A Novel Data Aggregation Method for Underwater Wireless Sensor Networks using Ant Colony Optimization Algorithm

Lianchao Zhang[1], Jianwei Qi[2]*, Hao Wu[3]
Tangshan Maritime Institute Tangshan
Hebei, 063000, China[1, 2]
ShiJiaZhuang University of Applied Technology, Shijiazhuang
Hebei, 050081, China[3]

***Abstract*—Underwater Wireless Sensor Networks (UWSNs) have a wide range of applications for monitoring the ocean and exploring the offshore environment. Sensor nodes are typically dispersed throughout the area of interest at different depths in these networks. Sensor nodes on the seabed must use a routing protocol in order to communicate with surface-level nodes. The suitability assessment considers network resources, application requirements, and environmental factors. By combining these factors, a platform for resource-aware routing strategies can be created that meet the needs of different applications in dynamic environments. Numerous challenges and problems are associated with UWSNs, including the lack of battery power, instability of topologies, a limited bandwidth, long propagation times, and interference from the ocean. These problems can be addressed through the design of routing protocols. The routing protocol facilitates the transfer of data between source and destination nodes. Data aggregation and UWSN protocols are widely used to achieve better outcomes. This paper describes an energy-aware algorithm for data aggregation in UWSNs that uses the improved ACO (Ant Colony Optimization) algorithm to maximize the packet delivery ratio, improve the network lifetime, decrease end-to-end delay, and use less energy.**

***Keywords*—UWSNs; routing; data aggregation; energy efficiency; ant colony optimization algorithm**

I. Introduction

During the past few years, wireless and emerging technologies have experienced significant advancements, especially the Internet of Things (IoT) [1, 2], Wireless Sensor Networks (WSNs) [3], artificial intelligence [4, 5], machine learning [6-8], smart grids [9], Blockchain [10], 5G connectivity [11, 12], and cloud computing [13], all of which have proven to be beneficial to society in a number of ways. Underwater WSNs (UWSNs) allow devices to receive, process, and communicate embedded in water for monitoring and exploration at different depths [14]. These devices are equipped with sensors that send information to a surface station after being received from the underwater environment [15]. The data are then processed based on the requirements of the application. The creation of UWSNs has been inspired by several factors, including the study of geological processes on the ocean's surface, the identification of mines, predicting and visualizing climate change, the analysis of the human impact on marine ecosystems, the discovery of areas containing underwater oil, the prevention of accidents, the tracking of mammals, fish, and other microorganisms, as well as the protection of water borders against invaders [16-18].

Sensor networks used for underwater communications differ from those used for wired communications. Underwater networks must be able to withstand extreme pressure and temperature changes. They also require specialized communication protocols to account for the longer transmission times and greater signal loss associated with underwater transmission. Additionally, acoustic waves are used for underwater communications, as radio waves cannot propagate through water. As a first point, energy consumption varies concerning the sort of application. Underwater networks must also be designed to be energy-efficient to ensure long-term operation. The second characteristic of such networks is that they typically work towards shared objectives rather than representing specific individuals. Maximizing throughout instead of ensuring relative fairness between nodes is the goal. Thirdly, the number of hops, link distance, and reliability are correlated in these networks. Several short hops rather than a single long hop are used in underwater networks; hence multi-hop data delivery uses less energy than single-hop data delivery. The end-to-end reliability of packet routing is, however, affected by many hops, especially when the environment is harsh underwater. As a final factor, individual companies using inexpensive equipment typically install these networks, so strict interoperability is unnecessary [19]. The subsurface environment may complicate UWSN design. Host conditions pose significant challenges in terms of node movement and 3D topology. Some underwater applications, such as detection and rescue missions, require ad hoc deployment, which is often unplanned and needs networks to be deployed in short timeframes [20].

UWSNs have attracted researchers' attention thanks to their wide range of applications in several sectors. Monitoring environmental conditions, oil and gas extraction under the sea, surveillance of military operations, smart farming, and communication are some of the many applications of UWSN [21]. UWSNs suffer from several significant issues, including highly energy-consuming, insufficient processing power of nodes, and short-term lifespans in routing protocols [22]. Therefore, it is a research challenge to reduce energy

*Corresponding Author.

consumption and processing in UWSNs to extend their lifetimes. There are two main types of data aggregation in UWSNs: unstructured and structured [23]. The amorphous category has no predefined structure for data gathering, so local information is utilized to aggregate data. Structured data aggregation networks have a defined structure. Structured data aggregation is classified into two categories: flat and hierarchical. A flat structure has objects that contribute to sensing and perform similar functions. Hierarchical approaches typically organize sensor nodes logically and enable them to communicate securely. There are three primary methods of implementing hierarchical structures: centralized, clustered, and tree-based [24].

The ACO algorithm for aggregating data from UWSNs is improved in this work. The first step is a description of network and optimization models. Second, an enhanced ACO algorithm is presented based on improvements to heuristic information, pheromone update procedures, and evaporation parameters. To improve the heuristic data of the conventional ACO algorithm, we provide heuristic information that considers distance and remaining energy. Also, the suggested adaptive scheme for the evaporation parameter enables the algorithm to perform a global search and reach a higher convergence rate. The article is organized as follows. In the second part, previous techniques are discussed. The proposed technique is thoroughly explained in Section III. Section IV presents the simulation results. The paper's fifth and final section offers some ideas for future research.

II. Related Work

As scientists construct UWSNs, they are challenged by significant mobility, propagation delays, limited bandwidth, and restricted battery and memory capacities. Tran and Oh [25] proposed a clustering approach that overcomes the UWSN's limitations. It is divided into four stages: the initiation stage, cluster head selection stage, clustering stage, and data aggregation stage. Efforts are being made to reduce the network's energy consumption, increase throughput, minimize data redundancy, and guarantee data accuracy.

UWSN sensor nodes continually lose power while performing underwater monitoring tasks. With limited replacement options for underwater sensor nodes, energy saving is key to increasing their lifespans. Data aggregation and clustering are potentially energy-saving techniques. An improved data aggregation method for cluster-based UWSNs is presented by Goyal, et al. [26], which employs a TDMA transmission schedule to eliminate collisions between clusters and an efficient sleep-wake-up algorithm to aggregate the sensed data, and by combining data aggregation, scheduling, and fusion, well-known existing protocols are improved to minimize energy consumption. Compared to existing protocols, the proposed scheme performs better concerning energy consumption, delay, and packet delivery rate than existing approaches.

A similarity function-based data aggregation with a Semaphore process is used by Ruby and Jeyachidra [27] to reduce energy consumption in UWSNs. A Date Palm Tree approach is used to cluster sensor nodes. Data aggregation nodes use Minkowski distance to check if readings collected from cluster members are similar. Data aggregators and cluster heads implement the Semaphore concept to ensure optimal network performance and reduce energy consumption. Packets can be moved from the data aggregators to the cluster heads through the message queue. Similarity measures in the proposed algorithm would lead to an improvement in link quality, redundancy, data delay, and energy consumption.

Krishnaswamy and Manvi [28] propose a palm tree-based approach for data aggregation and routing in UWASN. Petioles, rachis, leaflets, and spines make up the structure of palm trees. The sink node is connected to the junction of petioles. The proposed scheme creates fronds and leaflets by connecting them through spines. Several factors are taken into account when selecting master center nodes at the petiole junction, such as interconnection, petiole angle, Euclidean distance, and residual energy. The third step involves the identification of local centers at either end of the leaflet and linking them to the master centers via mobile agents. As for the fourth step, local aggregation considers leaflet nodes at local centers and carries them to a connected master center. Simulations are performed under various UWASN situations to assess the effectiveness of the scheme.

Wan, et al. [29] present an energy-efficient adaptive clustering routing protocol for UWSNs. Using a hierarchical network structure, the algorithm determines the size of the competition radius based on the distance between cluster heads and the base station. By avoiding early death, cluster heads can avoid excess competition radius and excessive energy burden. Based on the nodes' residual energy and transmission paths' energy loss, the algorithm can select the cluster head with the largest residual energy. This will optimize network energy consumption. To balance energy, routing rules are determined by residual energy levels to select between a single-hop routing node that is more energy-efficient and a multi-hop routing node that is more energy-efficient. According to simulation experiments, the proposed algorithm results in significant energy savings to the AFP protocol and DEBCR algorithm.

IoT-enabled depth base routing (IDBR) was proposed by Farooq, et al. [30] in order to maximize energy efficiency. MATLAB simulation was used to compare the IDBR with the standard DBR protocol. Both methods (IDBR and DBR) are analyzed based on delay, base station utilization, network lifetime, and energy consumption, alive nodes. Based on simulations, it is found that IDBR is 27.7% more energy efficient than DBR and improves network stability. IDBR also utilizes surface sinks more than DBR since sinks are used as relays, forwarding data to the base station directly, which gives field nodes more power. It increases the accessibility and security of the sensed data while improving the network's lifetime.

III. Proposed Method

The proposed method for data aggregation problems in UWSNs usually has a high delay, or they do not consider this problem. This section proposes a technique through the ACO algorithm to solve this problem, reduce energy consumption, and extend the underwater network's lifespan. The ACO algorithm always chooses the routes with the least number of hops to route data packets between sources and sink nodes.

A. Network Model

According to the suggested network model, all sensor nodes are dispersed over a three-dimensional space with fixed sensor placements, and the base station knows their locations. Since they are close, all sensors can send and receive data to and from the base station. The proposed model represents the network as a graph G=(V, E), where V is the set of nodes and E is the links between nodes, as seen in Fig. 1. In the model, sensors receive data from other sensors, integrate it with their data, create a packet without considering the amount of data received, and then send the packet. The problem is planned by a routing plan to deliver integrated packets from the sensors to the base station to reduce the energy consumption of the sensors, increase the network lifetime, and reduce the end-to-end delay. One solution is to use multi-hop communication by integrating the associated data. The problem is modeled as a graph with sensors representing the graph nodes. A maximum sensing range is considered for each node, which adjusts its neighborhood group and routing table. Each source node senses the sensing area regularly and sends data to the next node to receive from the base station.

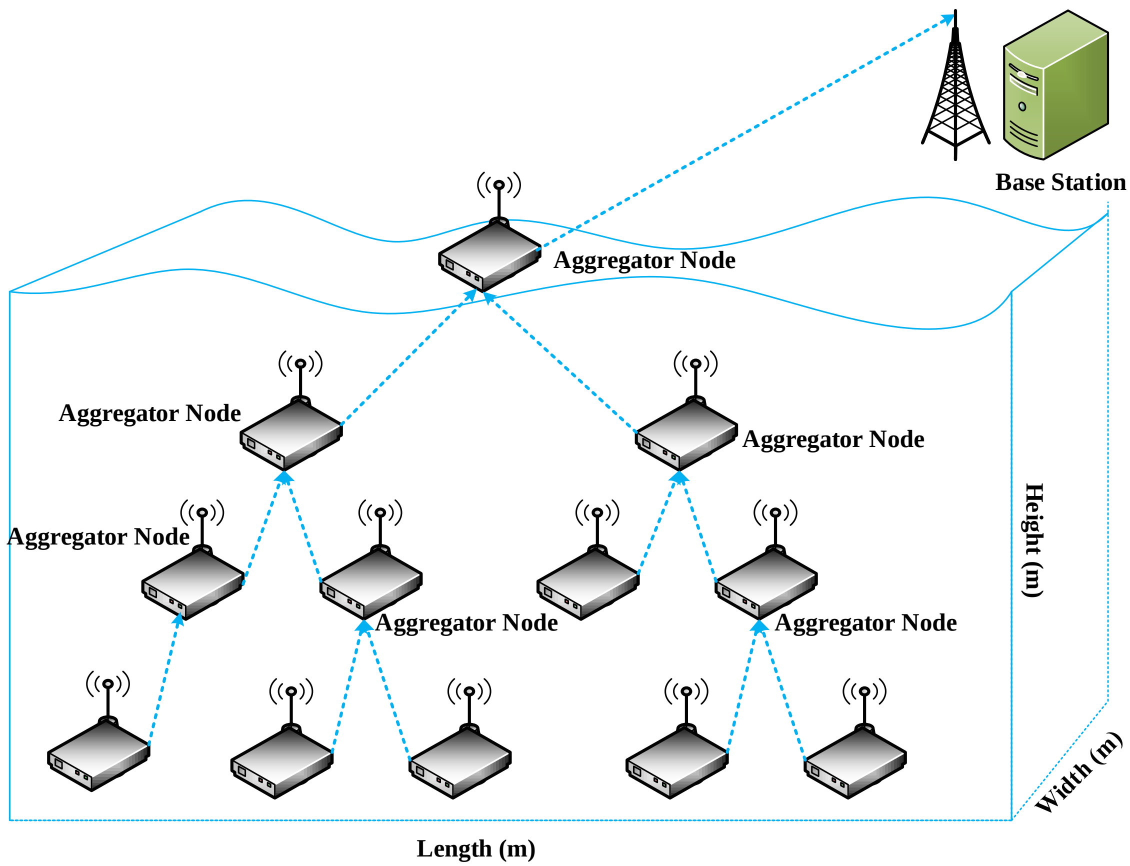

Fig. 1. The proposed network model.

B. Optimization Models

1) Attenuation model: Attenuation results from the conversion of sound energy to heat, and the energy absorbed by the water is accounted for according to the signal frequency. The Throb model [31] has the simplest equations for calculating attenuation based on signal frequency. The Throb equation is Eq. (1), where f is the signal frequency in kHz.

$$\alpha = 0.11 \times \frac{f^2}{1+f^2} + 44 \times \frac{f^2}{4100+f^2} + 2.75 \times 10^{-4} \times f^2 + 0.003 \quad (1)$$

2) Transmission loss model: The loss of transmission (no connection between the transmitter and the receiver) occurs because of the reduction in the sound intensity on the route (communication link) between the transmitter and the receiver. It depends on the range of the nodes and the signal attenuation. The transmission loss is defined and calculated by Eq. (2) and Eq. (3), where SS is the spherical distribution factor in the three-dimensional environment calculated as follows:

$$TL = SS + \alpha \times 10^{-3} \quad (2)$$

$$SS = 20 \times \log r \quad (3)$$

α is the attenuation coefficient, calculated by Eq. 1, and r is the communication area of the nodes in meters.

3) Signal-to-noise ratio (SNR) model: Generally, SNR is a criterion that indicates the proportion of the desired signal versus noise in the network. SNR is defined such that a higher ratio means that the amount of signal is more significant than the noise. In wireless sensor networks underwater, the SNR of the signal transmitted by a node is defined as the sum of the source level, transmission loss (TL), noise level (NL), and directional index (DI) of the signal transmission. This ratio is defined as follows:

$$\text{SNR} = \text{SL} + \text{TL} + \text{NL} + \text{DI} \tag{4}$$

SL depends on the Transmission Power (Pt) and Transmission Power Intensity (It), defined as follows:

$$SL = 10 \times \log\left(\frac{I_t}{0.067 \times 10^{-18}}\right) \tag{5}$$

The I_t of an underwater signal is calculated as follows according to the P_t:

$$I_t = \left(\frac{P_t}{2 \times \pi \times 1m \times d}\right) \tag{6}$$

Where I_t unit is m^2 because this ratio is estimated for a signal within a one-meter distance of the source node for shallow water, and d is the distance in meters between the nodes. TL is estimated using Eq. (2), and the considered DL is zero because of assuming that the receiver and transmitter of the signals (hydrophones) are distributed in an appropriate direction. NL in an underwater wireless sensor network is the sum of disturbance noises, the ships transportation noise, sound noise, and thermal noise, calculated by the following equation:

$$N(F) = N_t(f) + N_s(f) + N_w(f) + N_{th}(f) \tag{7}$$

In which the values of $N_t(f)$, $N_s(f)$, $N_w(f)$, and $N_{th}(f)$ are estimated as follows:

$$10\log N_t(f) = 17 - 30\log(f) \tag{8}$$

$$10\log N_s(f) = 40 + 20(s - 0.5) + 26\log(f) \tag{9}$$

$$10\log N_w(f) = 40 + 7.5\sqrt{w} + 20\log(f) - 40\log(f + 0.4) \tag{10}$$

$$10\log N_{th}(f) = -15 + 20\log(f) \tag{11}$$

S in Eq. (9) is the transportation factor, in Eq. (10), wind speed ranges from 0 to 1, and f in all of the above equations is the frequency in kHz.

4) Delay model: The suggested technique uses a propagation delay model to calculate delay using Eq. (12). Underwater propagation delay depends on the underwater sound speed and distance between the nodes.

$$t_p = \frac{d}{c} \tag{12}$$

Eq. (12)'s terms d and c represent the distance between two nodes and the sound speed (m/s), respectively. Sound speed for underwater acoustic communications is calculated using Eq. (13). A sound wave can be mechanical energy transferred by the source node. This wave can be propagated from one particle to another one through the ocean proportional to the sound speed.

$$C = 1449 + 4.6T + 0.055T^2 - 5.304 \times 10^{-2}T^2 + 2.374 \times 10^{-4}T^3 + \tag{13}$$

In Eq. (13), T stands for temperature, D for depth, and S is the saltiness of water (parts per 1000). Since the sea depth varies between 0 and 1500 meters, the water temperature and saltiness reduce with sound speed.

5) Energy consumption model for UWSN: Usage of energy in an underwater channel for data transmission between two nodes with These equations are used to calculate distance d:

$$E(d) = E_t(d) + E_r(d) \tag{14}$$

$$E_t(d) = l(E_{elec} + E_{amp}) + P_t \times \frac{l}{h \times B(d)} \tag{15}$$

$$E_r(d) = l(E_{elec} + E_{DA}) + P_r \times \frac{l}{h \times B(d)} \tag{16}$$

In the above equations, P_t and P_r are transmission and reception powers to transfer and receive energy E_t and E_r, l is the size of the data packet, B(d) is the existing bandwidth, and h are bandwidth efficiency (bps/Hz), calculated by applying Eq. (17):

$$h = \log_2(1 + SNR) \tag{17}$$

E_{elec} is the required energy to process one bit of the packet (data package), E_{amp} is the amount of energy consumed. These are the values they follow: $E_{elec} = 50nJ/bit$ and $E_{amp} = 10pJ \times bit^{-1} \times m^{-2}$. Moreover, E_{DA} in Eq. (16) is the required energy for data aggregation. In the proposed method, data aggregation is performed by each parent node. The energy consumption of this process is estimated using Eq. (18), where l is the length of the transmitted packet, EDa is the consumed energy for data aggregation, and n is the count of the aggregator node's children.

$$E_{DA} = l \times E_{Da} \times n \tag{18}$$

6) Lifetime model: The network lifetime is calculated by applying Eq. (19), where $e_{initial}$ The initial energy of the system. e_{total} The sum of the required energy for data transmission and reception is estimated using Eq. (14).

$$Lifetime = \frac{e_{initial}}{e_{total}} \tag{19}$$

7) The objective function: According to the models discussed in the previous sections, all parameters should be optimized to achieve the desired result. Therefore, the objective function used in this paper is a multi-objective optimization function given by Eq. (20), where E is the consumed energy, L is the lifetime, D is the end-to-end delay, α is attenuation, and TL is the transmission loss rate. W_1, W_2, W_3, W_4, and W_5 are the mentioned function coefficients used for the normalization of the results. These coefficients are between 0 and 1, and $W_1 + W_2 + W_3 + W_4 + W_5 = 1$.

$$Fitness = W_1 \times E + W_2 \times L + W_3 \times D + W_4 \times \alpha + W_5 \times TL \tag{20}$$

C. The Proposed Method

The proposed method uses the ACO algorithm to create the aggregation tree, and one ant is considered for each node. First, each creates a route through the heuristic function and pheromone set. The route is stored as a solution. The proposed procedural steps are as follows.

1) Solution generation by ants: This step generates a primary population, initialises parameters, and the ants present a solution.

- Step 1-1: Generating primary population

The number of nodes in a network and the primary ant population are related; additionally, each ant has an array with the IDs of the nodes on the route to the destination. Fig. 2(a) shows three arrays of the response. The last index shows the base station, and the first index of each array shows the source node. Fig. 2(b) displays the generated tree for the solutions.

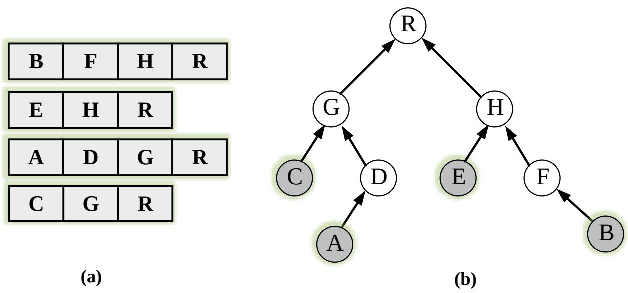

Fig. 2. Ant solutions.

- Step 1-2: The parameters initialization

In this step, the parameters should be set based on the problem. Thus, the correct values for the primary pheromone of the route and the heuristic function should be defined.

- The heuristic function definition: various functions can be used for the heuristic function in this problem. This function is proportional to the cost of the links. In the proposed method, the inverse Euclidean, a node's distance from the following node, is considered the heuristic function. Hence, an n*n matrix is generated to save the distance between the nodes. The heuristic function is shown in η that η_{ij} is the reverse distance between the ith and jth nodes.
- Pheromone definition: the amount of the pheromone between the ith and jth nodes shows the amount of the route goodness based on the ants' experience in the previous round. When the ants reach their destination, the pheromone is updated. In this paper, the primary pheromone for each route is the reverse Euclidian, the distance from the base station to the next node. An n*n matrix is created to save the primary pheromone in each route.

- Step 1-3: Solution generation by the ants

The ants are the answer generator routines that generate the answer by random movement on the graph G= (V, E). The ants should consider the policies and the limitations of the problem when moving on the graph. They search for a route to the base station to generate a solution. The probability of selecting the next step is computed by Eq. (21). The definitions related to Eq. (21) are presented in Table I. One of the nodes is selected randomly after calculating the probability of each node selection as the next step. The roulette wheel sampling method (a random selection method of a discrete distribution) is used for this aim. The ants continue their step-by-step movement until the ant reaches the base station. Each ant's solution includes a generated route from the source node to the base station that is saved in an array with the length of the route.

$$P_{i\to j}^{k} = P_{ij}^{k}\begin{cases}\frac{(\tau_{ij})^{\alpha}\times(\eta_{ij})^{\beta}}{\sum_{u\in N_i^k}(\tau_{iu})^{\alpha}\times(\eta_{iu})^{\beta}} & . \quad j\in N_i^k\\ 0 & . \quad j\notin N_i^k\end{cases} \tag{21}$$

- Step 1-4: The obtained solution evaluation

The generated answer by each ant is evaluated in this step. At first, to determine the distance between the nodes, Eq. (22) is used.

$$d = d + distance(n(i) + (n(i+1))) \tag{22}$$

In Eq. (22), n(i) is the source node, n(i+1) is the next node, and d shows the total distance between the source node and the base station. The entire route distance is calculated step-by-step and saved in d. Then the energy consumption, delay, lifetime, attenuation, and SNR of each route are computed based on the equations in the mentioned models.

2) Pheromone update: This step includes adding the pheromone and its evaporation. The goal of adding a pheromone is to increase the amount of the pheromone related to the optimal solutions performed after each repetition of the algorithm. The pheromones are evaporated in each round. Pheromone evaporation helps the ants to forget previously learned unacceptable solutions.

- Step 2-1: Adding pheromone

Shedding pheromone is performed in this step based on the obtained solutions from the ant colony optimization algorithm. Some pheromone is added to each edge from the ith to jth node passed by the kth ant proportional to the cost of the kth ant solution using Eq. (23). Q is a constant considered 1. Less cost of the key leads to adding more pheromones to the route.

$$\tau_{ij} = \tau_{ij} + Q/ant(k).cost \tag{23}$$

- Step 2-2: Pheromone evaporation

The route's pheromone is evaporated proportional to Eq. (24), in which ρ is the evaporation rate with the value of 0.05.

$$\tau_{ij} = (1-\rho)\times\tau_{ij} \tag{24}$$

IV. Experimental Results

MATLAB is used for the implementation and data analysis of the proposed method because this simulator is used in many types of research because of its high ability for mathematical calculations, high capability to show the results, high efficiency, and high data volume. Simulation parameters and the used variables of the planned method are presented in Table II.

Three scenarios show the proposed method's efficiency rather than the previous ones. End-to-end delay and the energy consumption of the proposed technique are compared with the previously proposed techniques in the first and second scenarios. The idea of using multiple sinks is identified in the third scenario, and its performance is compared with the methods that use only one sink. The first scenario has been performed based on the data of [32], and the parameters of this paper are shown in Table III. In this scenario, as shown in Fig. 3 to 6, the proposed method delay outperforms the Clustered-based Multipath Shortest-distance Energy efficient Routing protocol (CMSE2R), and the genetic algorithm regarding network lifetime, energy consumption, end-to-end delay, and packet delivery rate.

The second scenario has been performed based on the data of [33], and the parameters of this paper are shown in Table IV. In this scenario, as displayed in Fig. 7, the proposed method performs well regarding end-to-end delay compared to Depth Base Routing (DBR). The third scenario has been performed based on the data of [34], and the parameters of this paper are shown in Table V. Fig. 8 and 9 show that the planned method performs better in terms of energy consumption and delay than Firefly mating optimization inspired Routing Protocol (FFRP) and Particle Swarm Optimization (PSO) algorithm. The simulation findings demonstrate that the suggested method needs low energy compared with the previous methods, and its end-to-end delay is less than the previously proposed methods. A new idea is proposed and implemented to improve this method in which multiple sinks are used for data gathering instead of one sink. Also, the network lifetime improves in addition to the energy and delay reduction.

Considerations for the subsurface environment should be taken into account when evaluating UWSNs. The host conditions pose major challenges in terms of continuous node movement and 3D topology. Additionally, some underwater applications, including detection or rescue missions, are often ad hoc in nature, requiring both rapid deployment of networks and no advance planning. The routing protocol should be able to determine the location of the nodes in such circumstances without requiring any prior knowledge of the network. Furthermore, the network should be able to reconfigure itself under dynamic conditions so that the communication environment can be optimized. A significant consideration in the selection of a system is the relationship between the communication range and data rate and the specific conditions. Even when configured for higher data rates, a deep-water system may not be suitable for shallow water.

In practice, manufacturers' specifications of maximum data rates are mostly useful for establishing the upper performance bounds, which are not always achievable under specific conditions. Well-funded users have purchased multiple systems and tested them in specific environments in order to determine whether they are suitable for their needs. There is a need for an international effort to standardize the tests for acoustic communications, but this is not as simple as it sounds since private organizations or even government organizations that conduct comprehensive tests do not generally publish the results of their studies. Additionally, there is a lack of global standards for acoustic communication systems, which makes it difficult to compare the performance of different systems. Without a unified set of standards, it is difficult to determine which system is best suited for a particular application.

TABLE I. DEFINITIONS OF VARIABLES IN EQ. (21)

Parameters	Definition
P_{ij}^{k}	Probability of choosing node j as the next step by ant k
(τ_{ij})	The pheromone flow rate from node i to node j
(η_{ij})	The reverse of the distance between nod i to node j
N_i	The set of nodes
α	The controlling parameter for the relative effect of the amount of pheromone
β	The controlling parameter for the relative effect of the amount of heuristic function

TABLE II. SIMULATION PARAMETERS

Parameters	Description	Value
A(m×n×z)	Sensing area	100*100 – 500*500
N	Number of nodes	100-500
MaxIT	Max iteration	100-1000
L	Packet length	2-10 byte
$E_{initial}$	Initial energy	0.25 – 5 j
α	Ant colony constant	1
ρ	Pheromone evaporation rate	0.006
τ	Initial pheromones	1
Q	Ant colony constant	1
β	Ant colony constant	1

TABLE III. PARAMETERS FOR THE FIRST SCENARIO

Parameters	Values
No. of Nodes	300
Network Size	1500m x 1500m
Initial Energy	70 J
Simulation time	1000 sec
Data Packet size	64 bytes
Transmission range	100 m to 150 m
MAC Protocol (Shin & Kim, 2008)	802.11-DYNAV
The surface sink distance difference	100 m
Energy consumption for receiving	0.75w
Energy consumption for idle listening	8mw
Energy consumption for transmitting	2w

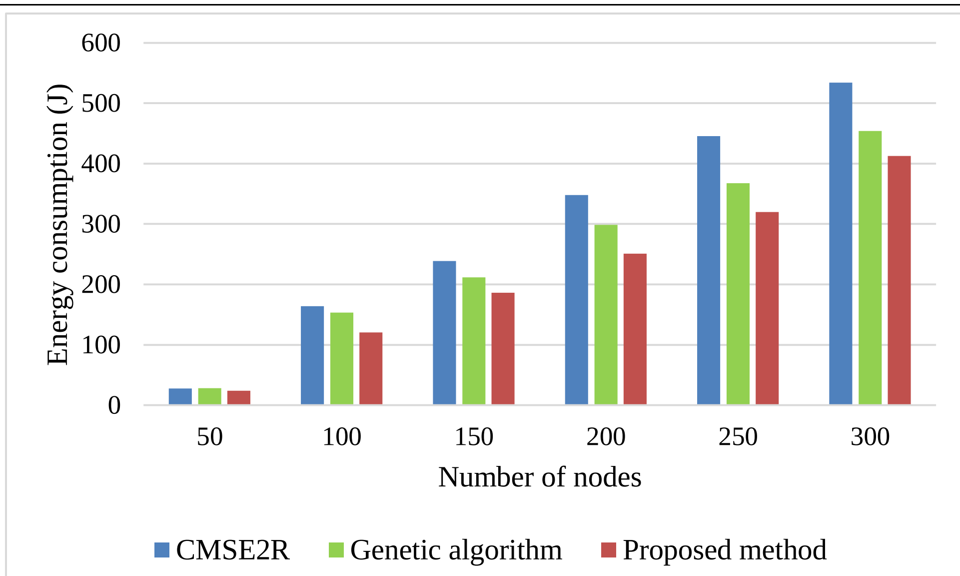

Fig. 3. Energy consumption comparison.

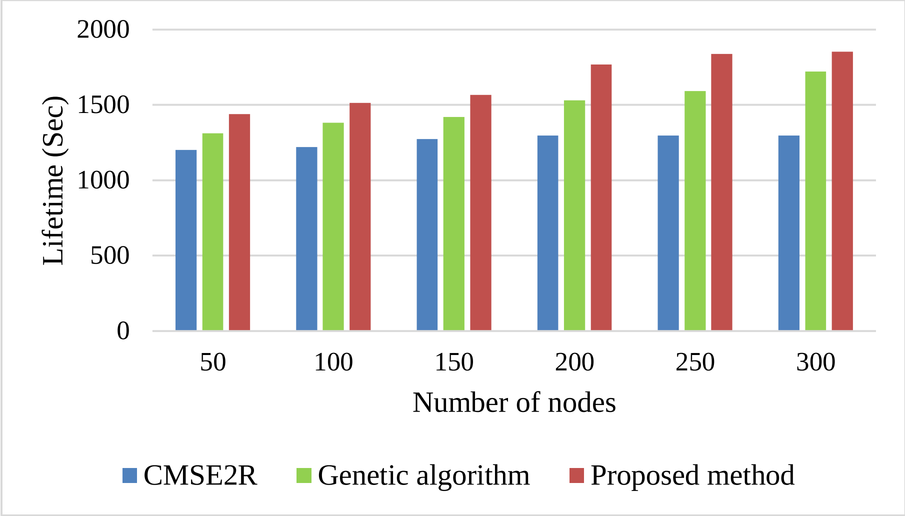

Fig. 4. Network lifetime comparison.

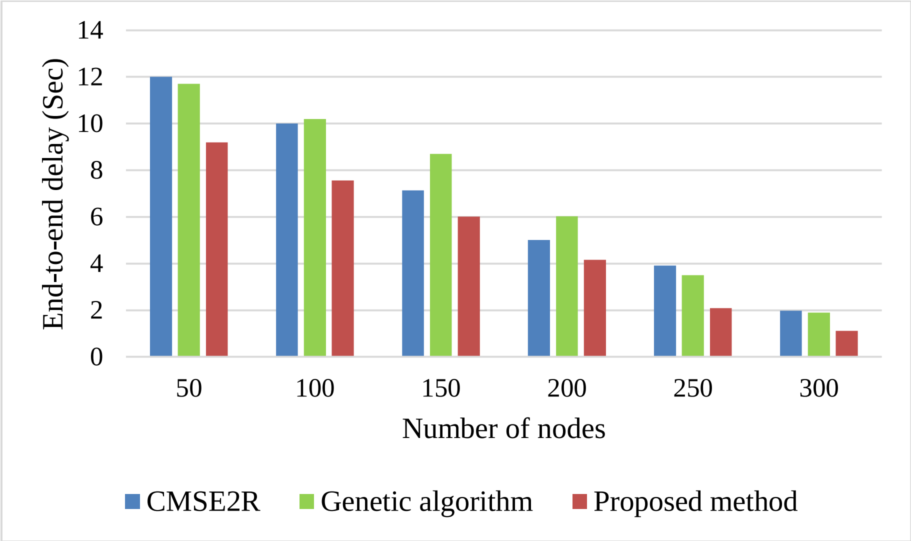

Fig. 5. End-to-end delay comparison.

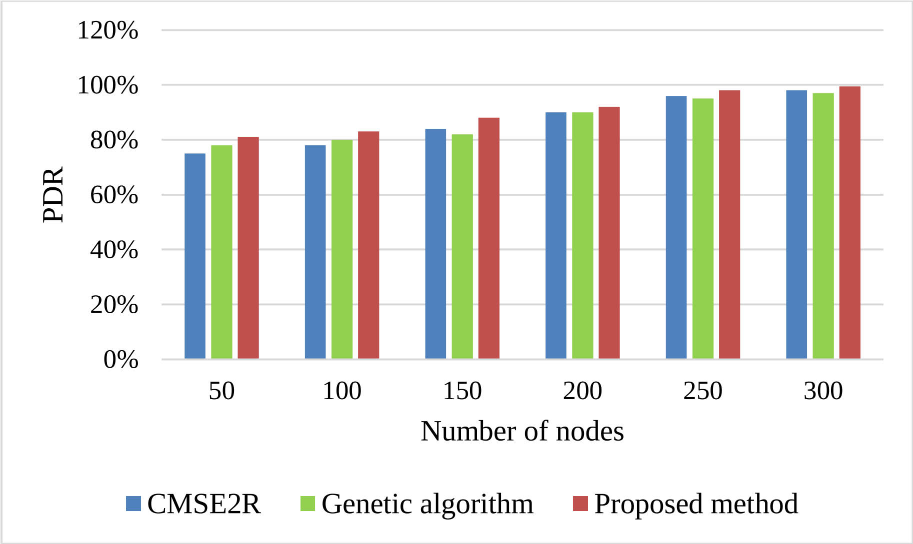

Fig. 6. Packet delivery rate comparison.

TABLE IV. PARAMETERS FOR THE SECOND SCENARIO

Parameters	Values
Data Packet size	512 bytes
Network Size	3000m x 3000m
No. of Nodes	30-150
Range (Transmitter/Receiver) of nodes	100m
Simulation time	70 sec

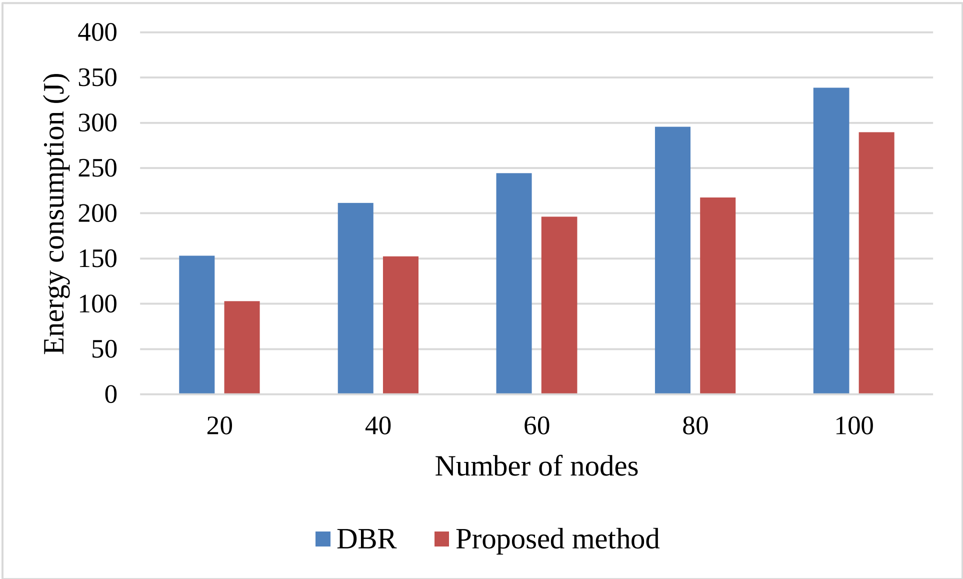

Fig. 7. Energy consumption comparison.

TABLE V. PARAMETERS FOR THE THIRD SCENARIO

Parameters	Values
Initial Energy	100 j
Network Size	1000m x 1000m
No. of Nodes	300
Data Packet size	30 bytes
Range (Transmitter/Receiver) of nodes	150m
Simulation time	130 sec

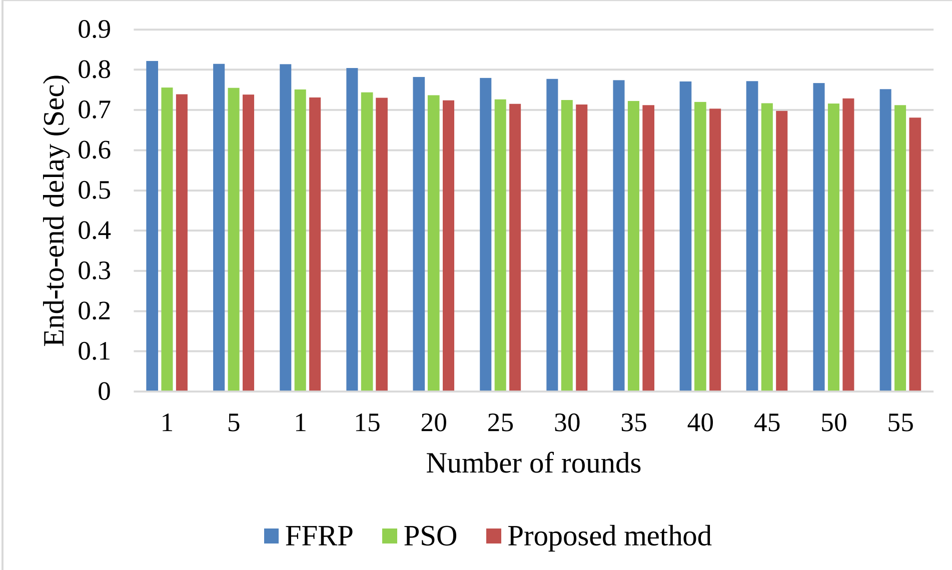

Fig. 8. End-to-end delay comparison.

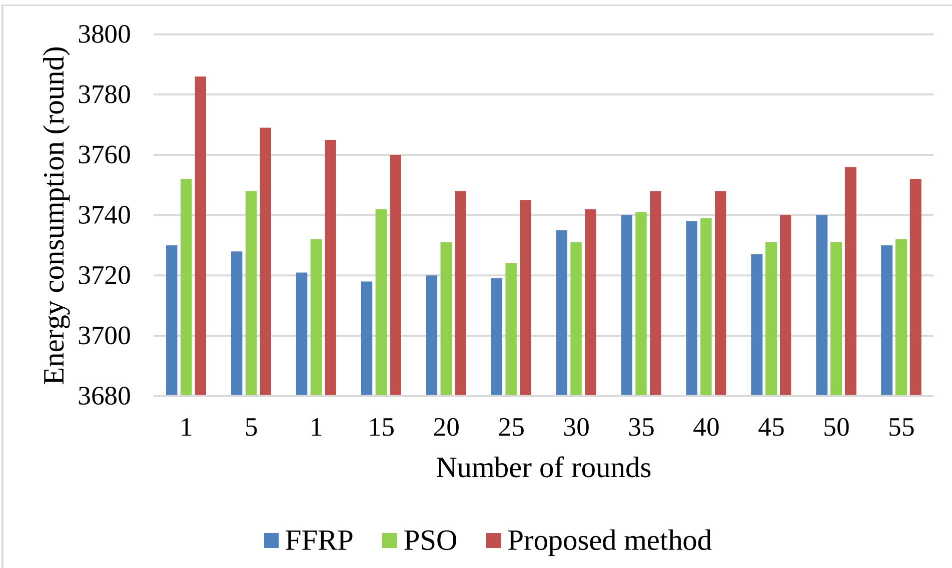

Fig. 9. Energy consumption comparison.

V. Conclusion

In order to mitigate the issue of excessive energy consumption in UWSNs, this work developed an energy-efficient data aggregation technique with the modified ACO algorithm. The paper made the following contributions. The heuristic information was enhanced using the distance factor and the residual energy of nodes. This research also included an improved adaptive technique for updating the evaporation parameter for the pheromone update mechanism, which can increase the algorithm's global search capacity and convergence rate. As a third point, this paper proposes ant searches. Simulation findings regarding packet delivery rate, end-to-end latency, network lifetime, and energy consumption demonstrate that the suggested technique surpasses existing ones. To achieve effective data aggregation, the aggregator must wait until the data is collected from various sensors and transmit them to the sink without any collisions or delays. In order to accomplish this, effective scheduling techniques are required. Therefore, in the future work we will develop a scheduling technique that will allow for the effective aggregation of data from the sensors. As the aggregated data is transmitted to the sink without delay or loss of quality, it considers both spatial and temporal co-relationships among the data. For energy balanced networks, the mobility of sensor nodes should also be taken into consideration in an intra- and inter-cluster data aggregation process.

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