Network lifetime-aware data collection in Underwater Sensor Networks for delay-tolerant applications

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Abstract. Development of energy-efficient data collection and routing schemes for Underwater Wireless Sensor Networks (UWSNs) is a challenging issue due to the peculiarities of the underlying physical layer technology. Since the recharging or replacement of sensor nodes is almost impossible after deployment, the critical issue of network lifetime maximization must be considered right from the beginning of designing the routing schemes. We propose a mobile sink (MS)-based data collection scheme that can extend network lifetime, taking into account power-constrained sensor nodes, partitioned networks with geographically distant data collection points and periodic monitoring applications with delay-tolerance. Lifetime extension is achieved by mitigating the ‘*sink neighbourhood problem*’ and by deferring the data transmissions until the MS is at the most favourable location for data transfer. Unlike the models available for terrestrial WSNs, we consider non-zero travel time of the MS between data collection points, thus making our model more realistic for UWSNs, both connected and partitioned. The performance of the proposed mobility-assisted data collection scheme is thoroughly investigated using both analytical and simulation models. The analytical results are compared to those of existing models to assess their effectiveness and to investigate the trade-offs. Results show that, with a network size of 60 nodes, the network lifetime achieved by the proposed model is 188% higher than that of static sink model and 91% higher than that of mobile sink model (MSM). The proposed maximum lifetime routing scheme is implemented in the network simulation platform OMNET++, for validating the analytical results as well as for evaluating other performance metrics that are not tractable via analytical methods. Both analytical and simulation results demonstrate the superiority of the proposed model in capturing realistic network conditions and providing useful performance indicators prior to network deployment.

Keywords. Underwater Sensor Networks; mobile sink; lifetime maximization; delay-tolerant application; non-zero mobile sink travel time; optimal routing; flow-based routing.

1. Introduction

The unique characteristics of acoustic communication such as high and variable propagation delay, limited and distance-dependent bandwidth, large error probability and high energy consumption make the development of efficient data collection and routing schemes a challenging issue for Underwater Wireless Sensor Networks (UWSNs) [1, 2]. The routing schemes developed for terrestrial sensor networks cannot be implemented as such in UWSNs. Proactive or table-driven routing protocols incur large signalling overhead for route establishment, whereas reactive protocols cause high latency. Geographical routing protocols are promising, but the requirement of location information in the underwater environment is quite demanding.

Energy efficiency is an important issue in the design of WSNs, while it is quite critical in the case of UWSNs. Since the sensors are deployed in large quantities in hostile/inaccessible environments, it is not feasible to recharge or replace the sensor batteries after deployment. Efficient management of the finite amount of stored battery power is quite important in maximizing the lifetime and usefulness of the UWSN. With static sink for data collection, the one-hop neighbours of the sink will be overloaded with relaying data from other nodes and this increased relaying overhead will make them deplete their energy faster than other nodes. This problem, called the ‘*sink neighbourhood problem*’ or ‘*hotspot problem*’, results in the partitioning of the network. Thus, due to the premature disconnection of the sink, the usefulness of the network is lost, even though majority of nodes in the network are still operational.

To mitigate the ‘*sink neighbourhood problem*’ and to fill connectivity gaps in the network, one strategy is to make

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use of mobility. Controlled mobility itself can be used in three ways in WSNs: (i) the sink itself moves among the sensor nodes to collect data, (ii) mobile relays used for data collection and subsequent delivery to static sink and finally (iii) the sensor nodes are mobile [3]. The first two approaches are more promising for improved energy efficiency and longer network lifetime, since sink and relays are considered to be resource-unconstrained. In mobile sink (MS)-based data collection, the sink moves between and stops at a fixed number of *sojourn points* in the network and the static sensor nodes transfer their data using ad-hoc multi-hop path. Data can be collected by the MS in real-time or in non-real-time. In real-time data collection, data generated at the sensors are immediately transferred to the MS at its current location. In non-real-time approach, the generated data are buffered at the sensors to be transferred to the MS at the most favourable sojourn point for extending the network lifetime. The real-time schemes are suitable for delay-sensitive applications and the non-real-time schemes for delay-tolerant applications. We consider network lifetime maximization with delay-tolerant applications.

There exist different definitions for network lifetime [4]. It can be the time until: (i) the first sensor node is drained of its energy; (ii) the first cluster head (CH) is drained of its energy; (iii) there is a certain fraction of surviving nodes; (iv) the sensing area is covered by at least k nodes; (v) the coverage drops below a predefined threshold and (vi) connectivity is lost; etc. Irrespective of the definition used, an empirical formula for determining average lifetime of WSNs in a general setting is available [5]. Assuming a WSN with total non-rechargeable initial energy E_i and no idle time power consumption, the average network lifetime $\mathbb{E}[\mathcal{Q}]$ is given by [5]

$$\mathbb{E}[\mathcal{Q}] = \frac{E_i - \mathbb{E}[E_w]}{\lambda \mathbb{E}[E_{comm}]} \quad (1)$$

where $\mathbb{E}[E_w]$ is the expected wasted energy (i.e., the total unused energy in the network when it dies); λ is the average sensor reporting rate and $\mathbb{E}[E_{comm}]$ is the expected communication energy for each reporting. Thus, the average network lifetime can be enhanced by employing techniques that can reduce the average communication energy $\mathbb{E}[E_{comm}]$ as well as the average wasted energy $\mathbb{E}[E_w]$. Hence, a lifetime-maximizing routing scheme should aim at not only reducing but also balancing the energy consumption among the nodes.

Mobility-assisted schemes for data collection achieve considerable enhancement in network lifetime by reducing and balancing the energy consumption among the nodes in a network [6]. While relaying overhead and hotspot is completely eliminated in MS-based single-hop data collection, it is geographically distributed among sensors in MS-based multi-hop data collection. Thus the achievable lifetime is maximum in the former case; however, the data

collection latency will be too high since the MS has to visit each node for data upload. Hence, single-hop data collection is appropriate for applications like recording of data for later scientific analysis. For applications with specific delay tolerance level D , we need multi-hop MS-based data collection schemes. Examples of such applications are continuous monitoring and periodic collection of data like pollution level or seismic activities, where the significance of the data is lost if delivered after the pre-specified deadline. In this paper we restrict our study to MS-based data collection with ad hoc multi-hop communication between the randomly deployed sensors and the MS moving around the sensing area and sojourning at certain locations (sojourn points) for certain times.

There exists the possibility of controlling the extent of multi-hop routing that is feasible for the network conditions and application parameters [7]. The choice of the extent of multi-hop routing depends on the deployment constraints of the sensing area, energy constraints of the static sensors, location constraints of the MS and the delay constraints of the underlying application.

Unlike the MS-based schemes available in the literature for terrestrial WSNs, we consider periodic data collection set-up where the MS makes a number of cycles in the deployment area, the underlying application can tolerate delayed information delivery and most importantly, the travel times of the MS between sojourn locations are not negligible. Network lifetime maximization problem for this setting involves two joint problems:

- scheduling problem to determine the duration for which the MS sojourns at each stop location,
- routing problem to identify the best path to forward sensed data from the sensor to the MS at the most favourable stop point.

It also involves the determination of the number of cycles that the MS travels around the network within the network lifetime such that the delay condition is satisfied.

We model the problem as a constrained optimization problem, considering the peculiarities of the underwater environment, resource limitations and application requirements. In particular, we formulate an optimization problem that maximizes the lifetime of the UWSN, subject to node energy constraints, node buffer space limitations, flow conservation constraints, channel bandwidth limitations, MS travel time constraints and application specific delay-bound restrictions.

We assume that the control station located at the ocean surface gathers necessary information, solves the optimization problem and provides the MS with the scheduling and routing information for lifetime maximization. Since the MS is assumed to be resource-unconstrained, it can transfer this routing information to the static nodes. Each node selects the next hop using the optimal routing information available, and tunes the transmission power according to transmission distance.

The major contributions of this paper include the following: (i) proposing a realistic MS-based framework, with non-zero MS travel time, for data collection in UWSNs; (ii) solving the network lifetime maximization problem using standard tools; (iii) investigating the performance metrics of the proposed framework; (iv) identifying the trade-offs in lifetime and latency; (v) comparing the proposed framework to those available in the literature; (vi) developing an energy-efficient routing protocol for UWSNs and (vii) validating the analytical results using a simulation model developed in OMNET++ [8]. The rest of the paper is organized as follows. A brief review of the related work is given in section 2. The system model, proposed framework and other available frameworks in the literature for comparison are presented in section 3. Details of performance evaluation are discussed in section 4. Section 5 discusses the analytical and simulation results and the paper is concluded in section 6.

2. Related work

The main research challenges in the area of UWSNs are identified in [1] and a detailed review and comparison of different routing techniques are given in [9]. Several routing protocols have been developed specifically for UWSNs, taking into consideration the characteristic features of the underwater environment. Vector-based forwarding (VBF) is a typical geographical routing protocol [10] and Hop-by-hop Vector-based forwarding (HH-VBF) [11] is its more energy-efficient version. Depth-based forwarding (DBR), Focussed Beam Routing (FBR), Q-learning-based energy-efficient and lifetime-aware protocol (QELAR), Minimum Cost Clustering Protocol (MCCP), Distributed Underwater Clustering Scheme (DUCS) and AUV-aided underwater routing protocol (AURP) are typical examples of UWSN routing protocols [9]. Distributed routing algorithms for delay-sensitive and delay-insensitive applications are proposed in [12]. Energy analysis of routing protocols for UWSNs is presented in [13] and energy-efficient routing schemes for UWSNs have been discussed in [14].

Shah *et al* [15] have presented a three-tier architecture based on random mobility of forwarding agents called MULEs to address the problem of energy-efficient data collection and to improve data delivery ratio in a sparse terrestrial sensor network. Somasundara *et al* [16] have discussed the use of controllably mobile elements to reduce and balance the sensors' energy consumption and to increase useful network lifetime in delay-tolerant networks and sparsely connected networks. The controlled use of relay nodes for data collection has been investigated in [6, 17] and [18].

Works on mobile-relay-based data collection showed that moving the sink would be more promising for achieving better trade-off between energy efficiency and

data collection latency. Gandham *et al* [19] have proposed to deploy multiple mobile base stations to prolong lifetime of sensor network. Chang and Tassiulas [20] have proposed that lifetime can be maximized if the traffic is routed such that the energy consumption is balanced among the nodes in proportion to their energy reserves, instead of routing to minimize the absolute energy consumption. Two algorithms, a flow redirection (FR) algorithm and Maximum Residual Energy Path (MREP) routing algorithm, to select the routes and the corresponding power levels to maximize the lifetime, were also proposed. Optimum placement of mobile base stations and energy-aware routing to provide increased network lifetime in WSNs were investigated in [21].

In [22], the authors have exploited the mobility of the sink to address the problem of maximizing the lifetime in a terrestrial sensor network. Sink moves along a grid from one node to the other and during its sojourn at a node, sensors communicate with it. The sink travel time is assumed to be negligible and network lifetime is calculated as the sum of sojourn times of the sink at all visited nodes. In [23], no assumption is made about any fixed arrangements of nodes like grid or fixed protocol like the shortest path. The authors have combined the model presented in [22] and the linear programming formulation for maximum lifetime routing presented in [20] to present another solution for lifetime maximization. Lifetime maximization is formulated as a joint optimization of scheduling problem that determines the sink sojourn times at the given locations and routing problem to deliver the sensed data to the current position of the sink in an energy-efficient way. Here also, the sink travel time is neglected.

Basagni *et al* [3] have proposed an analytical model and distributed protocols for determining the routes of the MS as a sequence of sites and the sojourn times at these sites such that the network lifetime is maximized. They have considered the cost of moving the sink from one site to another and proposed a Mixed Integer Linear Programming (MILP) model for lifetime maximization. Luo and Hubaux [24] have formulated lifetime maximization as a min-max problem. By considering sink mobility and routing jointly, they have developed a primal-dual algorithm to solve the lifetime maximization problem, but they too have assumed negligible travelling time between two sink positions.

An interesting extension of the model presented in [23] is proposed by Yun and Xia [25], where all the sensors do not communicate with the sink at all sink locations and data are buffered at the sensors until the sink reaches the most favourable or beneficial location (in terms of lifetime maximization). This model, called delay-tolerant mobile sink model (DTMSM), is useful for lifetime maximization in applications having a specified delay tolerance level D . However, they too have ignored the non-zero travel time of the sink.

The assumption of instantaneous jumps of the sink from one sojourn location to another is not realistic, especially

for UWSNs, where the sink locations have geographical constraints and the network can be easily partitioned due to harsh environments. As mentioned in [25], incorporation of non-zero travel time of the sink in lifetime maximization models, though not simple, can lead to interesting conclusions. The first paper in which this assumption is relaxed is that by Keskin *et al* [26]. They have developed two analytical models that employ constant sink velocity and realistic positive values of sink travel times. Also, the data accumulated during the sink travel time are taken into account, not ignored as in the previous models. However, it assumes the shortest path for routing, which is not optimal.

All the lifetime maximization models mentioned so far provide only centralized solutions, which are difficult to implement in WSNs, leave aside UWSNs. Though these models provide the maximum achievable lifetimes under the given conditions, developing practical distributed routing protocols considering all the underlying physical and MAC layer constraints, and achieving them is a difficult task, especially in the resource-constrained UWSNs. In this paper, we investigate network lifetime maximization in UWSNs using MS with non-zero travel time, considering all the challenging features of the underwater environment, and develop an optimal routing protocol to prolong the network lifetime in UWSNs with possibly disconnected component networks.

3. Proposed framework

3.1 System model

The system under consideration (figure 1) is a static two-dimensional UWSN for ocean bottom monitoring, used for delay-tolerant applications with a pre-specified delay

Figure 1. System model.

tolerance level D . Examples of such applications are continuous monitoring and periodic collection of data like pollution level or seismic activities, where the significance of the data is lost if delivered after the pre-specified deadline. The network is assumed to have a number of non-overlapping clusters, some of which may be partitioned from the rest of the network due to sparse deployment, harsh environment or resource limitations. A large number of energy-constrained static sensor nodes are assumed to be randomly and uniformly distributed within the clusters. Once deployed, the nodes rarely move in the bottom of the ocean [1, 27]. Static nodes are homogeneous and are capable of varying the transmission power according to the transmission range. The generated data are buffered at the sensors, waiting for its turn to be transferred to the MS, when the MS is at a sojourn location within the cluster.

The MS acts as a mobile CH, moving between the centre locations of the clusters and capable of collecting data from the sensors within the cluster using ad hoc multi-path communication. The MS is expected to finish one round of visit to all the sojourn locations within the delay tolerance level D . The cyclic motion of the MS is repeated until any one node in the network dies due to energy depletion. The MS is considered resource-rich and it can stop and collect data from the set of pre-specified sojourn locations. When it reaches a new visit location, it floods a packet to notify the neighbouring nodes of its presence and current location.

We include parameters and constraints that model realistic conditions of a network deployed in a highly constrained underwater environment. Depending on MS velocity and distance between the sojourn locations, MS takes non-zero travel time to move between the stop points. The earlier models with zero travel time assumption had neglected the packets generated during the MS travel times. We also consider the impact of finite buffer space and finite channel bandwidth on the performance.

Data generated at a sensor are transferred to the MS through the optimal multi-hop path if the MS is located at the centre of the cluster to which it belongs, and otherwise buffered in the sensor buffer. The proposed optimal flow-based routing scheme is the one in which each node probabilistically selects the next hop node where the routing probability for each neighbour is determined based on the optimal data transfer rates obtained by solving the optimization problem.

3.2 Network lifetime maximization

To facilitate better understanding of the proposed model and its merits over the existing lifetime maximization models, we present formulation of optimization problems for four models: the first three are from the literature of terrestrial sensor networks and the fourth one is the proposed model. In all the schemes, the sensor nodes are assumed to be uniformly and randomly distributed in the

deployment area and every node is assumed to generate data at a constant rate λ . The sensor nodes are assumed to have the same transmission range, but tunable transmission power that can be adjusted according to the distance over which data are to be transmitted. In other words, the energy expenditure for a data unit transmitted by node i depends on the choice of next hop node and it is not necessarily the same for all nodes. The total energy consumption per unit time at node i is the sum of the transmission energy consumption and received energy consumption per unit time. The sink is assumed to be power-unconstrained and not co-located with the static sensors. The neighbour set of node i may include the sink also.

We use the MILP model to determine the MS sojourn times at the visit locations, data transfer rates between the sensor nodes and between sensor nodes and MS, and the optimum number of MS cycles such that the network lifetime is maximized. The model does not assume any specific arrangement of nodes (like a grid pattern) or any specific routing protocol (like the shortest path). The variables used in the problem formulation are given in table 1.

3.2a Static sink model with sink located at the centre (SSM): It is assumed that the sink is located at the centre of the deployment area [28] and remains stationary during the network operation. As soon as data get generated at the sensors, they are transmitted towards the sink using ad-hoc multi-hop

path. To determine the flow rates $\{q_{ij}\}$ that maximize lifetime Z under the energy conservation and flow conservation conditions, the optimization problem is formulated as follows:

$$\text{maximize } Z \quad \text{subject to} \quad (2)$$

$$\left(\sum_{j \in S_i} e_{ij}^T q_{ij} + \sum_{j: i \in S_j} \gamma q_{ji} \right) Z \leq E_i, \quad i \in N \quad (3)$$

$$\sum_{j \in S_i} q_{ij} - \sum_{j: i \in S_j} q_{ji} = \lambda, \quad i \in N \quad (4)$$

$$Z \geq 0, \quad q_{ij} \geq 0, \quad i, j \in N. \quad (5)$$

The energy conservation constraint (3) stipulates that the total energy consumption for communication over the lifetime at each node should not exceed the initial battery energy. The flow conservation condition (4) states that, at each node, the sum of rate of incoming flow of packets and its own generation rate should be the same as the rate of outgoing flow of packets.

Though the SSM with optimal routing is better than fixed path routing as far as lifetime in a stationary sink network is concerned, it still suffers the ‘sink neighbourhood problem’, which leads to wastage of stored energy and premature death of sensor nodes close to the static sink. However, the concepts of optimal routing and lifetime maximization using constrained optimization are quite useful for developing improved analytical models and flow-based routing protocols.

3.2b Mobile sink model (MSM): This model [23] exploits sink mobility to balance energy depletion among sensors, by distributing the role of bottleneck sensors over time. The static sensors are randomly distributed in the network and the MS can be found at different sojourn locations (not necessarily co-located with the sensors) during network operation. The travelling time of the MS from one location to another is neglected. All sensors transfer data to the MS at all MS locations using ad-hoc multi-hop paths.

The network lifetime is the sum of sojourn times at all possible MS stop locations, which is limited by the fact that the total energy consumption for all MS locations cannot exceed the sensor’s initial energy. To find the optimal solutions for both scheduling and routing problems by determining the values of sink sojourn times $\{t_l\}$ and data transfer rates $\{q_{ij}^l\}$ with MS at all possible sojourn points, under node energy constraints for each sensor and flow conservation constraints for each location, the optimization problem is formulated as follows:

$$\text{maximize } Z = \sum_{l \in L} t_l \quad \text{subject to} \quad (6)$$

$$\sum_{l \in L} t_l \left(\sum_{j \in S_i^l} e_{ij}^T q_{ij}^l + \sum_{j: i \in S_j^l} \gamma q_{ji}^l \right) \leq E_i, \quad i \in N \quad (7)$$

Table 1. Variables used in mathematical formulation.

N	Set of static sensor nodes in the network
L	Set of locations in the network at which the MS may sojourn
t_l	Total MS sojourn time at position l in the network lifetime
e_{ij}^T	Energy required to transmit a packet from node i to j
γ	Energy required to receive a packet
q_{ij}	Packet flow rate from node i to j (with SSM model)
q_{ij}^l	Packet flow rate from node i to j with MS at l
$\hat{q}_{ij}^l = q_{ij}^l \times t_l$	Total data flow from node i to j with MS at l
S_i^l	Neighbour set of node i with MS at visit location l
W_i^l	Total data buffered at sensor i when the MS leaves location l
p_i^l	Amount of traffic originated from sensor i itself when the MS is at l
N_l	Set of nodes served by MS at location l
λ	Packet generation rate of a node in the network
E_i	Initial energy of sensor node i
R	Total MS travel time in a cycle
v	Constant speed of the MS between stop locations
$d_{l_1 l_2}$	Distance between MS locations l_1 and l_2
D	Maximum length of the MS tour in a visit cycle
Z	Lifetime of the network
C	No. of MS cycles in the network lifetime
Tx_{ij}	Packet transfer time over the link (i, j)
B	Buffer capacity of static sensors

$$\sum_{j \in S_i^l} q_{ij}^l - \sum_{j: i \in S_j^l} q_{ji}^l = \lambda, \quad i \in N, l \in L \quad (8)$$

$$t_l \geq 0, l \in L, \quad q_{ij}^l \geq 0, \quad i \in N, j \in S_i^l, l \in L. \quad (9)$$

The objective function (6) is to maximize the sum of MS sojourn times at all sink locations. The node energy constraints (7) have similar interpretation as in the previous case. The flow conservation constraint (8) applies to each MS location l separately. The optimization problem is converted to a Linear Programming Problem (LPP) by defining $\hat{q}_{ij}^l = q_{ij}^l \times t_l$. The solution of LPP provides the durations $\{t_l\}$ and the data transfer rates $\{q_{ij}^l\}$. The MS does not visit location l if the optimum value of t_l is zero for that location. As the travel time of the MS between two stops is considered negligible, the MS visiting order has no effect on the network lifetime and can be arbitrary.

3.2c Delay-tolerant mobile sink model (DT-MSM) [25]: Each node postpones the transmission of data until the MS is at the stop most favourable for extending network lifetime. Let D be the delay tolerance level of the application. It is assumed that the MS finishes one round of visits to all the stop locations in D time units and then repeats the cycle again and again until the network lifetime is reached. When a node i is not covered by the current sink location, it continues to generate data and buffer it until the MS reaches the favourable location for data transfer. Within a cycle of D time units, the data stored at each node are at most $D\lambda$. The sink travel time between the visit locations is assumed to be negligible as in the case of MSM. It is also assumed that the MS visits all locations in the order $1, 2, 3, \dots, |L| - 1, |L|, 1, \dots$ and may stay at some location for zero time. Two consecutive visits of the MS to the same stop takes time D and the MS makes C number of cycles in the network before the first node dies due to energy depletion. Thus, the objective is to maximize the number of cycles C , while the actual lifetime is DC .

$$\text{Maximize } C \quad \text{subject to} \quad (10)$$

$$\left\{ \sum_{l \in L} t_l \left(\sum_{j \in S_i^l} e_{ij}^T q_{ij}^l + \sum_{j: i \in S_j^l} \gamma q_{ji}^l \right) \right\} C \leq E_i, \quad \forall i \in N \quad (11)$$

$$t_l \left(\sum_{j \in S_i^l} q_{ij}^l - \sum_{j: i \in S_j^l} q_{ji}^l \right) = p_i^l, \quad \forall i \in N; \forall l \in L \quad (12)$$

$$p_i^l = \begin{cases} D\lambda, & i \in N_l, l \in L \\ 0, & i \in N \setminus N_l, l \in L \end{cases} \quad (13)$$

$$q_{ij}^l \geq 0, \quad \forall i, j \in N; \forall l \in L. \quad (14)$$

An important property of DTMSM is that the network lifetime is independent of the delay tolerance level D [25]. In DTMSM as well as in MSM, the MS travel time is

assumed to be zero. However, in UWSNs, which can be easily partitioned due to harsh environments, and in the underwater terrains, where the MS stop points have severe location constraints, the assumption of zero travel time of the MS is unrealistic. This assumption will lead to theoretical values of optimal network lifetime that are quite larger than the actual. Also, the data generated during the MS travel from one location to the other are simply ignored.

3.2d Delay-tolerant mobile sink model with non-zero travel time (DT-MSM-NZ): This is our proposed model with a specified delay tolerance level and non-zero travel time of the MS. Similar to the DTMSM model, MS makes multiple tours in the network, till any single node dies due to energy depletion. Network lifetime, which is the sum of the total sojourn time and total travel time for C tours of the MS, is to be maximized subject to node energy, flow conservation, delay bound, buffer size and channel bandwidth constraints. Thus, the optimization problem is

$$\text{maximize } Z = \sum_{l \in L} t_l + RC \quad \text{subject to} \quad (15)$$

$$\sum_{j \in S_i^l} e_{ij}^T \hat{q}_{ij}^l + \sum_{j: i \in S_j^l} \gamma \hat{q}_{ji}^l \leq E_i, \quad i \in N \quad (16)$$

$$W_i^l \begin{cases} = 0, & i \in N_l, l \in L \\ = W_i^{l-1} + \lambda \left[t_l + C \frac{d_{l-1l}}{v} \right], & i \in N \setminus N_l, l \in L \end{cases} \quad (17)$$

$$\begin{aligned} & W_i^{l-1} + \lambda \left[t_l + C \frac{d_{l-1l}}{v} \right] + \sum_{j: i \in S_j^l} \hat{q}_{ji}^l \\ & = W_i^l + \sum_{j \in S_i^l} \hat{q}_{ij}^l, \quad i \in N, l \in L \end{aligned} \quad (18)$$

$$\hat{q}_{ij}^l = 0, \quad i, j \in N \setminus N_l \quad (19)$$

$$\left(\sum_{l \in L} t_l + RC \right) \lambda \leq BC \quad (20)$$

$$W_i^l \leq BC, \quad i \in N, l \in L \quad (21)$$

$$\hat{q}_{ij}^l T x_{ij} \leq t_l, \quad i, j \in N_l, l \in L \quad (22)$$

$$\frac{1}{C} \sum_{l \in L} t_l + R \leq D. \quad (23)$$

Constraint (16) gives the energy conservation constraint at each node and it has similar interpretation as in the previous cases except for use of $\hat{q}_{ij}^l$, which is $q_{ij}^l \times t_l$. The queue length dynamics is represented by (17), which indicates that all packets stored in the buffer space of all nodes belonging to the cluster in which the MS currently sojourns will be collected by the MS before it proceeds to the next

cluster. At the same time, in the case of nodes belonging to other clusters, number of packets in the sensor buffer when the MS leaves location l will be the sum of the packets in the sensor buffer when the MS has left the previous location $l - 1$ plus the packets generated during its travel from $l - 1$ to l plus the packets generated during the sojourn of MS at l .

Constraint (18) gives the flow conservation for all nodes in the network for all MS sojourn locations. Its LHS is the sum of packets in sensor buffer i when the MS leaves $l - 1$, packets generated at i during the MS travel from $l - 1$ to l and the incoming packets from the neighbours of i . Its RHS is the sum of the outgoing packets from i to its neighbours, and the packets buffered at i when the MS leaves l . Constraint (19) means that there is neither inflow nor outflow of packets for nodes outside the cluster in which MS sojourns.

Constraints (20) and (21) are related to the conditions to be satisfied to avoid buffer overflow. With periodic data generation at rate λ and regular data collection with C visits of MS, network lifetime multiplied by λ is the average number of packets generated at any node during its lifetime. The buffer size of each node should be greater than the average number of packets generated at a sensor during one cycle time of the MS. Also, the maximum buffer occupancy of the sensors should not exceed the available buffer space.

Since the underwater channels have limited bandwidth, the time required to transfer the data from sensor to sensor and from sensor to MS is not negligible. Constraint (22) stipulates the minimum time the MS should spend at each sojourn location so that sensors in that cluster can upload data without data loss. Finally, (23) specifies the delay bound condition that the cycle time of the MS, which is the sum of sojourn time and travel time in a cycle, should not exceed the application-specified delay bound D .

4. Performance evaluation

4.1 Solutions of optimization problems

The constrained optimization problems in the previous section are solved using MILP techniques. The solutions give optimum sojourn times of the MS at visit locations, maximum network lifetimes, optimum data flows to be routed between different nodes and between nodes and MS, and the maximum number of MS visit cycles achievable within the network lifetime. Other relevant information like buffer occupancy and residual energy of static sensors are also collected from the optimization report for further study. With the number of cycles fixed for DTMSM and DTMSM-NZ and with some variable transformations, the optimization problems reduce to LPPs.

MATLAB and LINGO [29] are the computation tools used for solving the optimization problems. The number and locations of nodes, initial energy of sensor nodes,

number and locations of MS visit points, travel distance between the MS locations, available links and energy consumption for each link, data generation rates, available channel bandwidths between the nodes, etc., are set using MATLAB programs for different network scenarios. These output text files containing the network information required for solving the LPPs are fed as inputs to the optimization solver in LINGO.

LINGO is an optimization modelling software tool designed to build, solve and analyse linear, non-linear, quadratic, stochastic and integer optimization models in a fast and efficient manner. There is no need to specify or load a separate solver, because LINGO reads the problem formulation and automatically selects the appropriate one. It provides an integrated package, including the language for specifying the optimization model, environment for building and editing problems and a set of built-in solvers. It allows building models that pull data directly from databases/spreadsheets and output solution information right into database/spreadsheet. We can enter the optimization model in the Lingo *model window* and when the solver starts, it displays a *solver status window* showing the model classification, state of the current solution (feasible or infeasible, local or global optimum), value of the objective function and number of iterations required to solve the model.

4.2 Energy consumption for transmission over a link

In our mathematical formulation, we have assumed that the single-hop transmission energy consumption is dependent on the hop length and that the transmitting nodes are capable of tuning their transmission power according to hop length.

Transmission loss of an underwater acoustic signal is the sum of spreading loss and absorption loss. It is dependent on the hop length d , frequency of operation f and the nature of spreading indicated by the spreading coefficient k [30] as follows:

$$10 \log A(d, f) = k \cdot 10 \log d + d \cdot 10 \log a(f). \quad (24)$$

In the shallow water scenario, signals experience cylindrical spreading with $k = 1$ and in the deep water, spreading is spherical with $k = 2$. The absorption coefficient $a(f)$ as evaluated using Thorp's formula [31] increases very rapidly with frequency and it limits the maximum usable bandwidth at a given distance:

$$10 \log a(f) = \frac{0.11f^2}{1 + f^2} + \frac{44f^2}{4100 + f^2} + \frac{2.75f^2}{10^4} + 0.003. \quad (25)$$

A fundamental difference between the radio signals and the acoustic signals is the following: while the available

bandwidth remains constant in the former case, it decreases with distance in the latter [14]. For a given target signal-to-noise ratio SNR_{tgt} , noise power spectral density $N(f)$ and available bandwidth $B(d)$, the required acoustic transmission power $P_t(d)$ can be expressed as a function of the hop distance d [14]:

$$P_t(d) = \frac{\chi}{\xi} B(d) N(f) A(d, f) SNR_{tgt}, \quad (26)$$

where χ is a margin to ensure that the average receiver SNR is larger than the threshold value and ξ is a penalty factor that accounts for signal processing inefficiencies at the receiver. The corresponding electrical power requirement is determined using relation [30]

$$P_t^{el} = P_t(d) 10^{-17.2} / \eta, \quad (27)$$

where $10^{-17.2}$ is the conversion factor from acoustic power in dB re μPa to electrical power in Watts and η is the overall efficiency of the electronic circuitry [14]. Assuming the bandwidth efficiency of modulation to be 1 and denoting the distance-independent receiver power by P_r , the energy consumption for transmission is given by (28), where M (bits) is the packet size [14]:

$$E_{hop}(d) = \frac{(P_r + P_t^{el}(d))M}{B(d)}. \quad (28)$$

4.3 Packet latency and sensor buffer occupancy

Message latency is the time taken by the sensed data to reach the MS, which has two components, the queueing delay in the sensor buffer and the transfer time from the sensor to the MS over multi-hop path. Assuming that the static sensors are equipped with sufficiently large buffer space to avoid buffer overflow, either an M/G/1 queue with vacation model [32] or a *Polling* model with *exhaustive* service policy [33] can be effectively used for obtaining approximate values for the data latency and buffer occupancy [6].

We use a Polling model with exhaustive service, where the MS corresponds to the single server and the clusters correspond to the queues to be served. Unlike the model considered in [6], the data generated by all nodes in a cluster, awaiting transmission over multi-hop path to the MS located at the centre of the cluster, are to be considered for service at each visit location. Hence, the number of queues to be served is the same as the number of clusters, and the exhaustive service at a queue corresponds to collecting the data buffered so far plus those being generated by the nodes belonging to the cluster in which the MS currently sojourns.

With N representing the total number of sensor nodes in the deployment area, λ the data generation rate at each node

and $E[X]$ the mean time to transfer a packet to the MS over multi-hop paths, the total offered load in the system is given by

$$\rho = N\lambda E[X]. \quad (29)$$

In a cycle time D , the MS spends ρD time for data collection from the sensors and $(1 - \rho)D$ time for travelling between the sojourn locations, i.e., the total travel time R and the cycle time D of the MS are related by the relation

$$D = \frac{R}{1 - \rho}. \quad (30)$$

During a cycle time, $N\lambda D$ packets will be generated in the network and we have assumed that all the packets generated in a cycle time are collected by the MS within one cycle. Since there are $|L|$ clusters with N_l sensors in cluster l , the MS has $N_l\lambda D$ packets to be collected from cluster l at each visit. To ensure stability of the queueing system, the total offered load in the system ρ should be less than 1.

With the MS following a deterministic cyclic path with mean travel time between two consecutive locations s , the average waiting time encountered by packets can be determined by [6] the relation

$$E[Q] = \frac{N\lambda(E[X])^2 + s(N - \rho)}{2(1 - \rho)} \quad (31)$$

and the packet latency is $E[Q] + E[X]$. A sensor's buffer occupancy is maximum when the MS approaches the cluster to which it belongs and is emptied when the MS leaves it. The maximum sensor buffer occupancy is obtained by multiplying the MS cycle time by the data generation rate. To avoid buffer overflow, the sensor buffer size should be such that

$$B \geq \lambda D = \lambda \frac{R}{1 - \rho}. \quad (32)$$

4.4 Impact of degree of multi-hopping

Degree of multi-hopping permitted in MS-based data collection decides the relative improvement in network lifetime due to reduced and balanced energy consumption. At the same time, data delivery delay, the cost paid for lifetime enhancement is also decided by the degree of multi-hopping. Hence, quantifying these dependences will be useful for studying the energy-delay trade-off in MS-based data collection and for application-oriented design of the routing scheme in the network.

In our earlier work on delay and lifetime performance of MS-based data collection in UWSNs [34], the analysis of network lifetime improvement in MS-based single-hop data collection over multi-hop scheme was done. In MS-based single-hop data collection, irrespective of the position of

the nodes, each static sensor transmits only the packets originally generated by it and hence lifetime of all the nodes will be almost same. In multi-hop network, due to relaying, the number of transmissions to be carried out by a sensor node depends on its proximity to sink. We follow the approach used in [6, 16] to compute the number of transmissions and receptions to be undertaken by nodes at different hop distances from the sink.

For analytical tractability without losing generality, let us assume that each partition or cluster is of circular shape with radius Ψ and each static sensor node has a transmission range r . The circular deployment area in a cluster can be divided into a number of concentric annuli, each having width r . If N_l nodes are uniformly distributed in the cluster l with area A_l , the number of nodes in its annular region τ ($1 \leq \tau \leq \lceil \frac{\Psi}{r} \rceil$)

having area $A_l(\tau)$ is approximately equal to $N_l \frac{A_l(\tau)}{A_l}$ for large N_l . The number of transmissions $N_{tx}(\tau)$ and receptions $N_{rx}(\tau)$ to be carried out by the nodes belonging to annulus τ will be

$$N_{rx}(\tau) = N_{tx}(\tau + 1) \frac{A(\tau + 1)}{A(\tau)} \quad (33)$$

and

$$N_{tx}(\tau) = 1 + N_{tx}(\tau + 1) \frac{A(\tau + 1)}{A(\tau)} \quad (34)$$

with the corresponding values for nodes in the outermost annulus ($\tau = \lceil \frac{\Psi}{r} \rceil$) being one and zero, respectively.

As the energy consumption for reception is very small compared with that for transmission, it can be neglected, and the lifetime of a multi-hop network is limited by $N_{tx}(1)$, the number of packet transmissions from any of the single-hop neighbours of the sink. The lifetime of a node is expressed in terms of a metric, the maximum number of original packet transmissions that can be afforded by a node before being completely drained off its energy. For a fixed initial energy E_i and transmission energy consumption $E_{hop}(r)$, this metric for a node belonging to the annulus τ , represented by $\Theta(\tau)$, can be expressed as

$$\Theta(\tau) = \frac{E_i}{E_{hop}(r)N_{tx}(\tau)}. \quad (35)$$

Since the relaying overhead as indicated by $N_{tx}(\tau)$ increases with proximity to the sink, the lifetime metric $\Theta(\tau)$ will be maximum for the nodes in the outermost annulus ($\tau = \lceil \frac{\Psi}{r} \rceil$) and will be minimum for those in the single-hop neighbourhood of the sink ($\tau = 1$). With N_l nodes generating data at same rate, the lifetime metric of the cluster, expressed as

$$\Theta = N_l \times \min[\Theta(1), \Theta(2), \Theta(3) \dots \Theta(\lceil \Psi/r \rceil)] = N_l \times \Theta(1) \quad (36)$$

represents the total number of packets that could be transmitted to the sink before the first node (belonging to the

single-hop neighbourhood of the MS) dies due to energy depletion. We use the lifetime metric of the network for studying the impact of number of MS locations and degree of multi-hopping on network lifetime.

To evaluate $\Theta(1)$, the average number of transmissions $N_{tx}(1)$ to be carried out by any of the single-hop neighbours of the sink, corresponding to a single packet transmission from every sensor node in the outer annuli of the circular deployment area, is to be determined first. Using the results from [34], $N_{tx}(1)$ is almost equal to the ratio of the area of the deployment region outside one-hop neighbourhood of the sink to that of the region inside one-hop neighbourhood. Thus, considering a large number of nodes having transmission range r uniformly distributed within a circular deployment area with radius Ψ ,

$$N_{tx}(1) = \frac{\Psi^2 - r^2}{r^2}. \quad (37)$$

Substituting the value obtained from Eq. (37) in to Eq. (35), and subsequently in Eq. (36), we get

$$\Theta = N_l \times \frac{E_i}{E_{hop}(r)} \times \frac{r^2}{(\Psi^2 - r^2)}. \quad (38)$$

With MS-based single-hop communication, each node transmits only the packets generated by itself and hence Θ of the entire network is $NE_i/E_{hop}(r)$. The term $r^2/(\Psi^2 - r^2)$ is, in fact, the ratio of number of single-hop neighbours of the sink to the number of multi-hop neighbours. Keeping the sensor transmission range r fixed, larger the radius Ψ of the cluster, larger the number of multi-hop neighbours, smaller the ratio $r^2/(\Psi^2 - r^2)$ and smaller the lifetime metric Θ .

Keeping the total deployment area and transmission range of nodes fixed, the degree of multi-hopping required to ensure connectivity depends on the number of MS locations. Hence changing the number of MS visit points leads to change in the degree of multi-hopping, which in turn results in variation in the maximum achievable lifetime. To study this variation in optimum network lifetime with number of MS locations, we have considered three different cases using different trajectories and number of sojourn points as shown in figure 2. The same arrangement is used for studying the effect of number of MS visit locations on data delivery delay and thus to identify the trade-offs in MS-based lifetime enhancement schemes. Assuming 60 sensor nodes having transmission range 100 m uniformly distributed in a square deployment area of size 1000 m $\times$ 1000 m, the degree of multi-hopping is maximum with a single visit location of the MS and minimum (no multi-hopping) with 64 visit locations.

Keeping the degree of multi-hopping as a tunable parameter that can be varied from no multi-hopping at one extreme to full multi hopping at the other provides us with the flexibility to decide the same according to energy

Figure 2. MS trajectories with different numbers of sojourn points.

constraints of static sensors, location constraints of MS and deadline requirements of applications. It also permits us to achieve the energy–delay trade-off or lifetime–delay trade-off. If network lifetime is more important, reduce the degree of multi-hopping; if fast delivery is more important, increase the degree of multi-hopping. If the MS is not permitted to approach the sensor due to terrain constraints or to avoid disturbance to marine life, then single-hop data collection cannot be employed.

4.5 Optimum transmission range

In studying the energy–delay trade-off by varying the degree of multi-hop, we considered the transmission range of the sensors as given. In this subsection, we consider finding an optimal transmission range.

Network lifetime can be maximized by minimizing the maximum energy consumption of nodes in a network. In a multi-hop network, the single-hop neighbours of the sink have maximum energy consumption due to their relaying overhead. Hence, maximum network lifetime can be achieved if the energy consumption of nodes in the innermost annulus of the circular deployment area is minimized [35]. We focus on data collection within a single circular shaped cluster, with the MS located at the centre acting as the (CH) and static sensor nodes transferring data over multi-hop paths to the CH. Considering a large number of nodes having transmission range r uniformly distributed within the circular deployment area with radius Ψ , the number of transmissions and receptions to be carried out by nodes in the innermost annulus of the cluster can be evaluated using (34) and (33) as $\frac{\Psi^2}{r^2}$ and $\frac{\Psi^2 - r^2}{r^2}$, respectively.

With N nodes uniformly distributed in the circular area A , the number of nodes in the innermost annulus of area $A(1)$ will be $N \frac{A(1)}{A}$. If P_0 represents the power level required at the receiver input of a destination node, for successful

transmission over a distance r , the source node has to transmit at a power level equal to

$$P_t(r) = P_0 r^k a^r \quad (39)$$

where k and a are the spreading coefficient and absorption coefficient, respectively, discussed in section 4.2. To receive one bit of information, the receiver incurs a constant power expenditure of P_r , which depends on the receiver electronics and is independent of hop distance. If each node generates one packet of length M bits, the energy consumed by a ‘hotspot’ node in the single-hop neighbourhood of the sink will be

$$E_{\text{hotspot}} = \frac{M}{B(r)} \left\{ P_r \frac{\Psi^2 - r^2}{r^2} + P_t(r) \frac{\Psi^2}{r^2} \right\}. \quad (40)$$

For a given distance, bandwidth can be considered as a constant. Substituting the expression for range-dependent transmission power from (39), we get

$$E_{\text{hotspot}} = \frac{M}{B} \{ P_r \Psi^2 r^{-2} - P_r + P_0 \Psi^2 r^{k-2} a^r \}. \quad (41)$$

Optimum transmission range can be obtained by differentiating E_{hotspot} with respect to r and equating it to zero. Thus

$$\frac{d(E_{\text{hotspot}})}{dr} = \frac{m}{B} \{ -2\Psi^2 P_r r^{-3} + P_0 \Psi^2 \{ (k-2)r^{k-3} a^r + r^{k-2} a^r \ln(a) \} \} = 0 \quad (42)$$

which means that the optimum transmission range $\hat{r}$ satisfies

$$[(k-2) + \hat{r} \ln(a)] \hat{r}^k a^{\hat{r}} = \frac{2P_r}{P_0}. \quad (43)$$

Considering typical values of $P_0 = 1 \times 10^{-3}$ Js/bit and $P_r = 0.2 \times 10^{-3}$ Js/bit [27] and using numerical techniques for solving (43), optimum transmission range for different frequencies of operation can be obtained.

Transmission range of sensors influences the energy consumption of ‘hotspot’ nodes in two conflicting ways: increase in transmission range leads to increase in hop energy consumption as expressed by (28), where d represents the transmission range; at the same time, it leads to decrease in relaying overhead as expressed by (37). At lower transmission ranges, relaying overhead plays more predominant role in energy consumption of ‘hotspot’ nodes, while at higher transmission ranges, hop energy consumption does. If the transmission range of sensor nodes is less than the optimum value, degree of multi-hopping will be more, number of single hop neighbours of the MS will be less, relaying overhead of single-hop neighbours will be more and correspondingly network lifetime will be less. If the sensor transmission range is larger than its optimum value, sensor nodes will have to transmit over larger distances, resulting in increased energy consumption for transmission over a hop, thereby reducing the network lifetime.

4.6 Optimum cluster size

In studying the energy–delay trade-off by varying the degree of multi-hop, we have considered the circular cluster of given radius. In this subsection, we consider finding an optimum cluster radius.

The clustering characteristics of UWSNs differ significantly from those of terrestrial sensor networks, mainly due to sparse deployment and channel characteristics [36]. Since the transmission loss depends not only on distance but also on working frequency, optimal cluster size for UWSNs shows different properties from those of terrestrial WSNs. Optimal cluster size corresponds to the one that minimizes the total energy consumption in a cluster and thus maximizes the lifetime of the cluster. As already discussed in section 4.4, network lifetime is maximum with single-hop data transfer from the sensor nodes to the MS. Hence, we consider single hop data transfer from the static sensors acting as cluster members to the MS acting as CH and use an approach similar to the one used in [36] for determining the optimum number of clusters and thus the optimum cluster size. The optimal number of clusters can serve as a guide in fixing the optimal positions of the MS also.

Consider N sensors randomly and uniformly distributed in a circular deployment area A and c high-capacity CHs can be positioned at specified locations. Sensors organize themselves into clusters such that every node belongs to one and only one cluster. CHs collect data from cluster members and transmit it over single hop to the surface sink located at the centre of the deployment area. In our system model, the c CHs correspond to the same MS visiting c different clusters.

Let N_j be the number of sensors in the j^{th} cluster so that $\sum_{j=1}^c N_j = N$. The total energy consumption in the network will be

$$E_{\text{total}} = \sum_{j=1}^c \left\{ E_{CH}(j) + \sum_{i=1}^{N_j} E_{CM(ji)} \right\} \quad (44)$$

where $E_{CH}(j)$ is the energy consumption of the j^{th} CH and $E_{CM(ji)}$ is the energy consumption of i^{th} cluster member in the j^{th} cluster. Optimum cluster size can be determined by solving the equation obtained by differentiating the expected value of E_{total} with respect to cluster radius R_c and setting it to zero. Assuming shallow water with cylindrically spread signals and following the work in [36], optimal cluster radius $R_{c_{\text{opt}}}$ is obtained by solving the equation

$$\begin{aligned} & \frac{2e^{\sigma} R_c (R_c^3 \sigma^3 - 2R_c^2 \sigma^2 + 4R_c \sigma - 4) + 8}{\sigma^3 R_c^3} \\ & + \frac{1}{\sigma^3 R_c^2} (e^{-\sigma R_c} (-4\sigma e^{\sigma R_c} + 2e^{\sigma R} (\sigma^2 R_c + \sigma(2 - 2\sigma R + \sigma R_c)))) \\ & - \frac{1}{\sigma^2 R_c^2} (e^{-\sigma R_c} (-4e^{\sigma R_c} + 2e^{\sigma R} (2 + \sigma R(-2 + \sigma R) \\ & + \sigma R_c(2 - 2\sigma R + \sigma R_c)))) = 0 \end{aligned} \quad (45)$$

where R is the radius of the circular deployment area and $\sigma(f)$ (equal to $0.001 \times 10 \log a(f) \times \ln 10$) is treated as a constant for a given frequency.

Numerical solution of (45) gives the optimal value of cluster radius R_c such that the total energy consumption in the network is minimized. Once the optimal cluster radius $R_{c_{\text{opt}}}$ is obtained, the optimal number of clusters c_{opt} is computed by

$$c_{\text{opt}} = \frac{R^2}{R_{c_{\text{opt}}}^2}. \quad (46)$$

For a given deployment area and frequency of operation, as the number of clusters increases, transmission range of cluster members required to establish single-hop connectivity with the CH decreases, and energy consumption of static sensors decreases. At the same time, as the number of clusters increase, total energy consumption of CH nodes increases. These two factors influence the optimal number of CH nodes, or in other words, optimal number of MS sojourn locations. However, it may be noted that, though this value is optimum from the point of view of maximizing network lifetime, it need not be optimal from the point of view of MS cycle time and data collection latency. Hence it is advisable to consider the energy–delay trade-off also while deciding the optimum number of MS stop locations.

4.7 Optimum MS locations

So far we have considered that when the MS visits a cluster to collect data, it will stay at the cluster centre. Now we will consider an optimal location for the MS within each cluster.

From the point of view of network lifetime, DTMSM approach is equivalent to deploying multiple mobile base stations and allowing the static sensors to transfer data to the nearest base station. Such deployment of multiple base stations reduces the average hop length and/or average number of hops between the source–sink pairs, thus enabling increased network lifetime and improved data delivery [21]. Hence the approaches used in [19] and [21] for optimum placement of multiple base stations and the one used in [37] can be adapted to our problem of determining the optimum locations of MS that will maximize network lifetime.

The MS placement problem is formulated as an optimization problem and optimum locations of the MS are obtained as the solution of a MILP. In our problem formulation, two binary decision variables are used. F_{ij} is the routing variable and set to one if a sensor i sends its data to the sink at location j , and set to zero otherwise. G_j is the second decision variable, representing the sink location, and is assigned one if the sink is located at j ; it zero otherwise. Let C_{ij} represent the path cost from node i to sink location j ; it can be computed based on the energy consumption of nodes on the path.

The MS placement problem can be formulated as follows:

$$\text{minimize } \sum_{i \in N} \sum_{l \in L} C_{il} F_{il} \quad \text{subject to} \quad (47)$$

$$\sum_{l \in L} F_{il} = 1 \quad (48)$$

$$F_{il} \leq G_l \quad (49)$$

$$\sum_{l \in L} G_l = L_{max} \quad (50)$$

$$F_{il}, G_l \in \{0, 1\}. \quad (51)$$

The objective function as given in (47) minimizes the total path cost from each sensor to the sink node. Routing constraints (48) ensure that each sensor sends its data to only one sink. Constraint set (49) implies that to send data to location l there must be a sink located at that point. Constraint (50) sets the maximum number of sink locations to be L_{max} . Final sets of constraints (51) are the binary constraints on the decision variables.

Solution of this optimization problem is quite complicated; hence, we propose three heuristics for optimum MS placement: (i) consider the network to be consisting of a number of non-overlapping clusters and fix the centre of each cluster as an MS sojourn location, as we have already discussed and investigated in our system model; (ii) fix the optimum number of MS sojourn locations equal to the optimum number of CHs as evaluated using (46) and position the MS at each location such that single-hop connectivity between the cluster members and MS is

ensured and (iii) fix the number and locations of MS according to the latency requirements of the application, considering the energy–delay trade-off discussed in section 4.4.

4.8 Simulation study

We have used OMNET++-based simulation environment for implementing the proposed framework and validating the analytical results. The lifetime-aware QELAR [38] is a protocol developed specifically for UWSN. Its implementation in OMNET++ network simulator has provided us with an ideal platform for incorporating the optimal flow-based routing scheme with SSM, MSM, DTMSM and DTMSM-NZ models. Using these simulation models, we evaluated packet delivery ratio (PDR), average data delivery delay, network lifetime and residual node energy distribution in the network.

Flow based optimal routing: The sensor nodes use the flow rates $\{q_{ij}\}$ and $\{q_{ij}^l\}$ obtained by solving the optimization problems to route data in an energy-efficient manner. In [19], flow-based routing is implemented by keeping a counter at every outgoing link of a node. We use a probabilistic routing approach, q_{ij}^l being the optimal flow rate for the link (i, j) ; the optimal routing probability p_{ij}^l for forwarding a packet from node i to node j when the MS is at location l is

$$p_{ij}^l = \frac{q_{ij}^l}{\sum_{j \in S_i^l} q_{ij}^l}. \quad (52)$$

Every node creates a neighbour table, based on the ‘HELLO’ packet received from the neighbouring nodes. Optimal routing information obtained by solving the MILP is made available to every node once at the time of initialization, from which the optimum routing probabilities are computed using (52) and entered into the neighbour table.

When a node generates a data packet, it is either buffered there or forwarded to the MS, based on the current location of the MS. While forwarding, the node uses the routing probabilities stored in it. Each node needs to keep the information about its single-hop neighbours alone and there is no exchange of routing information after the initialization phase.

5. Analytical and simulation results

Assuming a two-dimensional deployment area with large number of sensor nodes randomly and uniformly distributed in the clusters, impact of various network parameters on the performance metrics of the proposed model has been studied. The important parameters and their values used in our study are tabulated in table 2. Unless otherwise

specified, the network under consideration is in deep water environment with number of sensors 80, number of MS locations 4, sensor transmission range 200 m and data generation rate 0.01 packets/s.

For evaluating the lifetime improvement of the proposed model over the existing models, we have considered 50 randomly generated network scenarios for each network size considered, with the packet generation rate fixed at 0.01 packets/s in all cases. The average of the optimum lifetime obtained with the 50 scenarios for each model is tabulated in table 3 and the residual energy distribution in table 4. The absolute value of the maximum lifetime of the proposed model DTMSM-NZ is much larger compared with that of SSM and MSM, due to reduced and balanced energy consumption among the sensor nodes. With a network size of 60 nodes, the lifetime achieved by DTMSM-NZ is 188% higher than that of SSM and 91% higher than

that of MSM. With 80 nodes, these values rise to 683% and 312% and with 100 nodes, 985% and 807%, respectively. The delay-tolerant model that assumes zero sink travel time (DTMSM) and the one with non-zero sink travel time (DTMSM-NZ) both give same values of network lifetime, expressed in absolute time unit. Later we will see the impact of non-zero travel time on the network lifetime expressed in terms of the number of MS cycles, which is more meaningful in periodic data collection [25].

As observed from table 3, the maximum lifetime decreases with an increase in the number of nodes N in the case of SSM and MSM, whereas it increases with the number of nodes in DTMSM and DTMSM-NZ. An increase in the number of nodes has two conflicting effects on the network performance: (i) increased number of generated packets leading to higher network load and congestion at the single-hop neighbours of the sink and (ii) larger number of single-hop neighbours of the sink leading to better distribution of relaying overhead among them. The maximum network lifetime will decrease or increase depending on which effect is more predominant in the network under consideration, which in turn depends on the deployment of nodes also. From our observation over the range of network size and the data generation rate we have considered, the former effect is more prominent with SSM and MSM, since all nodes transfer data to the sink at all locations. Hence the optimum lifetime has decreased with increasing number of nodes. In the case of DTMSM and DTMSM-NZ having limited degree of multi-hopping, the effect of increase in the number of bottleneck nodes was more pronounced than that of increase in traffic to be handled at each sojourn location. As we will see later in the case of DTMSM-NZ, this trend may change over a different range of network size and data generation rates.

The residual energy distribution, as illustrated in table 4 is obtained by observing the residual energy E_{res} of the nodes in the network at the end of network lifetime, for three different network sizes, each averaged over 50 randomly generated network instances. For each network instance, percentage of sensors whose residual energy satisfies the relations $E_{res} = 0$, $E_{res} \leq 0.25E_i$, $E_{res} \leq 0.50E_i$, $E_{res} \leq 0.75E_i$ is computed. The average percentage of nodes with their residual energy having the specified relation with the initial energy is tabulated in table 4 to study the impact

Table 2. Network parameters used.

Parameter	Value
Deployment area (m ²)	1000 × 1000
No. of nodes	60, 80, 100, 200
Spreading coefficient	1, 1.5, 2
No. of simulations	50
Packet generation rate (pps)	0.01, 0.02, 0.05, 0.1
Channel bandwidth (kHz)	10, 20
Packet size (bits)	1024
Initial energy (J)	1,00,000
Transmission range (m)	100, 200, 300, 400, 500, 750
No. of MS visit locations	1, 4, 16, 64

Table 3. Comparison of average network lifetime for different models.

Network size (N)	Maximum lifetime (s)			
	SSM	MSM	DTMSM	DTMSM-NZ
60	4,48,690	6,75,494	1.293 × 10 ⁶	1.293 × 10 ⁶
80	2,22,634	4,23,518	1.744 × 10 ⁶	1.744 × 10 ⁶
100	1,99,810	2,39,001	2.167 × 10 ⁶	2.167 × 10 ⁶

Table 4. Residual energy distribution with different models: average percentage of nodes for various network sizes, whose residual energy satisfies the given relation with initial energy.

N	Residual energy distribution											
	SSM				MSM				DTMSM-NZ			
	$E_{res} = 0$	$\leq 25\%$	$\leq 50\%$	$\leq 75\%$	$=0$	$\leq 25\%$	$\leq 50\%$	$\leq 75\%$	$=0$	$\leq 25\%$	$\leq 50\%$	$\leq 75\%$
60	40	43	50	58	78	81	84	88	27	34	42	66
80	37	43	47	55	44	50	57	62	49	53	60	76
100	24	27	29	37	36	39	44	49	61	69	77	89

of network size on energy balancing in each model and to see its corresponding impact on network lifetime shown in table 3. In the case of SSM with 80 nodes, at the end of network lifetime, only 37% of the nodes have exhausted their energy completely and 45% of the nodes still have more than 75% of their initial energy, which is simply wasted. In the case of MSM, the corresponding values are 44% and 38%, and in DTMSM-NZ they are 49% and 24%, respectively. This shows that in DTMSM-NZ, the distribution of residual energy is more balanced and wastage of energy is minimum among the three models considered. DTMSM shows a similar energy distribution as that of DTMSM-NZ and hence it is omitted from the table. The results presented in tables 2 and 3 demonstrate that, compared with SSM and MSM, our model DTMSM-NZ results in a fair balancing of energy consumption among the sensor nodes, leading to considerable increase in network lifetime and decrease in wastage of unused energy.

To find the optimum network size that provides maximum achievable lifetime in the DTMSM-NZ model, we have considered 6 different network sizes ($|N| = 60, 80, 100, 150, 200$ and 250) and 50 different network deployment instances with each size. Fixing the data generation rate at 0.01 packets/s, average value of the optimum network lifetime corresponding to each network size is evaluated for deep water, shallow water and intermediate underwater conditions. As discussed in section 4.2, the energy models for these three conditions differ in terms of the spreading of acoustic signals. For a fixed network size, energy consumption is the largest in deep water and the smallest in shallow water; therefore, maximum lifetime is the lowest in deep water and the highest in shallow water.

In all the three underwater conditions, the network lifetime is very small, with the total number of nodes being 60° , it increases with the number of nodes, reaches a maximum value and then starts decreasing. As the network size increases, the node density in the network also increases. Hence, there exist more alternative path, which can be used to route packets from every sensor to the MS in the optimal manner. Another factor that contributes to the increased network lifetime is the low transmission energy requirement due to the nodes being more closer. However, when we increase the network size beyond 200, the lifetime starts reducing drastically. The reason for this is the same as that observed in the case of SSM and MSM earlier, i.e., the predominance of the effect of increased network traffic over

those of reduced transmission energy requirement and increased number of alternative paths for routing. This behaviour is not a serious limitation for our application scenario, because generally UWSNs are not densely deployed in practice and there is no logic behind increasing the network size unnecessarily, provided the coverage and connectivity conditions are satisfied in the network. Hence we will limit the network size to 200 in our further studies. The average values of the maximum lifetimes obtained with different network sizes and underwater conditions are tabulated in table 5. The simulation results corresponding to deep water conditions are plotted in figure 3. The vertical bars indicate the standard deviation of the lifetime values about the mean value obtained with 50 deployment instances for each network size. A different simulation environment will affect the simulation results quantitatively, but the qualitative performance is not expected to change considerably.

Fixing the number of sensor nodes N to be 80, variation of network lifetime with MS travel time and channel bandwidth using the proposed DTMSM-NZ model is plotted in figure 4. As expected, as the MS travel time in a cycle R increases, the maximum lifetime (expressed in terms of number of MS cycles) decreases. The limited channel bandwidth also affects the network lifetime: with a lower bandwidth, the lower bound of the MS sojourn time

Figure 3. Impact of network size on network lifetime.

Table 5. Average network lifetime (in days) for different underwater environments.

Underwater environment	Spreading coeff. (k)	Network size N					
		60	80	100	150	200	250
Shallow	1	632	1672	2458	3254	3781	224
Intermediate	1.5	58.4	127.2	204	280	353	21.2
Deep	2	5.9	9.67	24.2	27.6	31.75	4.34

Figure 4. Variation of network lifetime with MS travel time.

will be more, since the transmission time of the stored packets will be high. With fixed travel time, as the sojourn time increases, cycle time increases and the number of cycles decreases.

Fixing the number of MS sojourn locations to be 4, impact of varying the transmission range and data generation rate of sensors on the network lifetime is illustrated in figure 5. A minimum transmission range is required to ensure multi-hop connectivity in the network, which was observed to be around 100 m in our set of experiments. As the transmission range increases, the average number of hops between a static sensor and the MS decreases, thus reducing the effect of ‘hotspot’ and increasing the network lifetime. When the transmission range reaches a certain level (500 m in our case), almost all the nodes in the cluster are within single-hop neighbourhood of the MS and hence no further improvement in lifetime is possible. For a fixed transmission range and number of sensor nodes, the optimal network lifetime is inversely proportional to the data generation rate of the sensors. Doubling the data generation rate has the effect of halving the optimum lifetime. In real situations where the data generation rate is expected to be very small, the network lifetime will be very large, on the order of several months.

The impact of change in MS cycle time on the total travel time of the MS, total sojourn time and network lifetime for two different values of MS travel time per cycle R is illustrated in figure 6. Network Lifetime, being the sum of total travel time and total sojourn time, is the same in both cases, and it is independent of the cycle time. Thus, our model with non-zero MS travel time inherits the property of the DTMSM model that the absolute value of the network lifetime is independent of the delay tolerance level D of the application. For a given travel time per cycle (say $R = 32$ s), larger the cycle time, larger the sojourn time or vice versa. For negligible travel time per cycle (case B with $R = 0.4$ s),

Figure 5. Impact of transmission range and data generation rate on network lifetime.

Figure 6. Variation of total travel time, sojourn time and lifetime with cycle time (A: $R = 32$ s; B: $R = 0.4$ s).

network lifetime is dominated by MS sojourn time for all cycle times. However, with a reasonably large travel time per cycle (case A with $R = 32$ s), it is dominated by the travel time at low cycle time regions and by the sojourn time at high cycle time regions.

Fixing the number of nodes to be 80 and the packet generation rate to be 0.1 packets/s, the influence of MS cycle time on the maximum number of cycles of MS operation and the sojourn time per cycle is illustrated in figure 7. As expected, as the MS cycle time increases, number of MS cycles decreases, keeping their product (the actual network lifetime) constant. Also, as the cycle time increases, the sojourn time per cycle also increases linearly with it.

Considering 50 different network deployment scenarios with 80 nodes having equal data generation rates, variation

Figure 7. Influence of MS cycle time on optimum no. of MS cycles and sojourn time/cycle.

Figure 9. MS travel time vs MS cycle time.

Figure 8. MS sojourn time vs MS travel time.

Figure 10. MS travel time vs sensor buffer size.

of average sojourn time per cycle with variation in MS travel time R and data generation rate λ is illustrated in figure 8. The vertical bar indicates the standard deviation of the observed values about the mean value. Due to larger number of packets generated per cycle, the optimal MS sojourn time increases with data generation rate and MS travel time.

Variation of the cycle time of the MS with MS travel time and data generation rate is illustrated in figure 9 and that of sensor buffer occupancy in figure 10. For a given packet generation rate, as the travel time increases, cycle time increases, more packets are generated and more packets have to be buffered. Similarly, for a given travel time/cycle, packets generated and buffered will be proportional to the data generation rate. This acts as a guide to design the sensor buffer size according to the MS travel distance and packet generation rate in the application concerned, such that no buffer overflow occurs.

Impact of variation in the number of nodes and packet generation rate on the number of packets collected in the lifetime of the network is illustrated in figure 11. It is interesting to note that the total number of packets collected in the network lifetime is independent of the data generation rate. This is quite natural, since doubling the packet generation rate has the effect of halving the network lifetime, thus keeping the number of packets same. Keeping the data generation rate fixed, variation in total number of packets follows the variation in network lifetime, since the number of packets generated in the lifetime equals the product of network lifetime and data generation rate. The network throughput, being the rate of successful delivery of data, is plotted in figure 12. Similar to network lifetime and packets collected, throughput also increases with the number of nodes within the range of network size considered here.

Figure 11. Total packets vs network size.

Figure 12. Network throughput vs network size.

The combined effect of sensor transmission range and network size on network lifetime is illustrated in figure 13. As we have already seen, both parameters contribute positively to lifetime improvement. For a given node density, lower the transmission range, larger the degree of multi-hopping and lesser the network lifetime. Also, for a given transmission range, higher the number of nodes, higher the number of alternative links available for routing and higher the lifetime. However, for a given network size, there exists a threshold transmission range beyond which further increase will not lead to further improvement in lifetime. Lifetimes achieved with the network having $N = 80$, $r = 100$ and that with $N = 60$, $r = 500$ are nearly equal, since they provide almost the same number of links in the network.

Figure 13. Impact of transmission range and network size on lifetime.

Figure 14. Impact of number of MS locations and system load on MS cycle time.

The cycle times of the MS for varying network conditions like number of MS locations, number of static sensor nodes and packet generation rates are plotted in figure 14. The mean travel time in a cycle depends on the number of visit locations, distance between the locations and the MS velocity. We have assumed constant MS velocity of 15 m/s. With $|L|$ equal to 1, the system becomes a static sink network with negligible data collection latency. The system load ρ increases with number of nodes N , data generation rate λ and packet transmission time. Care is to be taken to ensure that ρ does not exceed unity, failing which the stability of the system will be lost. With given N and λ , larger the value of $|L|$, larger the travel time of the MS and higher the cycle time of MS. For a given number of nodes N and number of MS locations $|L|$, the cycle time of MS increases with data generation rate. The average packet latency, as illustrated in figure 15, also shows a similar variation.

Figure 15. Variation of packet latency with MS speed and number of sojourn points.

Assuming 60 sensor nodes each having transmission range 100 m randomly and uniformly distributed in a square deployment area of size $1000\text{ m} \times 1000\text{ m}$, the impact of number of MS sojourn locations on degree of multi-hopping, routing overhead of ‘hot spot’ nodes, lifetime of ‘hot spot’ nodes and hence the lifetime performance of network is tabulated in table 6. To evaluate the lifetime metric, the initial energy of sensors is taken as 100000 J and the energy consumption for single-hop data transfer over a distance of 100 m is evaluated using Eq. (27) as 0.8 J. Larger the number of MS locations, less the degree of multi-hopping, less the routing overhead of single-hop neighbours as indicated by $N_{tx}(1)$ and higher the network lifetime as indicated by Θ . Due to maximum relaying overhead, SSM with unlimited multi-hopping provides the lowest lifetime. MS-based single-hop data collection approach with no relaying requirement provides the highest lifetime. DTSM-NZ based approach with limited multi-hopping gives intermediate results, permitting the flexibility to fix the number of MS sojourn points according to lifetime requirements of the network.

Figure 15 and table 6 demonstrate the inevitable trade-off in our MS-based lifetime-aware data collection for delay-tolerant applications. Higher the number of MS sojourn locations, higher the network lifetime, higher the data delivery delay and sensor buffer size requirement. Hence, if network lifetime is of more significance than data collection latency, it is important to increase the number of MS visit locations and reduce the degree of multi-hopping. If the application requires fast delivery of data or the sensor buffer space is limited, reduce the number of visit locations and increase the degree of multi-hopping. If the application is highly time-critical but not data-intensive (like disaster warning signal), it is better to go for static sink approach, ignoring its inherent limitation of unbalanced energy consumption and the lowest lifetime.

Table 6. Impact of number of MS stop points $|L|$ on network lifetime.

MS stop points $ L $	Cluster radius Ψ (m)	No. of hops	Relaying overhead $N_{tx}(1)$	Lifetime metric Θ
1	1500 (static sink)	8	5624	1320
4	375	4	1406	Packets
16	188	2	351	21,360
64	100	1	Nil	Packets
				1,25,000

Figure 16. Variation of PDR with network size and transmission range.

Based on simulation experiments with ideal channel assumption and varying transmission range of sensors, the variation of PDR with number of static sensors in the network has been studied and plotted in figure 16. For a fixed transmission range, as the network size increases, PDR increases due to larger node density and improved connectivity. For a given network size, as the transmission range of the sensor is increased, PDR increases due to improved connectivity and finally reaches the maximum value. Further increase in network size reduces the PDR due to increased interference between transmissions.

Assuming $k = 2$ and $P_r/P_0 = 1/5$, the optimum transmission range of the underwater sensor nodes in a multi-hop network, as evaluated by solving (43) using numerical techniques, is tabulated in table 7. The frequency of operation has no role on the relaying overhead of ‘hotspot’ nodes, but it strongly influences their hop energy consumption. As the frequency of operation increases,

Table 7. Variation of optimum transmission range ($P_r/P_0 = 1/5$).

Frequency of operation (kHz)	Optimum transmission range (m)
10	1071
15	800
20	642
25	539
30	467

Table 8. Optimum cluster radius and number of clusters ($R = 500$ m).

Frequency of operation (kHz)	Optimum cluster radius (m)	Optimum no. of clusters
10	500	1
15	249	4
20	153	11
25	135	14
30	177	8
40	252	4
50	299	3

absorption coefficient increases, transmission loss increases, hop energy consumption of ‘hotspot’ nodes increases and optimum transmission range decreases.

Assuming no data aggregation and radius of circular deployment area to be 500 m, optimum cluster radius and number of clusters obtained by solving (45) for different frequencies of operation are tabulated in table 8. For a given frequency, if the cluster radius exceeds the optimum value, energy consumption of cluster members increases, total energy consumption in the network increases and network lifetime reduces. On the other hand, if the cluster radius is less than the optimal value, number of clusters increases, energy consumption of cluster heads increases, total network energy consumption increases and network lifetime decreases. For a given network area, if the frequency of operation is increased, energy consumption of both cluster members and CHs increases and network lifetime is reduced. Over the range of frequencies under consideration, the optimum number of clusters is found to increase with frequency, reach a maximum value and then decrease.

6. Conclusion and future work

A lifetime-maximizing data collection framework for delay-tolerant applications in UWSNs has been proposed, taking into account the non-zero travel time of the MS. To maximize the network lifetime, a MILP problem has been formulated and solved using Matlab and Lingo. Solution of

the lifetime maximization problem provides optimal MS sojourn times, data flow rates and number of MS cycles subject to node energy constraints, flow conservation constraints, sensor buffer constraints and application-specified delay constraints. Considering the specific features of the underwater environment, a lifetime-maximizing flow-based routing scheme intended for UWSN applications with a specified delay tolerance level has been implemented in the OMNET++ network simulator. A thorough investigation of the performance of the proposed framework has been done using analytical and simulation techniques. The proposed framework is appropriate for both connected and partitioned UWSNs, and it improves network lifetime and PDR at the cost of high packet delivery latency and additional buffer space requirement. Results demonstrate that, with a network size of 60 nodes, the network lifetime achieved by the proposed DTMSM-NZ model is 188% higher than that of SSM and 91% higher than that of MSM. The absolute value of the optimal network lifetime is found to be independent of the delay tolerance level, but the maximum number of data collection cycles of the MS possible within the network lifetime decreases with it. As the number of MS sojourn locations increases, degree of multi-hopping decreases, maximum achievable lifetime increases and data delivery delay increases. Also, the routing complexity increases with degree of multi-hopping. Optimum transmission range and optimum cluster size have been determined using analytical techniques. The proposed lifetime-aware flow-based routing is suitable for distributed implementation and the results are expected to be useful for further studies in lifetime-aware UWSN designs.

As a future work, we would like to study distributed implementation of the optimization schemes presented here in the underwater environment. Incorporation of optimal MS placement in the proposed model and a comparative study of different placement schemes will be another interesting area of research. Development of efficient clustering and aggregation schemes, specifically suited for underwater environments, will be a challenging problem. Studying the impact of different MAC protocols on maximum network lifetime and development of a lifetime-aware distributed routing protocol for UWSNs will provide avenues for further studies in this emerging area of sensor networks.

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