A novel geo-opportunistic routing algorithm for adaptive transmission in underwater internet of things

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Abstract: Localisation of sensors in underwater internet of things (UIoTs) is difficult due to the mobility. This changing makes the routing decisions difficult, which results in unreliable communication. This paper proposes adaptive transmission-based geographic and opportunistic routing (ATGOR) protocol for reliable communication between nodes. ATGOR operates in two parts: election of a small cube to avoid redundant transmissions and selection of reliable nodes which forward data from the selected small cube for optimal transmissions. Furthermore, to guarantee the reliability of the data packets in a harsh acoustic environment, we propose mobility aware ATGOR (MA-ATGOR), which predicts the locations of neighbouring sensor nodes for successful data delivery. In addition, prediction of tthe locations of the sensor nodes helps in avoiding the void holes along with high packet delivery. The performance of the proposed routing protocols is validated based on the PDR, number of void nodes and energy consumption per packet, through simulations.

Keywords: underwater internet of things; UIoTs; adaptive transmission; void hole; geographic and opportunistic routing; mobility prediction.

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1 Introduction

The need to explore and monitor underwater activities has become researchers' prime interest because a big area (71%) of Earth's surface is comprises of water. Due to limited storage capacity of sensor nodes, the data of these nodes are stored on the cloud (Oliveira et al., 2019) for further preprocessing. In underwater internet of things (UIoTs), all sensor nodes collaborate within their communication range in an environment provided by grid (You et al., 2020) to ensure good network performance. These sensor nodes perform collaboration in a network through distributed computing (Chitharanjan and Senthil Kumar, 2021; Ren et al., 2020). This collaborative behaviour among sensor nodes has been useful for many marine applications such as mine reconnaissance, pollution monitoring, minerals extraction, etc. However, several challenges in underwater wireless senssor networks (UWSNs) make the routing decision difficult in underwater. One of the major challenges is the localisation of nodes because their location changes due to their movement with water current. This mobility of sensor nodes increases the occurrence of a void hole in the neighbourhood of sensor nodes, which consequently declines the network performance. Therefore, predicting the exact location of nodes requires a good routing mechanism. Moreover, efficient energy utilisation is considered to be one of the essential factors in measuring the performance of an algorithm designed for UWSNs. Therefore, a good arrangement of the sensor nodes is necessary to monitor, sense, and gather the information from the respective network.

In this manuscript, we have used the following terms alternatively:

1 UIoTs and UWSNs

2 sensors, sensor nodes, nodes, IoT nodes, and IoTs.

With the advent of advancement in sensing technology, monitoring of reachable and non-reachable areas in underwater is possible. However, the acoustic environment has unique features, e.g., limited bandwidth, high propagation delay, high absorption, attenuation of acoustic signal, dynamicity, etc. The earlier mentioned characteristics cause imbalanced energy dissipation, which results in low network lifetime.

Many studies are conducted on routing to enhance the lifetime of network. A routing scheme is proposed for increasing the lifetime of network by balancing the consumption of energy between network nodes. Yu et al. (2016) divide the network field via reuleaux triangle to ensure that the duplicate packets are discarded to ensure the effective neighbour node selection for efficient energy dissipation.

However, the existing neighbour nodes prediction mechanisms are not well grounded and the transmission ranges are fixed because of which energy wastage is inevitable. The forwarder node is selected by considering depth, which leads to cyclic selection of the node. This selection causes the node to deplete its battery very quickly, which results in creation of void holes. It discontinues the data communication among the network nodes. Additionally, if the potential neighbour is not found closer to the transmission threshold, the data signal will still be transmitted with exact allocated power without knowing that the power of the nodes is wasted. Furthermore, the above discussed routing strategies use reactive approach because of which delay increases while recovering from void hole.

Gul et al. (2019) addressed the above limitations and proposed adaptive transmission-based geographic and opportunistic routing (ATGOR). Geographic routing is a paradigm in which location or depth information of the neighbouring nodes is required to greedily select the next-hop forwarders. It eliminates the need for establishment and maintenance of complete paths. These characteristics make geographic routing suitable for energy constrained UWSNs having low data-rate. On the other hand, opportunistic routing is another paradigm, which provides a subset of neighbouring nodes instead of a single node as a forwarder. By employing opportunistic routing with geographic routing, the neighbouring set selection is useful for packet forwarding. The key challenge is the selection of neighbouring nodes that receives the packet. In this algorithm, the transmission range is dynamically adjusted based on the distance from the forwarder node. It avoids the unnecessary dissipation of the node's battery, which significantly contributes in the prolongation of the network lifespan. Moreover, two parameters are used for avoiding selection of forwarder nodes in cyclic way, which are depth and energy. The reason is that if the depth remains constant, the energy will change after every transmission of the data packet. In addition to our conference version, a mobility aware ATGOR (MA-ATGOR) is presented to predict the locations of mobile sensor nodes in UWSN. The mobility prediction mechanism minimises the energy dissipation by avoiding the void holes along with the decreased packet loss and minimum re-transmissions for the lost packets.

The contribution of this paper can be organised in following steps:

- our proposed routing strategies perform the adaptive transmission level adjustment and mobility prediction mechanism for void hole avoidance and efficient energy utilisation
- the network is divided logically into small cubes that provides us the better selection of next-hop forwarders
- the opportunistic routing paradigm is utilised for the selection of forwarders, consisting of eligible neighbouring nodes.

This work is organised as follows: Section 2 introduces some work related to adaptive and geospatial routing techniques. Section 3 highlights network model and problem statement. In Section 4, we have designed our proposed schemes and Section 5 provides a linear optimisation model. Section 6 describes simulation results. In the last, the paper ends with conclusion and references.

2 Related work

In this section, some related works on geographic and opportunistic routing protocols are reviewed. Noh et al. propose a technique in which the data sensed by the underwater sensors is transmitted to the sonobuoys using geographic and opportunistic routing. Moreover, the forwarding process towards sonobuoys is continued by searching the forwarders, this search and selection of forwarder nodes is based upon pressure level. In this technique, each node is aware of the void incurred from the source to destination through periodic beaconing. The next-hop forwarder sets are maintained by estimating the pressure levels of neighbouring nodes with a match of vertical direction towards the surface sonobuoys (Noh et al., 2012). Noh et al. present a routing algorithm in Noh et al. (2015). In this algorithm, the pressure level of sensors is used for the selection of forwarder nodes. Moreover, void recovery is also performed in this algorithm. A lower-depth-first recovery method is utilised to resume the greedy forwarding at local maxima. The local maxima node finds another node at lower pressure than itself to find a recovery path and resumes the greedy forwarding.

In Nicopolitidis et al. (2010), the process of broadcasting is scheduled in such a way that clients response within a short time interval. The proposed technique schedules the broadcast process and also reduces the high latency. Yu et al. (2015) propose a forwarding technique, which is unlike to vector-based forwarding (VBF), the transmission radius of virtual pipeline and transmission power levels are adjusted at each hop in AHH-VBF. It improves network reliability by adaptively adjusting the transmission radius in case of locally sparse and dense node distributions to avoid the void holes. The distance between source and reliable forwarder node is considered to adjust the transmission power, which has a positive impact on network's energy consumption. Besides this, for the selection of forwarder, its distance from the destination node is considered, which results in reduced end2end delay.

In Al-Salti et al. (2014), a multipath grid-based geographic routing (MGGR) strategy uses three-dimensional grid-based environment with mobile sensor nodes and utilises some localisation service to find the locations of the nodes. The sensor nodes communicate in a grid-by-grid manner by exploiting available disjoint paths from sources to destinations. In MGGR, when there is not a node in any of the cell then void avoidance is performed. When MGGR encounters a void region, the negative acknowledgment is sent to the sender node informing the void path. The source node finds an alternative path from the set of alternative disjoint paths. The grid-by-grid communication and void bypassing provide high delivery ratio with reduced end2end delay. Coutinho et al. (2015) propose a depth adjustment-based technique to forward the sensed data to the surface sinks. Furthermore, the depth adjustment is performed for void recovery.

Han et al. (2019) design a prediction-based data collection model that is built to overcome data unbalancing in the underwater environment. In the proposed mechanism, AUV travels around a predefined trajectory to collect data from sensor nodes. The proposed mechanism achieves a higher network lifetime: however, time complexity of the network is compromised in achieving a better packet delivery ratio (PDR). A stateless opportunistic routing mechanism is designed in Ghoreyshi et al. (2018) that utilises the information of communication voids received from the neighbouring nodes. An energy-efficient routing mechanism based on chaotic compressive sensing (Li et al., 2018) is proposed that uses the random-access method and shortest path selection to overcome the challenges in the underwater environment. A cross-layer mechanism proposed in Tran-Dang and Kim (2019) includes two-hop forwarding mechanism for data transmission. The selection of the forwarder nodes is made through cooperation to improve the reliability of the relay node. The proposed mechanisms generate a reliable network model that can last for a longer time; however, the computational overhead of the network is increased during redundant transmission.

An artificial intelligence (AI)-based network model is designed in Su et al. (2019) that uses on and off policy to train the network, and adaptively changes the routing path based on the network condition. Moreover, the routing mechanism introduced in Sivakumar and Rekha (2020) determines the set of forwarder nodes through memetic flower pollination (MFP). The mechanism consists of multi-sink architecture and obtains optimal route through the best fitness value. Both schemes increase the packet delivery; however, the computational complexity is the major drawback of these schemes.

A two-way routing mechanism is proposed in Ali et al. (2019) that divides the network into regions. One-hop and two-hop data forwarding is considered in a multiple sinks' environment. Each sink travels around its fixed path and collects data from sensor nodes in one or two hop fashion to improve the packet delivery. Rahman et al. (2018) analyse the mobility of the sensor node by proposing a hybrid model of VBF and spherical division to improve the delivery of data, and consequently decreases the energy consumption. In an aim to reduce the delay in opportunistic routing, Mazinani et al. (2018) have designed a mechanism that uses the time of arrival for nodes to find the node's location. All these mechanisms aim to reduce the network's energy consumption at the expense of increasing the communication overhead.

The authors propose an energy balanced model in Feng et al. (2019) where they consider the selection of relays based on the depth of the nodes. Moreover, they balance energy consumption by adaptively changes the energy level of nodes. However, the end2end delay is compromised in improving network performance. To reduce the total end2end delay of the network, Zhong et al. (2018) provide a direct transmission mechanism with the presence of mobile nodes. The decision to send data directly to the sink or through mobile nodes depends on the network's condition. These mechanisms do not provide optimal data delivery due to excess of direct transmission.

Coutinho et al. (2020) propose a mechanism that selects next hop forwarder nodes based on four parameters, namely energy, link quality, density, and packet advancement. The transmission power level of nodes is adjusted to reduce the energy dissipation of nodes. The proposed mechanism improves the PDR in expense of high end2delay. The introduced mechanism in Javaid et al. (2017) exploits the information of sensor nodes, and selects forwarder nodes based on the available energy of the nodes in the network. The nodes with high residual energy are selected as data forwarders thus, reducing the traffic load on low energy nodes in the network. However, with the passage of time, the performance of the network deteriorates due to high packet drop. The high packet drop occurs when the residual energy of each node becomes lower than the residual energy of the network.

Sher et al. (2018) improve the data delivery by introducing a four-way mechanism to avoid void holes and reduce collision in the network. For efficient data delivery, the forwarder nodes are selected based on the residual energy of the nodes. The PDR of all four schemes is improved, however, the energy consumption and end2end delay are still compromised. The work proposed in Usman et al. (2020) uses the mechanism of terrestrial routing in underwater IoT networks. Different cases are considered in which single sink and multi-sinks are deployed to analyse the performance of the network. The proposed mechanism enhances the network performance in expense of high deployment cost.

To increase the performance of the network, Ahmed et al. (2019) introduce cooperative and non-cooperative mechanisms for CH selection. A hybrid energy equating game is played cooperatively and non-cooperatively between nodes for the selection of CHs. The high residual energy nodes with minimum pay off are selected as CHs for data transmission. The PDR is increased and energy consumption is minimised. However, the end2end delay of the network is increased due to high computational cost.

A sector-based opportunistic routing is performed in Celik et al. (2020) that searches for optimal paths for efficient data delivery towards the destination. It exploits the topology information locally and globally from the IoT sensor nodes. Optimal routing is performed with minimum energy consumption and low end2end delay. However, the total travel distance of the proposed scheme is relatively high that results in increasing the total delay of the network. The designed protocols in Butt et al. (2019) use Dijkstra algorithm to reduce the energy consumption of nodes and attain reliable data transmission. However, the delay is increased while routing the data through greedy paths towards the destination. Awais et al. (2019) reduce the energy consumption of the network by providing two schemes. Both schemes reduce the interference and collision in the network by selecting forwarder nodes based on a greedy approach. Reliable data delivery is achieved in expense of high end2end delay.

Several authors have discussed malicious and random attacks in the IoT networks. These attacks result in removing the most important nodes in the network. Therefore, making the network robust against these attack is the main focus of the researchers. Qiu et al. (2017, 2019) aim to increase the network resilience using multi-population genetic algorithm. A similar issue is solved using an adaptive robust evolutionary algorithm in Qiu et al. (2020). Moreover, the proposed mechanisms based on cooperation and entropy in Khan et al. (2020) increase the network performance against the malicious attacks. However, high computational cost is involved in making the network robust against the attacks.

Due to the importance of IoT networks, Chen et al. (2019) propose a backpropagation machine learning approach for the construction of robust topology against the malicious attacks. Similarly, a deep deterministic learning policy model is proposed in Chen et al. (2020) to improve the network's stability against the attacks. Moreover, the research in Parra et al. (2020) detects different types of attacks through a distributed deep learning approach. However, all aforementioned schemes focus on making the network resilient against different types of attacks. They fail to focus on other performance parameters like energy consumption, end2end delay and PDR. The nodes failure problem is also seen in Bu et al. (2018). Here, a VBF mechanism is adopted where the selected forwarder nodes close to the sink die rapidly, leaving out the network's communication gap.

3 Preliminaries

In this section, the acoustic network model for the ATGOR and MA-ATGOR is discussed in detail to understand the acoustic communication architecture. Then, the problem statement is briefly presented, which shows our motivation behind this proposal. The details are given as follows:

3.1 Network model

The network model is built by assuming that 'n' sensor nodes are distributed in $3D$ network field, a cube of volume 'V' is formed by this field. Moreover, this cube is divided into 'M' small size cube having volume 'v', denoted as $C_1, C_2, ..., C_M$. Each small cube has its own identification (CID), which represents the cube coordinates. If two cubes are adjacent, it means they have a common side or a common corner. Let suppose, the sensor nodes have uniform deployment with same initial energy and each sensor generates equal bits of data per second. Where, each sensor measures a few spatial factors like temperature and salinity. Such assumptions relate to clustering methods which have the advantages of scalability and robustness (Harb et al., 2015).

The sensor nodes are assumed to be equipped with the acoustic modems for underwater communications. Whereas, the sink nodes have both radio and acoustic modems for terrestrial and acoustic communications, respectively. The assumptions on which our proposed work is based upon are:

- All sensor nodes know their locations at the time of deployment through the localisation services (Zhou et al., 2010).
- The sensor nodes are anchored and can only move randomly in a horizontal direction because of the water currents (Coutinho et al., 2015).
- The sink nodes are special nodes that receive many packets simultaneously without any collision. In addition, they have no energy constraints.
- Every sensor can adjust its transmission power dynamically for avoiding unnecessary energy dissipation.
- The sensor nodes in a small cube directly communicate with the sensor nodes of the adjacent small cubes.

3.2 System models for sink deployment and mobility analysis

In our work, the energy, computational and memory resources for sink nodes are unlimited contrary to the ordinary sensor nodes. Therefore, the deployment of multiple sinks is varied to provide the maximum coverage and guaranteed connectivity among the network nodes. In order to analyse the effects of sink deployment, we have used two deployment schemes:

1 geospatial division-based sink deployment (GDSD)

2 GDSD with adaptive mobility (GDSD-AM).

In GDSD, let assume that a set of sensor nodes $n = \{n_1, n_2, ..., n_i\}$ is uniformly distributed over the 3D network field as shown in Figure 1. The volume of whole network is uniformly divided into V regions. There are total S number of sinks deployed in the network. The $S/2$ sinks are deployed over water surface. The rest $S/2$ are uniformly distributed inside the defined dimensions of the acoustic network field. The sinks, which are deployed inside the water, covers the equal volume and every sensor node has the ability to compute its distance from every sink. The small cube in Figure 1 shows the communication among the sensor nodes.

A and C are represented as void nodes, responsible for resuming the communication. The depths of both nodes are adjusted to B and D, respectively. After the depth adjustment, the sensor nodes resume the data forwarding by finding a potential node. The sensor nodes communicate in a multihop manner to forward the sensed data towards the destination. Furthermore, the collected data is sent to the surface sinks via mutihopping.

Similar to GDSD, a set (n) of sensor nodes is uniformly deployed over the network field in GDSD-AM. There are S' sinks deployed in the network in GDSD-AM, which are uniformly distributed in V' regions. Each region consists of S'/n sinks deployed at its top surface as shown in Figure 2. Where, n is any real number depending upon the requirement of regions in the network field. A cube shown at the right side of Figure 2 exhibits the communication within a region from the network field. It can be seen that the node A is a void node and informs its nearest sink to adjust its depth to a new position $S-2$. Unlike to GDSD, the sink nodes adaptively adjust their depths.

Figure 1 GDSD system model

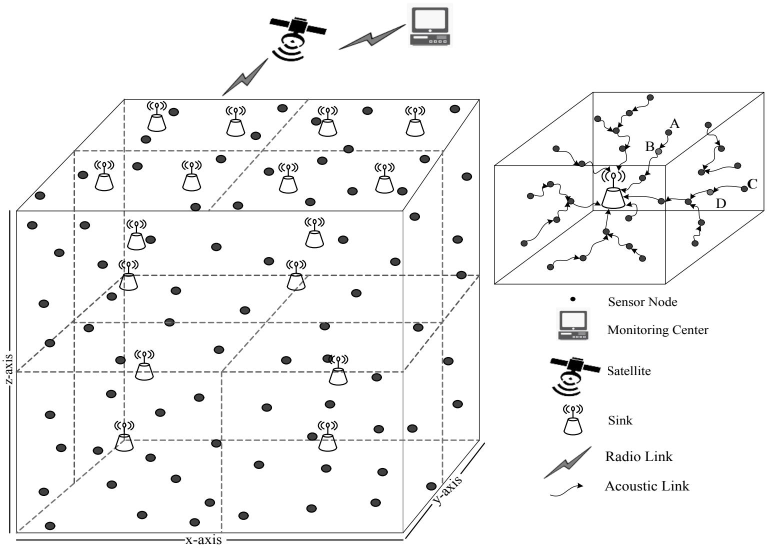
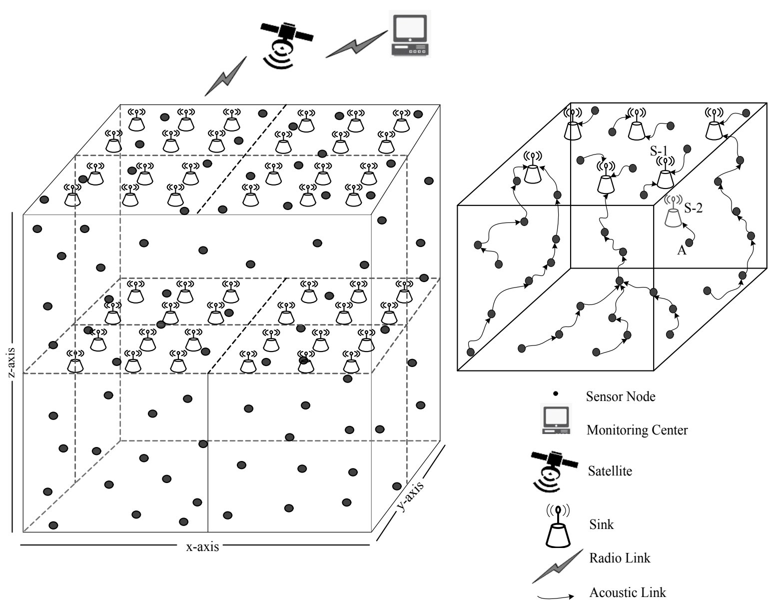


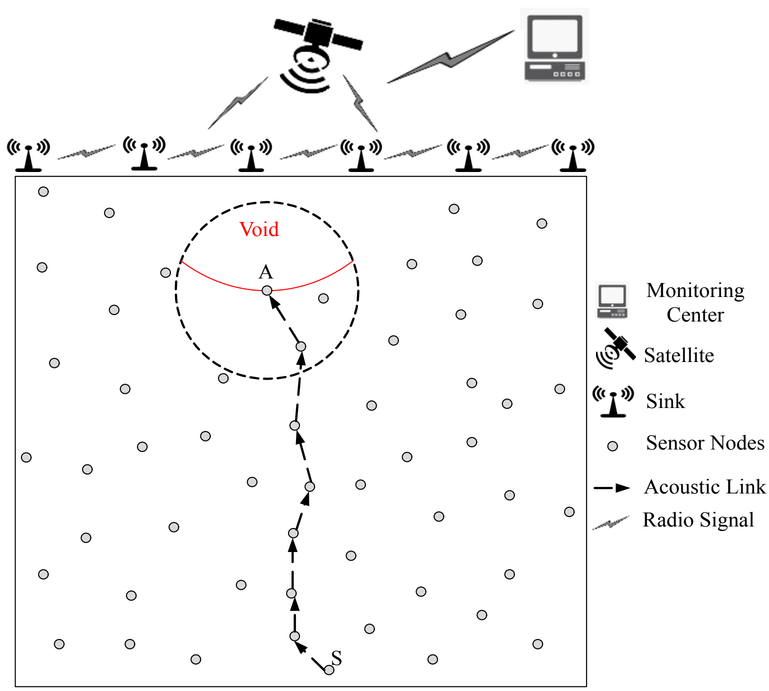
Figure 2 GDSD-AM system model



3.3 Problem description

In this section, we explore the void hole problem. The void hole occurs due to water currents, sparse deployment and depletion of node battery. Therefore, a dynamic adjustment of transmission power is required for optimal energy dissipation to have uninterrupted communication among the network nodes. The void regions are illustrated in Figure 3.

Figure 3 Void hole problem (see online version for colours)



Although, the adaptive transmission power avoids the void regions, however, the geographic and opportunistic depth adjustment-based routing (GEDAR) utilises the fixed transmission power to establish communication among the network nodes (Coutinho et al., 2015). In GEDAR, a source node S initiates the communication via establishing links with its neighbour nodes that are within its transmission range. To recover the data packet, the GEDAR performs adjustment of depth using based apparatus to resume the network operations shown in Figure 3. However, after one hop recovery of void nodes, the sensor nodes are still prone to transmission failure. Thus, moving the void node at a new depth does not eliminate the threat of void hole occurrence and also consumes high energy with increased delay.

4 The proposed schemes

In order to have continuous operations in harsh acoustic environment, the problems of data loss, signal attenuation, data re-transmissions and void hole occurrence need to be addressed very carefully. A few of them are discussed in the subsequent section. For delivering data packets successfully at the destination in multi-hop manner by avoiding void holes, an adaptive transmission-based routing algorithm is proposed to address both void hole and mobility issues in UWSN.

4.1 ATGOR

To describe the proposed transmission strategy clearly, we make some definitions as follows:

1. Effective transmission region (ETR) is the region in which every sensor node in another cube is closer to the destination as compared to the source node.
2. Eligible neighbour cube (ENC) is defined as the neighbouring cube of a source cube, which has the lower depth than the source cube.
3. Eligible neighbour node (ENN) is the neighbouring node of a source node possessing less distance from the destination than the source node.

Given that the sensor node deployment is uniform over a network field; where, sensor nodes continuously sense, gather and transmit their data to the nearby sink. The consumption of energy is dependent on the distance between source and destination. Now, if we keep the transmission power constant then a lot of energy will be consumed which results in shorter network lifespan. The detailed discussion of working mechanism of ATGOR is discussed as follows:

4.1.1 Enhanced periodic beaconing

In ATGOR, the sensor nodes obtain the location information of the reachable sinks and the neighbouring sensor nodes through the dissemination of periodic beacon messages. Every sink deployed at the surface of the water have global positioning system to determine its location. The sink nodes disseminate beacon messages to localise the underwater nodes. The beacon message, which is sent after specific intervals includes sequence number, ID, and its X and Y coordinates. Recent messages that are sent from the sink are identified by sequence number. The Z coordinate is not considered here, the reason is that the sinks nodes can only move in horizontal direction and cannot have vertical movement. Moreover, each sensor node has node's ID, sequence number, CID and X, Y and Z coordinates of nearby sinks. The sequence number is increased after specific time interval s seconds. When a most recent beacon message is received, the entry is refreshed on the basis of sequence number. To minimise the collisions, the periodic beaconing proves to be useful than the flooding mechanism of control messages (Yu et al., 2015). Every node checks its sequence number when they receive beacon message and if it is greater than the earlier received beacon then it updates its entries of the reachable sinks. Similarly, the neighbouring nodes update their entries upon receiving the beacon message if the entries are more recent than the existing entries. When a sensor node broadcasts a beacon message, it sets up a new timer. Algorithm 1 shows the mechanism of enhanced periodic beaconing.

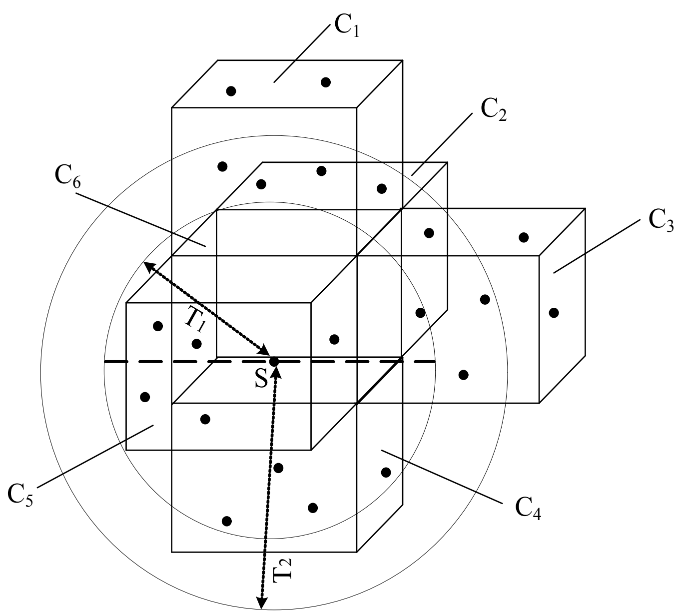
Algorithm 1 Enhanced periodic beaconing

Broadcast periodic beacon (node)
Q a new beacon message
if the timeout expired **then**
  $Q.coordinate \leftarrow loc(node)$
  $Q.seq - num \leftarrow seq - num(node)$
  $Q.CID \leftarrow CID(node)$
  Broadcast Q
  Set a new timeout
end if
Receive beacon (node, Q)
if Q is from a sink **then**
  if Q.seq-num >seq-num **then**
    update the reachable sink entry
  else
    $update - neigh(Q.seq_num, Q.CID, Q.ID, Q.loc)$
  end if
end if

4.1.2 Determine the next-hop small cube

Let us say, a sensor node S is located in the logical cube C_5, as shown in Figure 4. The solid line circle around S shows its transmission range. The upper hemisphere of the circle represents the ETR of the S. It can be seen that there is no sensor node available in the next small cube to S.

Figure 4 Adaptive transmission in ATGOR



Here, C_6 represents a void cube between source and destination node. Figure 4 shows that S adjusts its transmission power dynamically to find small cube nearer to it.

The big solid line circle shows the adjusted transmission power of node S. Whereas, the C_2 is within the ETR, thus, C_2 can be called as ENC for the source node S. The sequential steps of small cube selection are given in Algorithm 2.

Algorithm 2 Election of ENC

Initialise all the parameters
Node n_i receives packet from node n_j
Computes the coordinates of source node n_j
Acquires CID
Find ENC in ETR
if An ENC is found by n_i **then**
  Acquire its CID
end if
if There exist any void cube **then**
  From $T_{\max}$, other level is chosen
  Go to 5
end if

4.1.3 Forwarder set selection

In traditional multi-hop routing, a single node is selected as a forwarder where the probability of re-transmission increases if void hole occurs. The opportunistic routing is a definitive solution in which the set of forwarder nodes are elected to transmit one data packet. If one node fails to deliver the data packet then a node with less priority is nominated to proceed with the transmission process. In our proposed work, the opportunistic routing is used to select a set of neighbouring nodes from the ENC. The selected neighbouring nodes are named as ENN and prioritised based on the depth by assigning a holding time. Whereas, we have also exploited the geographic routing in combination with opportunistic routing to select a node from ENN set that has highest residual energy among all. It is necessary to avoid the hidden terminal problem within a CID in opportunistic routing. If there is comes any situation that the nodes with highest priority are unable to send data packets, then the nodes with low priority begins to send data packets. All important step of forwarder node set selections are shown in Algorithm 3.

Algorithm 3 ENN set selection

begin
ENN forwarder set selection
All nodes within the CID are found
The coordinates of all nodes are acquired in ENC
CID is acquired
The priorities are assigned to ENNs
end

4.1.4 Calculating the holding time

To prioritise the ENNs, the holding time is calculated as follows (Coutinho et al., 2015):

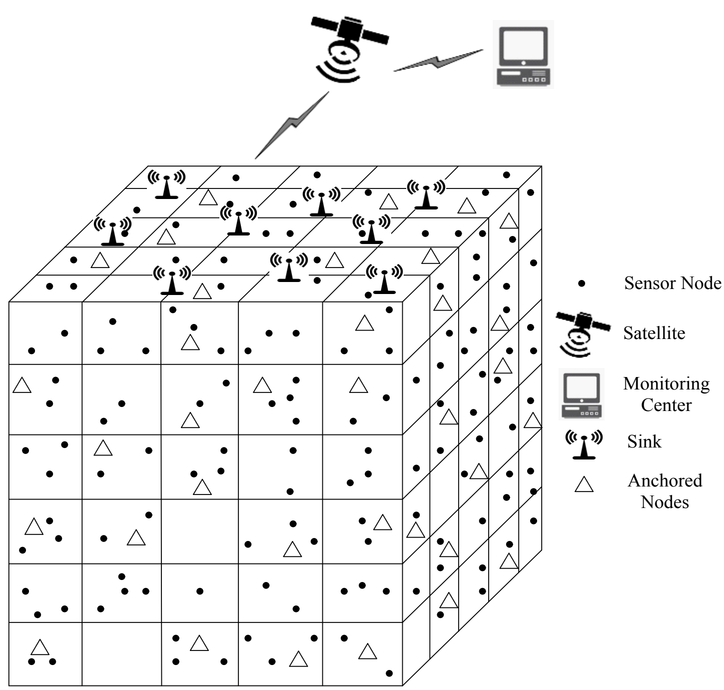
$$t_h = t_p + \sum_{k=1} \frac{D(n_k, n_{k+1})}{s} + i \times t_{proc}, \tag{1}$$

where t_p is the propagation time, t_{proc} denotes the processing time of the packet, $D(n_k, n_{k+1})$ represents the Euclidean distance and s shows the sound speed of the signal in the acoustic medium. The propagation time t_p shows the delay required for the complete propagation of the transmitted packet. This time is calculated as: $t_p = \frac{(R-D(n_i,n_j))}{s}$: here, R represents communication range.

4.2 MA-ATGOR

In the UWSNs, the awareness of the locations of the sensor nodes is very critical. Furthermore, the pervasive coverage an aqueous environment in the presence of inevitable node mobility is very challenging in the UWSNs. In this section, we present a mobility aware routing protocol to predict the location of nodes, which are mobile due to water currents. This section begins with the network model and followed by the discussion of mobility prediction mechanism in ATGOR.

Figure 5 MA-ATGOR system model



4.2.1 System model of MA-ATGOR

The movement of underwater sensor nodes is not a complete random process. The movement of one node is closely related to the movement of the nearby nodes because of the inherent temporal and spatial correlations of sensor nodes. Thus, an ordinary sensor node deduces its mobility pattern from the mobility pattern of its neighbouring nodes. On the other hand, the anchor nodes also communicate with other anchor nodes to analyse their mobility pattern. Moreover, the spatial correlation is measured for the ordinary nodes in the neighbouring region. The anchor nodes serve as the intermediate nodes between the sinks and the ordinary nodes. We assume that there are 'n' ordinary sensor nodes, which are deployed by following random uniform distribution over a 3D network field. In addition to the network model of ATGOR, there are 'j' anchor nodes deployed at uniform random locations as depicted in Figure 5.

Due to low capabilities of sensor nodes, it is desired to utilise the node energy very efficiently. The anchor nodes are the powerful sensor nodes having ability to communicate with sinks. The ordinary nodes communicate with the anchor nodes by locating them within their communication ranges.

4.2.2 Localisation of anchor nodes and the mobility prediction

The anchor nodes periodically measure their locations for delivering data packet. Let us assume, the anchor nodes predict their locations after a certain prediction period 'T_1'. For every anchor node, the mobility speed vector is represented through $\mathbf{V} = [v_1, v_2, ..., v_k]$. Here, v_k denotes the average speed of the nodes at period 'k'. We employ a linear prediction model according to the mobility pattern of the nodes as formulated in equation (2).

$$v(k) = \sum_{p=1}^{l} \varsigma_l v(k-l), 1 \leq p \leq l, \tag{2}$$

where p is prediction steps' length and ς denotes the coefficient of linear prediction model. ς can be computed from the localisation data, based on the previous prediction step. In localisation period, 'k' is an anchor node, which measures its actual location by disseminating the beacon messages to the surface sinks. At the same time, it measures its expected new location based on the past measurements as follows:

$$Loc_n(j,k) = Loc_a(j,k) + \sum_{p=i}^{k} T_1 \times v(p), \tag{3}$$

here, $Loc_n(j,k)$ is anchor node's new location 'k' and $Loc_a(j,k)$ is the actual location of the anchor node 'k'. We consider the kinematic model to predict the node mobility due to water currents (Beerens et al., 1994). The kinematic model measures the node speed in x and y directions because the depths of the anchor nodes are fixed in the z dimension as:

$$v_x = k_1 \lambda v \sin(k_2 x) \cos(k_3 y) + k_1 \lambda \cos(2k_1 t) + k_4, \tag{4}$$

$$v_y = -\lambda v \cos(k_2 x) \sin(k_3 y) + k_5, \tag{5}$$

where v_x and v_y are the speeds in the x and y directions, respectively, k_1, k_2, k_3, k_4, k_5, v and λ show the environmental factor(s), i.e., water currents and bathymetry.

4.2.3 Localisation of ordinary nodes and mobility prediction

The spatial and time correlations are utilised to perform mobility prediction for ordinary sensor nodes. If the velocities of its neighbouring nodes are known, the velocity of node 'n' in the x and y directions can be predicted as:

$$v_{x,y}(n,k) = \sum_{j=1}^{n} \varphi_{nj} v_{x,y}(j,k), \tag{6}$$

where n is the number of neighbours and φ is the related coefficient between the velocities of the anchor node and the ordinary node. It is computed as: $\varphi_{nj} = \frac{1/d_{nj}}{\sum_{j=1}^{n}(1/d_{nj})}$. Here, d_{nj} denotes the Euclidean distance between nodes n and j. This mobility prediction is incorporated into the localisation process and then the location of an ordinary sensor node can be calculated as:

$$Loc_{exp}(n,k+1) = Loc_c(j,k+1) + T_1 \times v(j), \tag{7}$$

where $Loc_{exp}(n,k+1)$ and $Loc_c(j,k+1)$ represent the expected location of the ordinary sensor node and the current location of the reference node, respectively. After performing this localisation, the routing is performed similar to the ATGOR.

5 Linear programming and graphical analysis

Linear programming is widely accepted and used quantitative optimisation technique, it provides optimal solutions. The optimal solution is obtained by formulating a linear optimisation problem, which consists of an objective function to be maximised or minimised, decision variables and the linear or nonlinear constraints. The decision variables are continuous and can take on any real value, which satisfies the defined constraints.

In this section, we optimise the energy consumption and the PDR for our proposed schemes and geometrically represent the feasible regions. Let us say, a set 'B' of values forms a feasible region. This set is represented in the Euclidean plane formed by decision variables according to the defined constraints. A subset of values from 'B' is said to be the feasible solution if it is within the feasible region. Among all feasible solutions, the one that maximises or minimises the objective function is an optimal solution.

- *Energy consumption minimisation:* It is necessary to minimise the consumption of energy in data communication for prolonging the network lifespan. For minimal energy dissipation, we define the following objective function.

  $$\min \sum_{i=1}^{n} (E_{tx}(i) + E_{rx}(i)), \tag{8a}$$

  where $E_{tx} = l \times P_t$ and $E_{rx} = l \times P_r$. l, P_t and P_r are the packet size, power required for transmission and power used in reception, respectively. The constraints are:

  $$E_{residual} \geq E_{tx}, \tag{8b}$$

$$D_{communication} \leq R_{max}, \tag{8c}$$

$$E_{tx} \geq 0, E_{rx} \geq 0, D_{communication} \geq 0. \tag{8d}$$

Figure 6 ATGOR: energy consumption (see online version for colours)

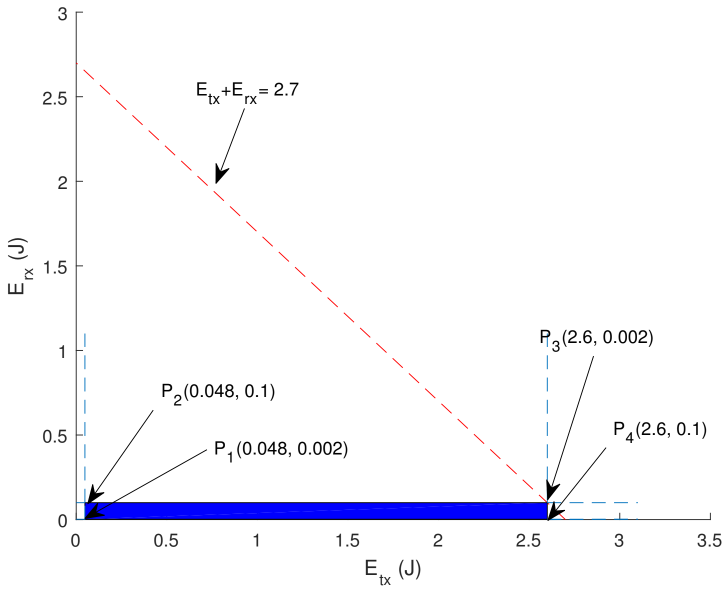
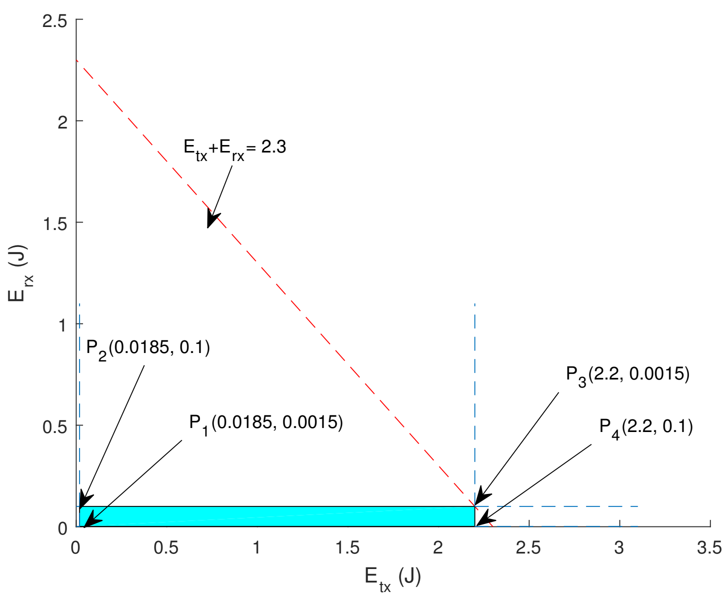


Figure 7 MA-ATGOR: energy consumption (see online version for colours)



- *Graphical analysis for ATGOR:* Consider a scenario, where energy consumption of transmission and reception (with units of joule) can be represented as follows:

$0.05 \leq E_{tx} + E_{rx} \leq 2.7$, $0.002 \leq E_{rx} \leq 0.1$ and $0.048 \leq E_{tx} \leq 2.6$. Figure 6 shows that all the solutions in feasible region are acceptable. Now, each vertex of the bounded region is tested as: P_1: (0.048, 0.002), P_2: (0.048, 0.1), P_3: (2.6, 0.002) and P_4: (2.6, 0.1).

Hence, it is evident that all the solutions in the bounded region are valid. Any value of the energy consumption lying within this region is feasible for the better network performance. A point where the energy consumption value is minimum, is an optimal solution.

- *Graphical analysis of MA-ATGOR:* Similar to ATGOR, we perform the graphical analysis for MA-ATGOR by following bounds: $0.02 \leq E_{tx} + E_{rx} \leq 2.3$, $0.0015 \leq E_{rx} \leq 0.1$ and $0.0185 \leq E_{tx} \leq 2.2$. Figure 7 shows the feasible region for energy consumption, which consists of all the feasible solutions. Now, we test every vertex depicted in Figure 7 at: P_1: (0.0185, 0.0015), P_2: (0.0185, 0.1), P_3: (2.2, 0.0015) and P_4: (2.2, 0.1). Therefore, it can be concluded that all solutions calculated by MA-ATGOR are valid.
- *PDR maximisation:* We have a scenario in which we have 25 sinks and maximum number of sensor nodes are 450. Our objective is to minimise the consumption of energy with maximised PDR.

$$\max(PDR), \tag{9a}$$

the constraints are given as,

$$Pkt_{tx} \geq 0, \tag{9b}$$

$$Pkt_{rx} \geq 0, \tag{9c}$$

$$PDR \geq 0, \tag{9d}$$

$$D_{communication} \leq R_{max}. \tag{9e}$$

These are non-negative constraints for the number of packets transmitted and received.

- *Graphical analysis for ATGOR:* The number of packets successfully received at the sink can be represented against the node density of network. The PDR of the network at some specific node densities 150, 200, and 450, are 0.28, 0.65 and 0.89, respectively. Figure 8 shows the bounded region for PDR of the network at different node densities. These points are within the feasible region and provide feasible solutions for the network. The optimal solution is at the point where PDR of the network is maximum.
- *Graphical analysis for MA-ATGOR:* Similar to the above graphical methods, we perform the graphical analysis of PDR for MA-ATGOR at node densities 150, 200 and 450, the obtained values are 0.33, 0.52, and 0.94, respectively. Thus, it is proved that above calculated values are within the feasible region, seen from Figure 9. The optimal solution for MA-ATGOR is the feasible solution with maximum value.

Figure 8 ATGOR: PDR (see online version for colours)

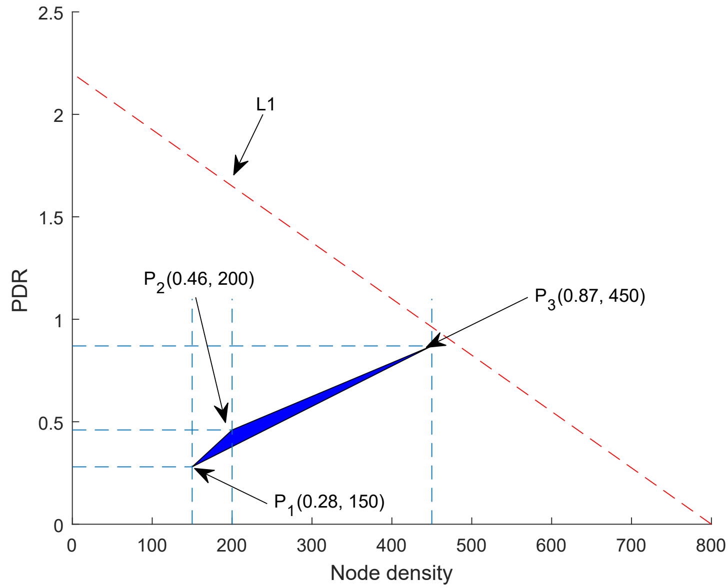
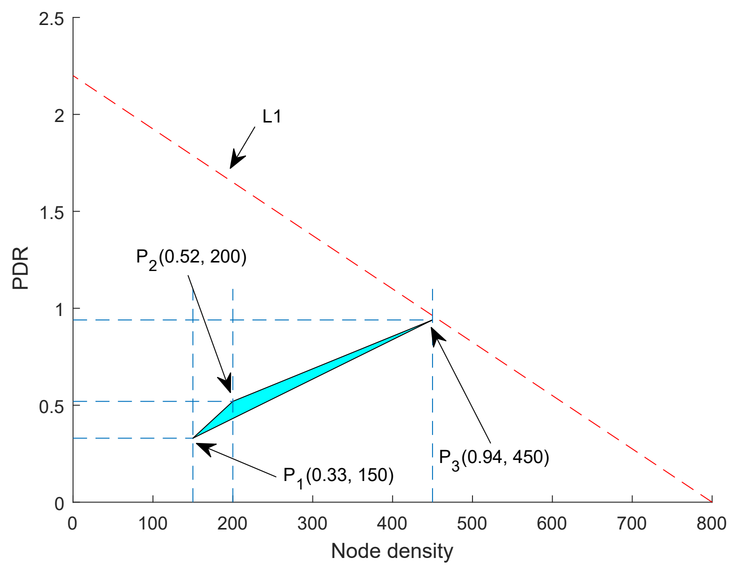


Figure 9 MA-ATGOR: PDR (see online version for colours)



6 Simulation results and discussion

To verify the efficiency of ATGOR in terms of void hole avoidance and maximised PDR, it is compared with a depth adjustment technique named as GEDAR.

6.1 Parameter settings

For conducting simulations, 150–450 sensor nodes and 25 sinks are deployed in 1,500 m × 1,500 m × 1,500 m region. 20% of deployed nodes are anchored nodes. The initial energy of each node is 10 W. 150 m, 200 m, 250 m, 300 m, 350 m, 400 m and 450 m are different transmission ranges for sensor nodes. The size of data being sent in the network is 150. The amount of energy consumed in transmission of data and reception of data are 2 W and 0.1 W, respectively. Moreover, the energy for idle state is 10 mW.

6.2 Performance metrics

The proposed protocol is evaluated by considering:

1 PDR is the ratio of number of packets received successfully at sink to the packets transmitted from the source nodes

2 fraction of void nodes, which represents the ratio of average void nodes to the total number of nodes and the efficiency of the proposed transmission scheme

3 energy consumption per packet of each node is computed through the energy depletion per received packet from each node and it is measured in joules.

6.3 Results and analysis

6.3.1 Sink deployment and sink mobility analysis

In this section, the proposed schemes is compared with GEDAR. For simulations, 150–450 sensor nodes are deployed over a (1,500 × 1,500 × 1,500) m^3 region. V and V' has a value of 8; each region has dimensions of (750 × 750 × 750) m^3 and the transmission range of sensor nodes is 250 m. S and S' possess the values 16 and 48, respectively. The energy consumption values for transmission, reception, idle state, depth adjustment, packet size and data rate are taken from Coutinho et al. (2015).

Figure 10 shows the influence of node density on the network's energy consumption. This figure shows that energy consumption decreases with high node density. Moreover, GEDAR has high consumption of energy due to depth adjustment. For low densities, the energy consumption is high because more sensor nodes perform depth adjustment in the absence of forwarder nodes. GDSD and GDSD-AM have low energy consumption due to the distributed sink deployment.

The proposed deployment results in short communication distances because less transmission power is needed to transmit the data packet towards the destination. Figure 11 shows the PDR of the network. GDSD-AM has the highest PDR at different node densities because the displacement of sensor nodes decreases with adaptive mobility of sinks unlike to GDSD, GEDAR-16 and GEDAR-48. The improved PDR is a result of the availability of sink nodes at shorter distances.

The energy constrained nodes do not perform the depth adjustment. Thus, the energy consumed for depth adjustment is preserved in GDSD-AM. The fraction of void nodes is shown in Figure 12. The proposed schemes have less fraction of void nodes due to the geospatial division of nodes with uniform distributed sink deployment. In GDSD, the centered sink deployment leads all the sensor nodes to transmit the sensed data at the optimal distances. While, in GDSD-AM, the sinks move adaptively to the new positions to recover the packet. On the other hand, a packet is transmitted at longer distances to reach the surface sinks in the GEDAR, so the fraction of voids is high. Hence, the proposed strategies help in improving the overall network performance with minimum energy cost among the compared scenarios.

Figure 10 Energy consumption GEDAR, G-GDSD and G-GDSD-AM (see online version for colours)

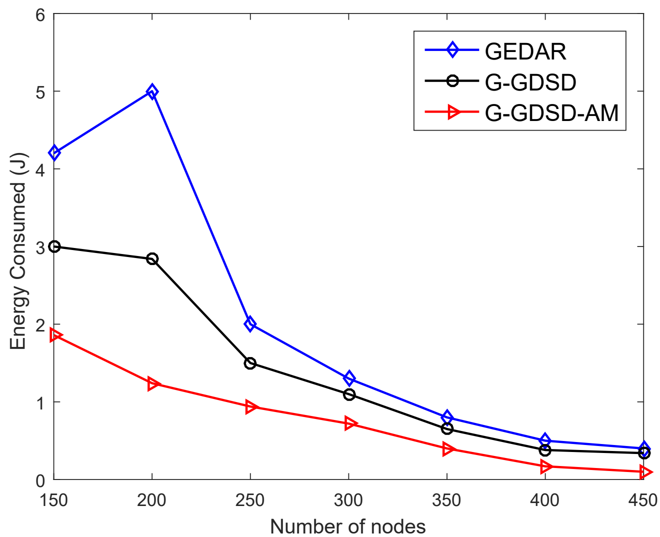


Figure 11 PDR at sink nodes (see online version for colours)

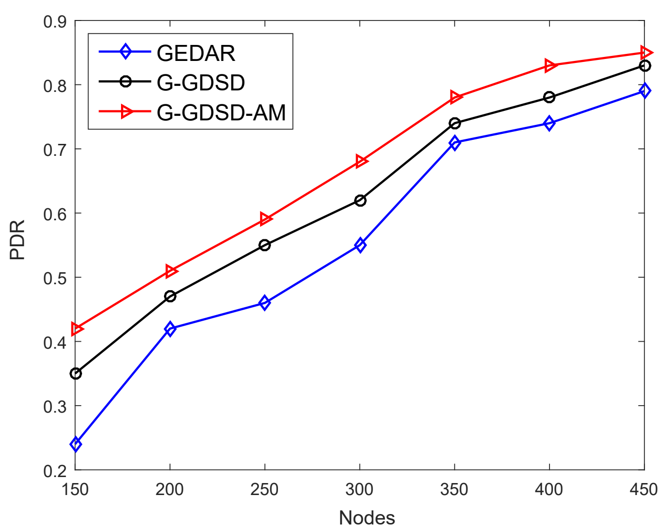


Figure 12 Fraction of void nodes via GEDAR, G-GDSD and G-GDSD-AM (see online version for colours)

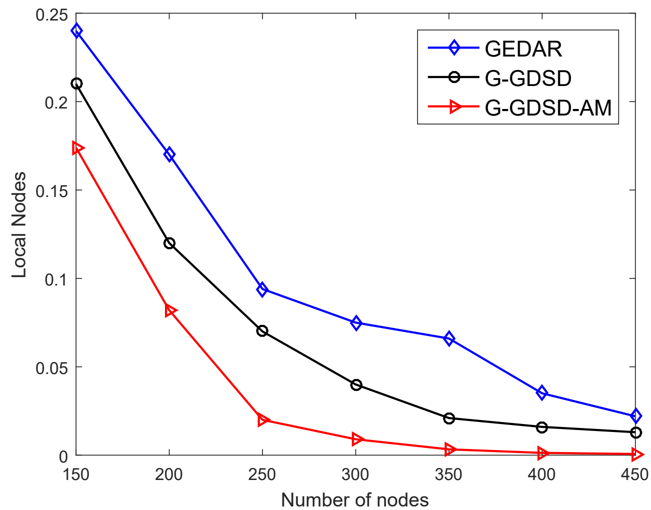
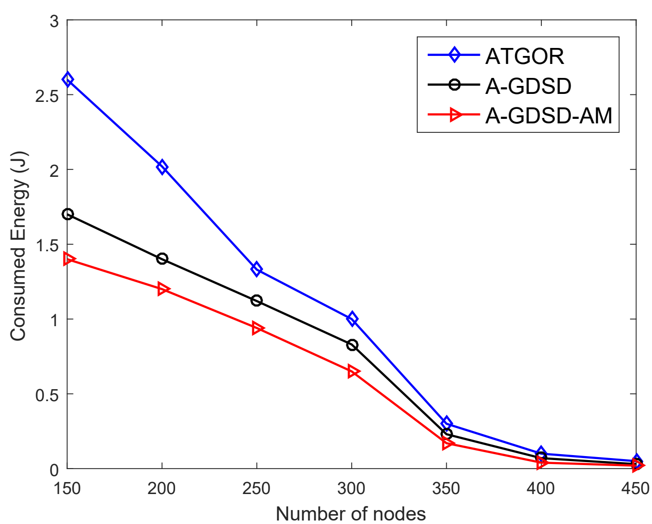


Figure 13 Energy consumption ATGOR, A-GDSD and AGDSD-AM (see online version for colours)



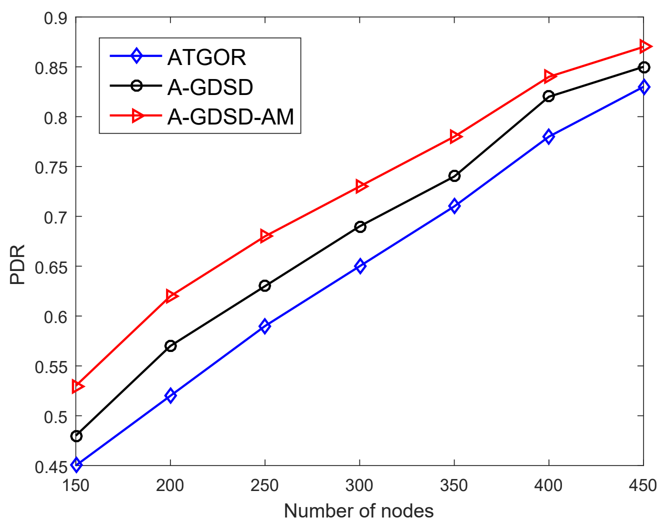
6.3.2 Analysis of the proposed schemes with sink mobility

For better understanding, we divide our simulation analysis of the proposed schemes into two scenarios as follows:

Scenario 1

Figure 13 shows that the void nodes reduce as the density of nodes keeps on increasing. The reason is that the sensor nodes adapt transmission range. A trade-off is found between finding a reliable forwarder node and energy consumption. When any forwarder node is not found by sensor nodes, then they adjust their depth. In this depth adjust, a lot of energy is consumed. However, at the cost of this extra energy, the sensor nodes can find reliable forwarder nodes. Moreover in ATGOR, the sensor nodes adjust their transmission range adaptively to find the nearest sink and overcome void holes. Therefore, our proposed strategy helps in avoiding void holes. Furthermore, we present the ATGOR scheme with the attributes of GDSD and GDSD-AM. On the other hand, Figure 14 shows that our proposed strategy has improved PDR. The reason is that PDR improves with increased node density. Because, when the number of nodes in a particular region is increased, there would be less chance of existing void holes in the network. Moreover, when there are many nodes in a particular area then there are great chances of finding reliable neighbour nodes, which results in enhanced PDR. Additionally, by adjusting the transmission range, more sinks are found in shorter, which also results in improved PDR. The energy consumed in sending a packet from each node is shown in Figure 15. Energy consumption reduces with increased node density because a lot of neighbours are available for packet forwarding.

Figure 14 Packets received at the sinks with different transmission level (see online version for colours)



MA-ATGOR predicts the node mobility pattern based on the neighbours movement, which results in improved network performance. MA-ATGOR is further tested with the sink deployment and mobility schemes. Figures 16, 17 and 18 show the fraction of void nodes, the PDR and the energy consumption, respectively. It can be seen that MA-ATGOR has less number of void nodes than the ATGOR. The sink deployment and sink mobility schemes help in improving the network performance. The MA-ATGOR reduces the communication cost because it minimises the consumption of energy, which is due to the location prediction mechanism. In MA-ATGOR, high number of nodes results in decreased consumption of energy, which further improves location coverage.

The MA-ATGOR overcomes the packet drop problem by predicting the locations of the sensor nodes. With the increase of node density, the MA-ATGOR shows higher

PDR. The M-GDSD and M-GDSD-AM prove to be efficient in minimising the energy consumption and fraction of void nodes. Moreover, the packets received at the sinks are also increased.

Figure 15 Fraction of void nodes via ATGOR, A-GDSD and A-GDSD-AM (see online version for colours)

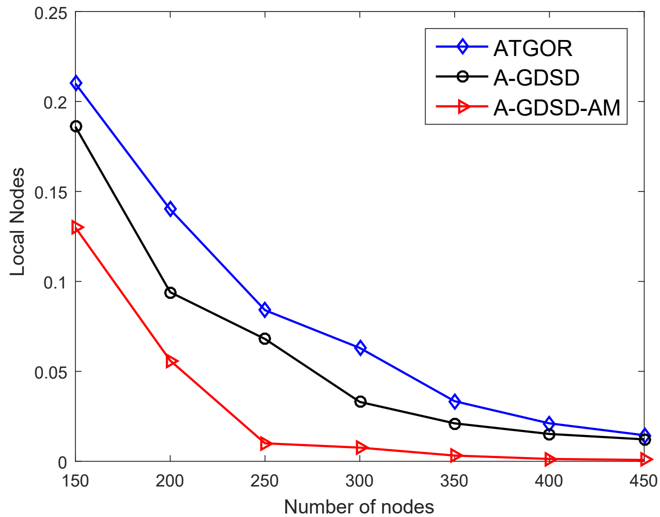
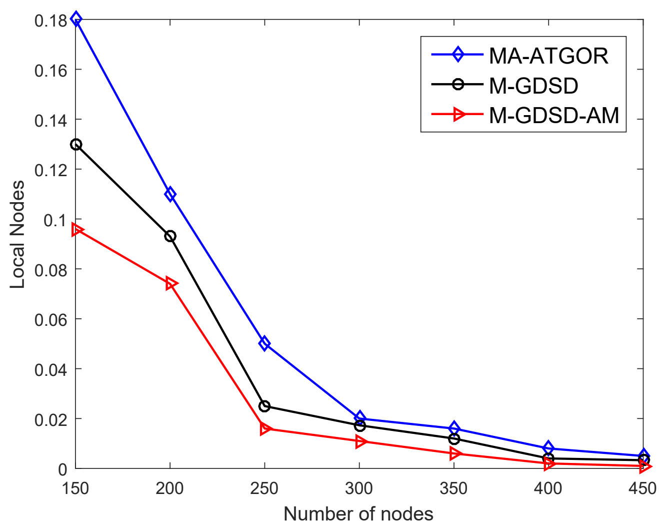


Figure 16 Energy consumption MA-ATGOR, M-GDSD and M-GDSD-AM (see online version for colours)



Scenario 2

In this scenario, we analyse the impact of transmission range on the network performance. The impact of different transmission level on PDR are shown in Figure 19. 150 m, 200 m, 250 m, 300 m, 350 m, 400 m and 450 m are transmission ranges, denoted by T_1, T_2, T_3, T_4, T_5, T_6 and T_7, respectively.

Figure 17 Packets received at the sinks using MA-ATGOR, M-GDSD and M-GDSD-AM (see online version for colours)

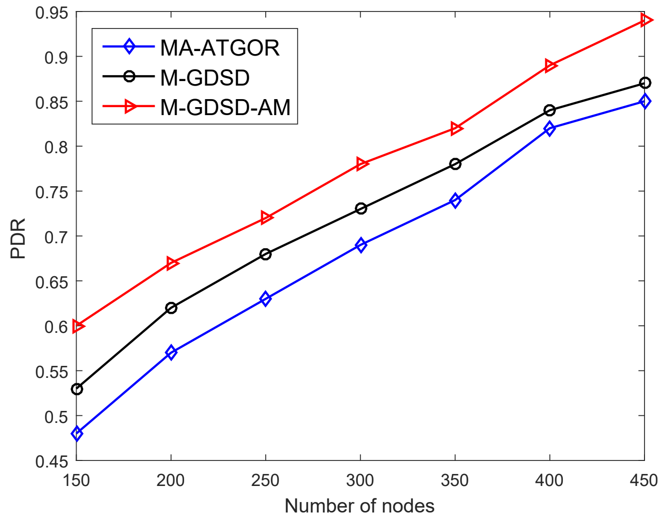
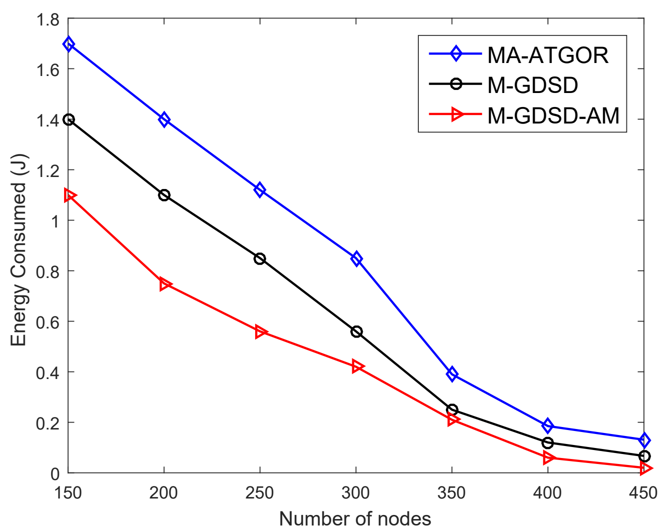


Figure 18 Fraction of void nodes via MA-ATGOR, M-GDSD and M-GDSD-AM (see online version for colours)



The transmission levels are chosen by considering the suitable distances because too long transmission range deteriorates the network efficiency. The transmission range increases, which results in enhanced PDR. Hence, it is concluded that the packets sent from source are reached to destination successfully.

Figure 20 shows the number of nodes at various transmission level. The increase in the transmission range has positive impact on reducing the void nodes. As the transmission level increases, the number of void nodes decreases. The issue of void area us solved by high transmission level. Figure 21 shows the consumption of energy in sending each packet. High transmission levels lead to greater transmission distances resulting in greater energy consumption. At high node densities, the energy consumption is less because high node density requires less void areas to overcome.

Figure 19 Packets received at the sinks (see online version for colours)

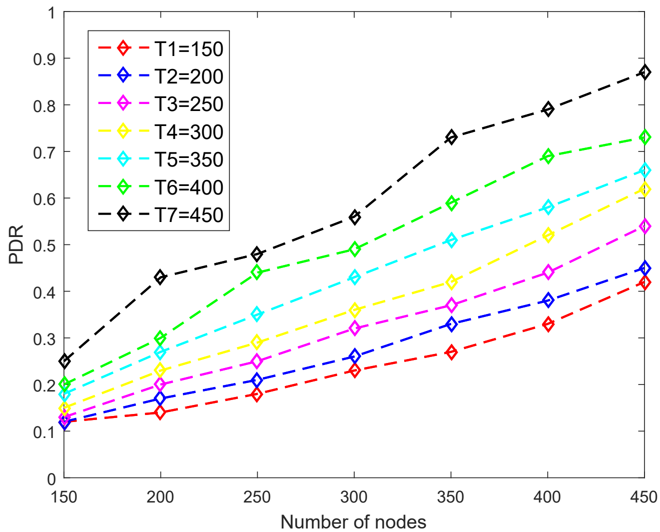
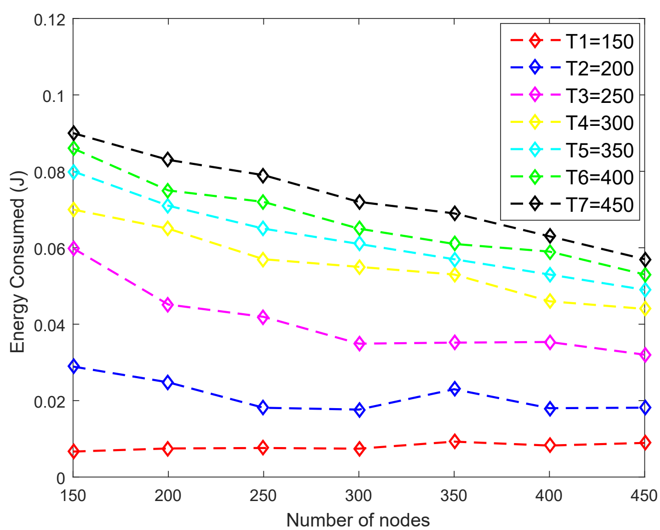


Figure 20 Energy consumption per packet (see online version for colours



Similarly, we perform the simulation analysis at various transmission ranges for MA-ATGOR. Figure 22 shows less number of void nodes than ATGOR for same transmission levels. The MA-ATGOR performs better localisation of sensor nodes, resulting in improved network performance. It can be seen from Figure 23 that the MA-ATGOR has minimum energy consumption than the ATGOR. When MA-ATGOR encounters less number of void nodes, it results in less packet drop and minimum re-transmissions. With mobility prediction of neighbouring sensor nodes, the PDR of the network is increased as shown in Figure 24.

Figure 21 Fraction of void nodes with different transmission for ATGOR (see online version for colours)

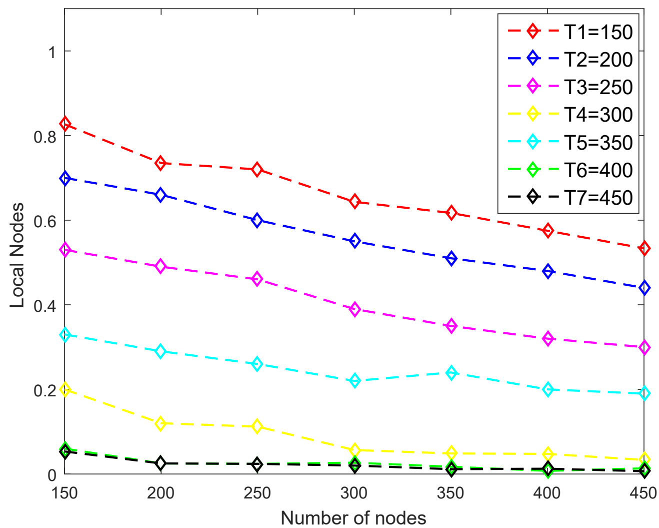


Figure 22 Fraction of void nodes with different transmission for MA-ATGOR (see online version for colours)

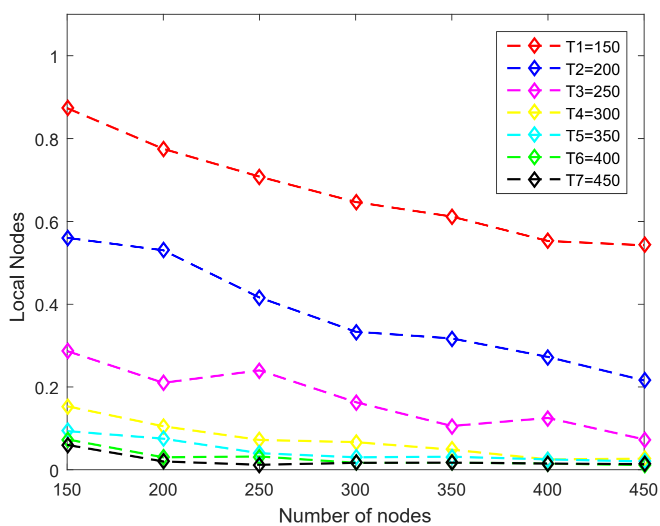


Figure 23 Energy consumption per message (see online version for colours)

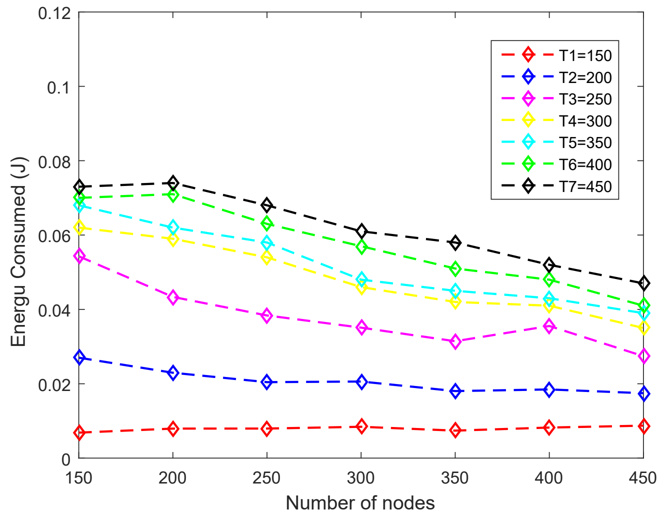
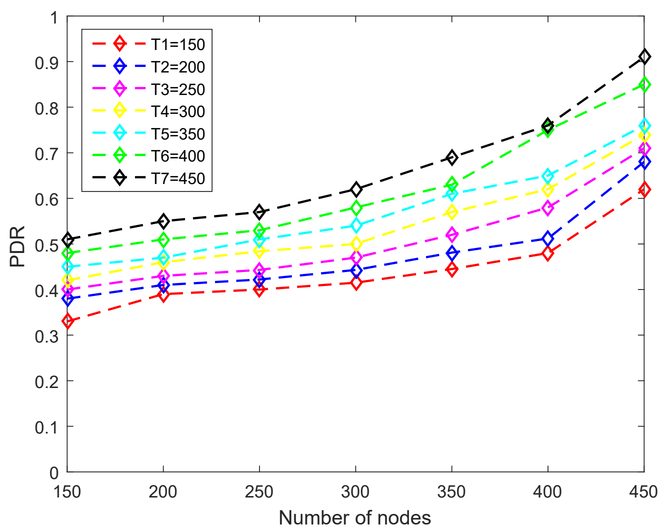


Figure 24 Packet delivery ratio (see online version for colours)



7 Conclusions

In this paper, we have kept in mind the harsh environment of UWSN and proposed two routing mechanisms that continuously report nodes' activities towards the sinks in the underwater network. Before performing routing activity, we initially divide the 3D network field into small logical cubes for efficient data transmission. We have learned that the presence of multiple sinks can efficiently increases the delivery of data packets. For this purpose, we have deployed multiple sinks in our proposed schemes. Moreover, it is also concluded that due to adjustment of depth, the consumption of energy is high. Therefore, the ATGOR performs limited depth adjustment of nodes. In ATGOR, distribution of neighbours is considered for the selection of forwarder node. In an empty adjacent cube, void regions are avoided by using ATGOR, because it has ability to adjust its communication range. In this way, it selects most reliable node within its new adjusted communication range. To further circumvent the effect of void nodes and depth adjustment, the proposed MA-ATGOR performs the mobility prediction for neighbouring nodes. The MA-ATGOR gives precise locations of the neighbouring nodes, which reduces energy consumption and provides better network coverage. To find out how we can maximise and minimise our objective function, we have considered linear optimisation for the evaluation of our proposed model. It shows that the adaptive transmission power, the geo-opportunistic routing and mobility prediction results in improved PDR.

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