severe as the number of nodes increases, making scalability a critical factor in protocol design. Thus, a more energy-efficient and optimization techniques are required for identifying the optimal path. However, the traditional optimization approaches also faced significant challenges in minimizing energy consumption leading to higher delays and longer transmission paths. This gap in performance motivated the development of hybrid algorithms that can integrate global search efficiency with adaptive mechanisms for real-time adjustments. Therefore, a new technique known AdAOA has been developed for routing in IoT-UWSN. Firstly, the IoUT network is simulated, and then the routing process is done by utilizing the AdAOA model with several multi-objectives, namely PDR, delay, distance, and energy. Here, the AdAOA is developed by the incorporation of two models including AOA and Adaptive concept. Furthermore, the newly presented AdAOA technique attained the maximum residual energy of 93.307 J, and minimum distance and delay of 28.521 m and 0.231 sec. These results demonstrate not only its superiority over baseline methods but also its potential as a practical routing protocol for real-world IoUT applications. Future work focuses on implementing DL approaches for predicting the energy consumption for making adaptive and smart routing decisions.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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