This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3021623, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2020.DOI

Lifetime Maximization of Sensor Networks Through Optimal Data Collection Scheduling of Mobile Sink

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This work is supported by a grant for the Research Fellowship funded by the Information and Communication Technology Division, Ministry of Posts, Telecommunications and Information Technology, Government of Bangladesh.
The authors are also grateful to King Saud University, Riyadh, Saudi Arabia for funding this work through Researchers Supporting Project number RSP-2020/18.

ABSTRACT The problem of maximizing lifetime of a sensor network is still challenging mainly due to the stringent delay-deadline of real-time applications and heterogeneity of sensor devices. The problem is further complicated when the network contains many obstacles. In maximizing network lifetime, existing literature works either merely address issues of application delay-deadline and presence of obstacles, or analyze primitive data collection approaches for such an environment. In this paper, we formulate optimal data collection schedule of a mobile sink in an obstructed sensor network as a mixed-integer linear programming (MILP) problem. The proposed data collection scheduling finds an optimal set of rendezvous nodes over a preformed Starfish routing backbone, and corresponding sojourn duration so as to maximize the network lifetime while maintaining delay-deadline constraint in an obstructed network. The proposed Starfish-scheduling ensures a loop-free traveling path for a mobile sink across the network. The results of performance evaluation, performed in network simulator-2, depict the suitability of Starfish scheduling as it outperforms state-of-the-art-works in terms of extending network lifetime and data delivery throughput as well as reducing average end-to-end delay.

INDEX TERMS Network-lifetime; Data collection schedule; Obstructed sensor networks; Starfish routing backbone; Mobile sink; Sojourn location; Sojourn duration.

I. INTRODUCTION

In this era of Industry 4.0 [1] [2], sensor networks play important roles for collecting data from wide-range of real-time applications including industrial process monitoring, nuclear power plant monitoring, precision agriculture, big-data gathering, e-health, smart grid, smart city [3], etc. In the upcoming years, the sensed data will lead to developing embedded intelligent systems for most industrial and domestic applications [4] [5]. The efficiency of these real-time applications highly depends on delivering data within the bounded delay-deadline and minimizing end-to-end data delivery delay. Consequently, sensor networks inherently focus on ways of efficient data routing so that energy consumption is minimized and network lifetime is maximized. In mobile-sink based sensor networks, the sink typically collects data traveling across the network and this technique has already been proven not only to enhance the network lifetime but also to minimize average end-to-end data collection latency to a great extent compared to its static counterpart [6] [7]. However, still, there is room to further optimize the network lifetime while maintaining delay-deadlines for real-time applications.

The problem of maximizing lifetime of sensor networks has been well studied in the literature [8] [9]. The primitive

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strategies follow optimal coverage and connectivity [10], opportunistic transmission schemes, dynamic beam-forming [11] [12], etc. Further improvement of network lifetime is achieved through greedy energy-efficient routing, clustering techniques, and machine learning approaches [13]. Though the strategies can achieve an extended network lifetime, they lack to maintain delay-deadline for real-time applications. A set of recent studies has been found to further minimize energy consumption by designing an efficient traveling path of a mobile sink while collecting sensed data from different regions in the network [14] [15]. These are achieved through predictable path planning or dynamic cluster-based data collection strategies [16].

In the literature works, data collection strategies using a mobile sink are broadly grouped into two categories: direct-contact based and rendezvous-node based. In the former strategy [17] [18] [19] [20], the mobile sink periodically travels to all source sensor nodes and collects sensed data directly from them. Even though this strategy can completely avoid message-relay overheads and increase network lifetime, the strategy sacrifices application delay-deadline and therefore it's not applicable for real-time data collection applications. Moreover, it increases the traveling path length for the mobile sink, causing higher data delivery latency.

In rendezvous-node based data collection strategy [21] [22] [23], a mobile sink only visits and collects data from a few rendezvous nodes over a designated tree-like backbone [24], cluster-heads [25] [26] or routing-backbones (e.g., Honeycomb [27], Fish-bone [28], Starfish routing backbone [29], etc.), instead of visiting all sensor nodes in the network. In this strategy, ordinary sensor nodes send their data packets to a few rendezvous nodes ahead of time, reducing the moving path length of the sink as well as the data collection delay. The problem of selecting rendezvous nodes over a given routing backbone (at which a mobile sink halts) has been addressed in [22] [30] [31] [32]. The key philosophy of these works is to develop an energy-efficient traveling path avoiding multi-hop communication, to minimize end-to-end data collection latency, or to reduce computational complexity for determining mobile sink's path. The problem is further investigated in [33] [34] [35] [36] [37] for networks containing several obstacles, opposing free movement of the sink.

In [29], we developed a routing backbone following the water vascular process of a sea fish, namely starfish. The work aimed to minimize energy consumption in an obstacle-free sensor network, and later, in our pioneer work [38], it was investigated for an obstructed-network. However, both works have considered the random sink mobility model rather than finding an efficient data collection scheduling based on data arrival rate, sojourn duration at rendezvous nodes, etc. Moreover, exhaustive visits through all rendezvous-nodes on cluster-heads or backbone nodes also become infeasible for real-time applications due to violation of application delay-deadline. Thus, the problem of determining an optimal set of rendezvous nodes together with sojourn duration at each of them aiming to maximize network lifetime for a time-constraint application is still challenging. Moreover, in presence of obstacles in the network and heterogeneous data generation rates of sensor nodes, a data collection strategy that might further enhance network performances and lifetime of the network has not yet been well-explored in the literature.

In this paper, we offer a novel data collection scheduling for a mobile sink in an obstructed sensor network adopting Starfish routing backbone [29] [38]. The Starfish routing backbone has been developed in our earlier work that spreads backbone nodes throughout the network. In this work, the proposed data collection schedule addresses the problem of determining an optimal set of backbone nodes over the Starfish routing backbone, together with sojourn duration at those backbone nodes aiming to maximize network lifetime. This mechanism is also driven by time-constraints of underlying applications and data generation rates around the backbone nodes. The key contributions of this paper are summarized as follows:

- We formulate the problem of maximizing lifetime of an obstructed network as a mixed-integer linear programming (MILP) that finds an optimal set of rendezvous nodes along with corresponding sojourn duration
- The proposed data collection schedule of a mobile sink maintains application requirements on end-to-end data delivery delay.
- It also guarantees loop-free travel-scheduling among the rendezvous nodes, ensuring balanced energy consumption as well as reduced data delivery delay.
- An experimental analysis, performed in network simulator version-2 [39], shows significant performance improvements on network lifetime, end-to-end delay, data throughput over state-of-the-art-works.

The rest of this paper is organized as follows. Section II provides a study on state-of-the-art works related to backbone-node based data collection scheduling of a mobile sink. The network model, along with assumptions, and the proposed optimal data collection scheduling (namely, Starfish) of a mobile sink are stated in Section III and Section IV, respectively. Section V presents the simulation environment and experimental results of the proposed Starfish data collection scheduling with comparative analysis. Finally, Section VI concludes the paper.

II. RELATED WORKS

Recently, diverse developments of the Internet of Things (IoT) devices and applications have dramatically changed data collection strategies in sensor networks. Devising an efficient data collection mechanism is important for increasing the network lifetime and decreasing the end-to-end data collection latency from source nodes to the mobile sink. We have come across a handful of literature works focusing on mobile sink based data collection strategies that are grouped into two categories: direct-contact based [18] [19] [20] and rendezvous-node based [22] [24] [25] [36] [37].

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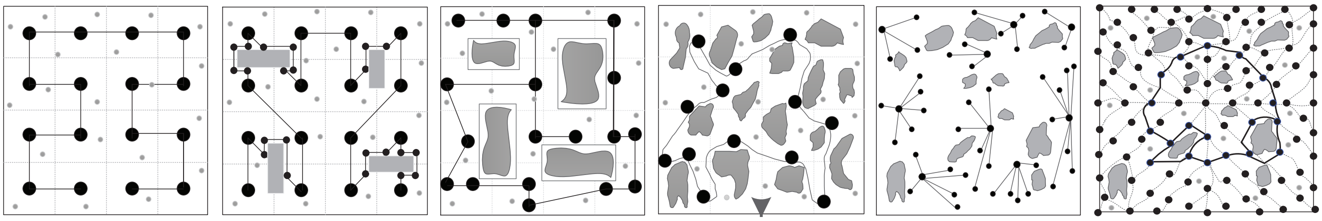

(a) Moore-curve [19] (b) Z-curve [20] (c) Spanning-graph [35] (d) VPS [36] (e) LAS [37] (f) Starfish-backbone [38]

FIGURE 1: Data collection strategies of a mobile-sink in state-of-the-art works

In a direct-contact based data collection strategy, a mobile sink travels all source nodes in the field of interest, and a typical traveling path is determined by a well-known traveling salesman problem (TSP) [17]. Apart from that Hilbert- [18], Moore- [19], and Z-curves [20] are employed in a network to formulate traveling paths for a mobile sink to collect data through one-hop communication. A mobile sink visits along a Hilbert-curve [18], a continuous fractal space-filling curve, to collect data from the sensors. However, a mobile sink cannot return to the starting location along Hilbert-curve. Therefore, a Moore-curve [19] is developed as the loop version of the Hilbert curve, as shown in Fig. 1(a). Data collection scheduling along both Hilbert- and Moore-curves is easy to develop with similar recursive constructions for a large network. However, the path length of a mobile sink shows polynomial growth for the larger networks. Besides, their constructions become more complicated, while the network contains either path-restricted or location-restricted obstacles in the network [8]. Z-curve [20] tried to minimize data collection time through bypassing obstacles in the network, as depicted in Fig. 1(b). Since a mobile sink collects data from each sensor directly, these approaches can completely avoid message relay overhead, broadcasting sink's fresh location, etc. Thus, direct-contact based data collection strategies essentially increase network lifetime. However, they suffer from exaggerated traveling path distance, higher data delivery latency, buffer overflow, and meeting application's hard delay-deadline, etc. Therefore, direct-contact based strategies are not suitable for time-constraint data collection in sensor networks.

To mitigate these problems, in rendezvous-node based data collection strategy, a mobile sink collects data from a few rendezvous nodes [22] [23] over a designated tree-like backbone [24] [28], cluster-heads [35] [36] [37] or routing-backbone [29] [38], instead of traveling all source nodes in the network. In the literature, rendezvous-node based strategies have been developed for two varieties of networks: obstacle-free and obstructed-networks. In the former type, a mobile sink can travel to any rendezvous node along a straight-line direction without any interruption. On the contrary, an obstructed-network area may contain building, tree, pond, lake, forest, mountain, etc. opposing free movement of the mobile sink along the straight-line direction between two rendezvous nodes.

In an obstacle-free-network, a set of rendezvous nodes (RNs) constructs a one-time stationary path for data collection based on residual energy of sensors to maximize network lifetime [21] [22] [30] [31] [33] [34]. In [21], weighted rendezvous planning (WRP) selects RNs, and to avoid hot-spot problems in sensor networks through adopting the shortest path tree and traveling salespersons for path construction. Though it works efficiently for a smaller network, it has higher computational complexity for larger networks. Meanwhile, the expected sojourn time to the corresponding RN is optimized to enhance network lifetime in different works [22] [30]. The sojourn time of a mobile sink in [30] is determined over each grid of a network. This work suffers from buffer overflow, increased data loss, and energy hole problems while collecting data. To further improve the network lifetime, Basagni et al. [22] determine an optimal tour over rendezvous-nodes so as to maximize network lifetime. Sensor nodes, located within the transmission range of RNs, can send data directly to the mobile sink, while others send data through multi-hop communication to the mobile sink.

However, these works lack from applying in a non-grid network, or an irregular node distribution in the network. Recently, Wen et al. [33] proposed energy-aware path construction (EAPC) scheme by selecting RNs on the spanning-tree and constructing a data collection path using a convex polygon algorithm. Since the path is not the shortest and the mobile sink traverses more distance in the network, application delay-deadline is violated. In [31], Gharaei et al. proposed a collaborative approach (namely, CMS2TO) to balance the energy consumption of the cluster heads (CHs) in the network. Since it focuses on the lifetime of CHs, hot-spot regions are created around the CHs. In [34], the authors proposed an efficient path planning for reliable data gathering (EARTH) that determined RPs based on distance and hop-count. Similar to the CMS2TO, the nearby nodes to the RPs die quickly in EARTH approach for large-scale wireless sensor networks (WSNs). To enhance the reliable data collection, trust-based energy-efficient data collection techniques have been proposed in [40] [41].

Based on the aforementioned literature review, we observe that these works optimize network performances in terms of energy consumption, data delivery delay, network lifetime, data throughout, sojourn time [42] [43], etc. for obstacle-free networks. However, obstacles are an integrated part in a practical scenario, and aforementioned cluster-head and tree-based routing protocols become complicated to construct

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sink's tour. Moreover, a few work addresses data collection schedule in an obstructed network [35] [36] [37] [38] [44] [45]. In this consequence, to overcome the complexity of the data collection scheduling in a network containing obstacles, Xie and Pan introduced spanning graph-based data collection scheduling [35] of a mobile sink, in which they developed a heuristic path planning algorithm to skirt obstacles, as shown in Fig. 1(c). In [36], the authors developed the shortest viable path scheduling (VPS) for a mobile sink based on a road-map, as shown in Fig. 1(d), which aimed to construct a tree-like graph (or similar to a convex-hull) using dynamic programming for a unicycle robot or mobile sink. Though this approach reduces data collection time significantly, it suffers from higher data traffic load. Besides, it is inappropriate for larger networks since its computational complexity is $\mathcal{O}(\mathbb{N}^3)$, where $\mathbb{N}$ is the number of all sensor nodes. In another work, Redhu and Hegde proposed the landmark-assisted scheduling (LAS) [37] for a mobile sink, as shown in Fig. 1(e). The key philosophy of the work is to identify the optimal clusters and associated landmark nodes to minimize energy consumption. Since this approach uses random walks over a network, and then it performs matrix multiplication operations over its Markov model, its computational complexity is also $\mathcal{O}(\mathbb{N}^3)$, similar to VPS.

Recently, rendezvous node selection and data collection approaches have been developing for obstructed-networks using artificial intelligence [44], fuzzy logic [45], and machine learning algorithms. In [44], Ghabel et al. proposed DGOB algorithm for data collection over an obstructed-network that was executed into two phases, cluster- and tour- constructions. This approach exploited hierarchical agglomerative clustering, ant colony optimization, and genetic algorithms to construct clusters in the presence of obstacles. In [45], Verma et al. developed fuzzy-logic based effective clustering (FLEC) that used three-tier communication-based approaches: nodes to cluster heads (CHs), CHs to super cluster heads (SCH), and then SCH to mobile sink. Both works [44] [45] exhibit higher computational complexity to select efficient rendezvous nodes in a large scale network.

Moreover, most of above works for obstructed-networks exhibit higher end-to-end data collection latency using a mobile sink due to scheduling periodically over a large circular-path [36] or cluster heads [37] [44] [45] to collect data. These works also violate the delay-deadline of real-time applications and increase energy consumption among the sensor nodes significantly. To mitigate these issues, as a preliminary version of this work, we developed the Starfish routing backbone in an obstructed-network [38], as shown in Fig. 1(f). A brief description of its construction is presented in subsection III-A. Though we improved network lifetime by balancing energy consumption throughout the network and minimized end-to-end delay in [38], data collection was scheduled by random mobility of a sink in the network. Therefore, this work still lacks an efficient data collection scheduling over the Starfish routing backbone by a mobile sink.

Furthermore, in an obstructed-network, a few works have considered sojourn duration and data arrival rate at rendezvous nodes (RNs), and application delay-deadline in selecting visiting nodes. Consequently, what would be the optimal rendezvous nodes and sojourn duration at individual RN have been left unexplored. Motivated by the above challenges of real-time data collection, in this paper, we have developed data collection scheduling of a mobile sink aiming to determine an optimal set of rendezvous nodes in an obstructed-network at each round, together with sojourn duration at each rendezvous node so as to maximize the lifetime of sensor networks. The proposed data collection scheduling mechanism, over an established routing backbone, is driven by delay-deadline of underlying applications including sojourn locations, sink's sojourn duration, and data generation rates around the rendezvous nodes. Such a data collection schedule is expected to offer an extended network lifetime and reduced end-to-end data delivery delay. What we unfold in the next section is the obstructed-network model followed by operational details of an optimal data collection scheduling over the Starfish routing backbone [29].

III. NETWORK MODEL AND ASSUMPTIONS

This section introduces the network model of an obstructed wireless sensor network (WSN) of $2a \times 2b\ m^2$ $(a \geq b)$ area with network-center at (u, v), as shown in Fig. 2 and Fig. 3. Here, obstacle means a bounded area in WSNs across which a mobile sink cannot travel (e.g., forest, ponds, hills, mountains, etc.). The network contains a mobile sink (acts as a central controller) that travels throughout the network to collect sensed data from nodes. We assume, $\mathbb{N}$ is the set of stationary sensor nodes in the network each having initial residual energy ε^0, and transmission range r $(0 < r < b)$. Since connectivity among sensor nodes and mobile sink needs to be guaranteed to receive all sensed data for future processing, we consider a pre-constructed routing backbone in the network. In this paper, we have adopted the Starfish routing backbone from one of our earlier works as discussed in [29] [38]. Its backbone nodes are categorized into ring-canal nodes ($\mathbb{Z}$) and radial-canal nodes ($\mathbb{B}$). The construction of a Starfish routing backbone is briefly described in subsection III-A.

In this work, we consider the classic energy consumption model for a sensor node, as described in [15] [43]. Since most of the energy is dissipated during transmitting and receiving states of a node, the energy consumption for transmission (E) and reception ($\tilde{E}$) for each bit is measured as follows.

$$E = E_{transmit} = \begin{cases} \xi_{elec} + \xi_{fs} d^2 & \text{if } d < d_0 \\ \xi_{elec} + \xi_{amp} d^4 & \text{if } d \geq d_0 \end{cases} \quad (1)$$

$$\tilde{E} = E_{receive} = \xi_{elec} \quad (2)$$

In the equations, ξ_{elec}, ξ_{fs}, and ξ_{amp} represent energy dissipated by the transmitting circuit, required energy for amplification in free space, and for multi-path attenuation

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model, respectively. If the transmission distance d is less than the threshold value d_0, as considered a boundary value between free space and multi-path, the power amplification loss adopts as a free space model. On the other hand, if the transmission distance is greater than or equal to the threshold value d_0, the multi-path attenuation model is adopted.

A. CONSTRUCTION OF STARFISH ROUTING BACKBONE

The key philosophy of designing a Starfish routing backbone is to spread backbone nodes throughout the network aiming to balance energy consumption among the nodes. Motivating from the water vascular process of a sea-fish called "Starfish", we construct a Starfish routing backbone that contains backbone nodes on a central ring-canal and several radial-canals throughout the network [29]. The central ring-canal is formed in the middle of the network and is also circularly connected with ring-canal nodes, as depicted in Fig. 2(a). On the other hand, the radial-canals are spread out to the periphery from the principal-axes of the network, as depicted in Fig. 2(b).

The primary objective of constructing ring-canal is to alleviate the hot-spot problem at the network center. To construct the ring-canal, an optimal radius (R) of a reference circle is estimated, and then the ring-canal nodes are selected nearby every r distance away starting from any node on it, as depicted in Fig. 2(a). To ensure the efficiency of the Starfish routing backbone, an optimal radius of the ring-canal R is estimated proportionally to the maximum number of radial-canals using mixed-integer linear programming (MILP), as explained in Lemma 1, in the light of our another work in [46]. Then the ring-canal nodes $\mathbb{Z} \subset \mathbb{N}$ are selected over the reference circle (having radius R) every r distance interval. For instance, $\mathbb{Z} = \{z_1, z_2, \ldots, z_6\}$, as shown in the Fig. 2(a).

On the contrary, the key philosophy of constructing radial-canals is to spread the backbone nodes across the network so that the source nodes from all areas of the network can access at least one of the backbone nodes on radial-canals. At first, few designated nodes are chosen every $2r$ distance away along principal-axes, as shown in Fig. 2(b), and then the radial-canals are prolonged toward the edge of the network parallel to both principal-diagonals. Later, a central controller (or the mobile sink) selects radial-canal nodes (e.g., $\mathbb{B} \subset \mathbb{N}$) over principal axes, principal diagonals, and all radial-canals

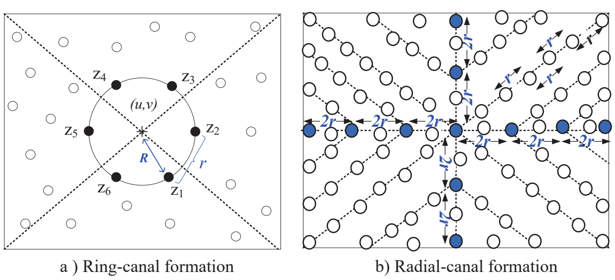

FIGURE 2: Ring-canal and radial-canals of a Starfish routing backbone

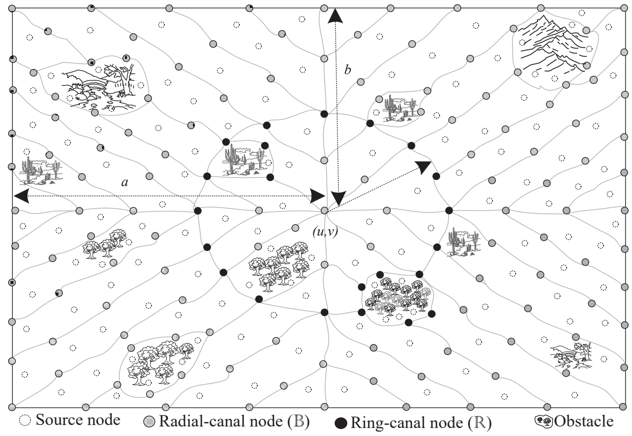

FIGURE 3: Network model and Starfish routing backbone in an obstructed-network

approximately every r distance away. Finally, all of these ring-canal and radial-canal nodes are connected to construct the Starfish routing backbone. Since the network model contains obstacles in the network, the controller selects backbone nodes for both ring-canal and radial-canal surrounding the obstacle following the obstacle-detection strategy described in [47]. In the network, any application may adopt trust-based energy-efficient data collection techniques [40] [41] for secured data transmission.

Lemma 1. Given that a and b $(a \geq b > r)$ are the halves of two sides, respectively, of a rectangular network. Then the optimal radius of the ring-canal of a Starfish routing backbone is estimated as $R \cong (a+b)/\pi$, if and only if the number of radial-canals has a linear relationship with the number of backbone nodes on the ring-canal.

Proof. Since the backbone nodes on the ring-canal are positioned approximately every r distance away, the number is measured for the central ring-canal with radius R as $2\pi R/r$. Meanwhile, the number of radial-canals of the Starfish routing backbone is estimated for the given network as $(2a+2b)/2r$, since the radial-canals are rayed out approximately every $2r$ distance away along both principal-axes. If and only if the number of backbone nodes on the ring-canal and that of radial-canals has a linear relationship, or equal proportion (i.e., $2\pi R/r \cong (a+b)/r$), the Starfish routing backbone contains the optimal radius of the ring-canal that is estimated as $R \cong (a+b)/\pi$, and thus the Lemma 1 is proved.

B. PROBLEM STATEMENT

In this paper, we assume a network containing obstacles like trees, forest, building, mountains, etc. that oppose free movement of the mobile sink between the nodes, as shown in Fig. 3. In the network, each source node $i \in \mathbb{N}$ sends data packets to nearby radial-canal ($\mathbb{B}$) or ring-canal ($\mathbb{Z}$) backbone nodes, which then relays to the mobile sink in multi-hop fash-

TABLE 1: Notations

Symbols	Descriptions
$2a \times 2b$	Network area
$\mathbb{N}$	Set of all sensor nodes
r	Transmission range of a sensor node
R	Optimal radius of the ring-canal
T	Minimum value of application delay-deadline
C	Set of cycles be completed by mobile sink
D^c	The worst-case end-to-end delay of a packet in a cycle c
σ_m^c	Data arrival rate at sojourn location m in cycle c
S_m^c	Sojourn duration at m in a cycle c
$\mathbb{B}$	Set of nodes on radial-canal
$\mathbb{Z}$	Set of nodes on the ring-canal
$\mathbb{R}^c$	Power set on ring-canal nodes $\mathbb{Z}$ during cycle c
$\mathbb{M}_n^c$	Set of optimally selected sojourn locations during cycle c
ε_m^c	Residual energy of a rendezvous node m at cycle c
ε_m^0	Initial residual energy of a node
e_m^c	Total energy required at m in cycle c
E	Energy expenditure to transmit a bit of data
$\tilde{E}$	Energy expenditure to receive a bit of data
q_m^c	Bit-length of a packet at m in cycle c
A^c	Set of sink's traveling-arcs in cycle c
f_{lm}^c	A variable determining sink from l to m at cycle c
h_m^c	A variable determining sink's sojourn at m in a cycle c
δ	The expected end-to-end delay per hop for a packet
H^c	Hop-distance for a packet in a cycle c
$\rho_{H^c}^{z^c}$	Inter-hop transition probability of a packet

ion over the preformed Starfish routing backbone. We assume that source nodes are producing data packets with different delay-deadlines and T is the minimum value of deadlines in the network. While any backbone node collects data from a source node, it takes responsibility to forward data to the mobile sink over starfish routing backbone nodes. However, scheduling the sink's mobility within the obstructed-network would still improve the efficiency of data collection and network lifetime.

The details of the proposed optimal data collection scheduling, namely Starfish scheduling, are explained aiming to maximize network lifetime and improve data collection efficiency in Section IV. The symbols and notations are summarized in Table 1.

IV. DATA COLLECTION SCHEDULING

In this section, we have developed an optimal data collection scheduling of a mobile sink so that lifetime of a sensor network can be maximized while maintaining application delay-deadline. In the network, a mobile sink visits any set element of $\mathbb{R}^c$ in each cycle $c \in C$, where $\mathbb{R}^c$ denotes the power set on $\mathbb{Z}$ $(i.e., \mathbb{R}^c = P(\mathbb{Z}))$, and $C = \{0, 1, 2, \dots\}$. This choice is motivated by the fact that data collection over the optimal size of the ring-canal (of Starfish routing backbone [29]) offers minimum energy expenditure in the network, in the light of our earlier work in [46]. Moreover, the computational complexity of finding optimal sojourn locations over ring-canal nodes would be less compared to that when all nodes are explored. The following subsections describe optimal data collection scheduling, namely Starfish scheduling, in detail.

A. OPTIMAL DATA COLLECTION SCHEDULING

In the proposed scheduling, we assume, the mobile sink sojourns (or halts) at sojourn location $m \in \mathbb{M}_n^c$ and $\mathbb{M}_n^c \in \mathbb{R}^c$ for a duration of S_m^c in a cycle c, where $n = \{1, 2, \dots, |\mathbb{R}^c| - 1\}$. Since the network contains obstacles among nodes, arc set is defined as follows, $A^c = \{(l, m) : f_{lm}^c = 1\}$, where $f_{lm}^c = 1$ indicates that there exists a traveling path avoiding obstacles between sojourn locations $l \in \mathbb{M}_n^c$ and $m \in \mathbb{M}_n^c$ in a cycle $c \in C$; 0 otherwise. The sojourn duration of the mobile sink at a rendezvous node in a particular cycle depends on the data arrival rate. Here, sojourn locations are those that are optimally selected among rendezvous nodes in a cycle. We assume σ_m^c and S_m^c are, respectively, the data arrival rate and the sojourn duration at corresponding location $m \in \mathbb{M}_n^c$ in a cycle $c \in C$. The sojourn duration S_m^c is measured as follows,

$$S_m^c = \frac{\sigma_m^c}{\sum_{j \in \mathbb{Z}} \sigma_j^c} \times D^c, \; \forall c \in C, \forall m \in \mathbb{M}_n^c \tag{3}$$

where D^c is the worst-case end-to-end data collection latency from the farthest source node of the network to the mobile sink for a cycle c. Since the central controller is aware of both data arrival rate at each rendezvous nodes on the ring-canal and sink travels around the preformed ring-canal, it can determine the worst-case end-to-end delay D^c for a network instance [29]. To support real-time applications, worst-case end-to-end delay D^c for a cycle cannot exceed the minimum value of application delay-deadline T (i.e., $D^c \leq T$).

Now, we assume ε_m^c be the residual energy of a rendezvous node $m \in \mathbb{M}_n^c$ at a particular cycle $c \in C$. While routing data, a node requires energy E and $\tilde{E}$ for transmitting and receiving each bit, respectively. Therefore, the total energy required by a rendezvous node $m \in \mathbb{M}_n^c$ during sojourn period S_m^c can be computed as,

$$e_m^c = S_m^c \cdot \sigma_m^c \cdot q_m^c \cdot (E + \tilde{E}), \; \forall m, \; \forall c, \tag{4}$$

where q_m^c is the bit-length of a packet. While selecting a sojourn location $m \in \mathbb{M}_n^c$ in a cycle c, its residual energy ε_m^c must be greater than the required energy e_m^c. At the end of a cycle, the residual energy of a rendezvous node is updated as, $\varepsilon_m^{c+1} = \varepsilon_m^c - e_m^c$. At the initial cycle, i.e., $c = 0$, ε_m^0 is considered as the initial residual energy and energy expenditure, $e_m^0 = 0$.

The key objective of the proposed Starfish data collection scheduling is to maximize network lifetime that is translated as maximizing sojourn duration over the optimal set of rendezvous nodes of Starfish routing backbone. A rendezvous node is interpreted as a sojourn location when the mobile sink halts for a certain duration and collects data. We maximize total sojourn duration so as to increase the network lifetime since sink's data collection lasts until the network is dead. The objective function and the constraints of the mixed-integer linear program (MILP) are formulated as follows.

$Maximize:$

$$L = \underset{\mathbb{M}_n^c \in \mathbb{R}^c}{\operatorname{argmax}} \sum_{\forall c \in C} \sum_{\forall m \in \mathbb{M}_n^c} S_m^c, \tag{5}$$

$subject\ to,$

$$e_m^c < \varepsilon_m^c, \ \forall c \in C, \forall m \in \mathbb{M}_n^c \tag{6}$$

$$\sum_{m \in \mathbb{M}_n^c} e_m^c h_m^c / S_m^c < \sum_{m \in \tilde{\mathbb{M}}_n^c} e_m^c h_m^c / S_m^c, \forall c, \forall \tilde{\mathbb{M}}_n^c \tag{7}$$

$$h_m^c \in \{0,1\}, \ \forall c \in C \tag{8}$$

$$D^c \leq T, \ \forall c \in C \tag{9}$$

$$\mathbb{P}^c(j \overset{k}{\rightsquigarrow} m) = True, \forall j \in \mathbb{Z} \cup \mathbb{B}, \exists k \in \mathbb{Z} \cup \mathbb{B} \cup \emptyset, \\ \exists m \in \mathbb{M}_n^c, \forall c \in C \tag{10}$$

$$w_l^c - w_m^c + |\mathbb{M}_n^c| \cdot f_{lm}^c \leq |\mathbb{M}_n^c| - 1, \ \forall (l,m) \in A^c, \\ \forall c \in C \tag{11}$$

$$0 \leq w_l^c < w_m^c, \ \forall c \in C \tag{12}$$

$$f_{lm}^c \in \{0,1\}, \ \forall c \in C \tag{13}$$

Here, Eq. (5) is the objective function and Eq. (6) - Eq. (13) are the constraints. The objective function schedules the mobile sink so that it can maximize network lifetime L, which is translated as finding out optimal sets of rendezvous nodes $\mathbb{M}_n^c$ to maximize sojourn duration for allowable cycle $c \in C$. In the objective function, sojourn duration S_m^c is related to the data arrival rate at that location in a cycle c that is measured following Eq. (3).

We formulate the network lifetime maximization problem in such a way that the mobile sink persistently travels over rendezvous nodes (RNs) until the residual energy of an RN is exhausted. The energy constraint in Eq. (6) finds candidate RNs on the ring-canal to be selected as a sojourn location, if and only if energy expenditure e_m^c in a cycle c is less than the remaining residual energy ε_m^c of the node. At the end of a cycle, residual energy of RNs is updated as $\varepsilon_m^{c+1} = \varepsilon_m^c - e_m^c$ in order to discover its feasibility to be a sojourn location in the next cycle.

The energy efficiency constraint in Eq. (7) helps us to single out all the alternative paths that are not as energy-efficient as the selected one $\mathbb{M}_n^c$ in a cycle. In Eq. (7), the set of all alternative paths $\tilde{\mathbb{M}}_n^c \in \tilde{\mathbb{R}}^c$ and $\tilde{\mathbb{R}}^c = \{\mathbb{R}^c \setminus \mathbb{M}^c\}$. Both constraints in Eq. (6) and Eq. (7) force to select a set of energy-efficient rendezvous nodes as sojourn locations for a cycle c so that energy consumption is minimized per unit time. Moreover, as there exists at least one energy-efficient path during data collection for each cycle, the lifetime of the network is maximized for all completed cycles. Eq. (8) defines a binary variable h_m^c that determines whether the mobile sink sojourns at m in a cycle c or not. Therefore, the constraints in Eq. (6) - Eq. (8) jointly select $\mathbb{M}_n^c$ among ring-canal nodes in the network.

The Eq. (9) ensures that the worst-case end-to-end delay D^c for a cycle cannot exceed the minimum value of application delay-deadline T. The worst-case end-to-end delay D^c is bounded by hop-distance $H_{min}^c \leq H^c \leq H_{max}^c$ that is estimated using Lemma 2 and Lemma 3. This constraint guarantees the effectiveness of data collection schedule for a real-time application in the network. The connectivity constraint in Eq. (10) ensures that there exists at least one path from any backbone node $j \in \mathbb{Z} \cup \mathbb{B}$ to a sojourn location $m \in \mathbb{M}_n^c$, either directly or via a forwarding backbone node $k \in \mathbb{Z} \cup \mathbb{B}$. Since there exists Starfish routing backbone in the network and it guarantees single-hop connectivity of at least one backbone node from any source node, the connectivity constraint in Eq. (10) holds until the network is dead.

In the network, the mobile sink travels to the selected sojourn locations over the ring-canal nodes, where it may exist sub-loop nodes due to the presence of obstacles. The constraints in Eq. (11) and Eq. (12) jointly determine the order of visiting sojourn locations and ensure that no sub-tour would be formed among the nodes. At last, f_{lm}^c represents a binary variable in Eq. (13) determining whether the mobile sink travels from sojourn location l to m among rendezvous nodes during path selection; therefore, if $f_{lm}^c = 1$, then $w_l^c < w_m^c$. Since each sojourn location $m \in \mathbb{M}_n^c$ is associated with a weight $w_m^c > 0$ and an increasing weight (i.e., $w_l^c < w_m^c$) is maintained for each visiting sojourn location, it inherently prevents forming any sub-loop of a path for the mobile sink during traveling sojourn locations.

Finally, the formulation maximizes sojourn duration over the optimal set of sojourn locations for a maximum number of cycles until the residual energy is exhausted. This inherently helps to achieve extended network lifetime during data collection in the network.

B. FEATURES OF THE PROPOSED SCHEDULING

In this subsection, we explain different characteristics of the proposed Starfish data collection schedule. We analyze the worst-case end-to-end data delivery delay using Lemma 2 and Lemma 3. Since the network contains sub-cycle nodes on the ring-canal due to the presence of obstacles, the proposed Starfish scheduling could be inefficient if the mobile sink travels over sub-cycles. Therefore, we present Lemma 4 to prove that the MILP model avoids sub-loop among the sojourn locations for a cycle c. Finally, Lemma 5 proves that the selected set of rendezvous nodes $\mathbb{M}_n^c$ for a cycle c over the Starfish routing backbone is optimal.

Lemma 2. For a given network $2a \times 2b$ $(a \geq b > r)$ containing a Starfish routing backbone and sensor nodes with transmission range r, the extreme hop-distance H^c is bounded by $\lceil (b - R)/r \rceil \leq H^c \leq \lceil (\sqrt{a^2 + b^2} + R(\pi - 1))/r \rceil$ for a data packet.

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Proof. In the network, the minimum hop distance of a packet to the ring-canal typically exists along the minor axes (ignoring obstacles), and thus the minimum hop distance is bounded by $H^c_{min} = \lceil (b - R)/r \rceil$, since $b \leq a$. Accordingly, the maximum hop distance from the farthest node (e.g., the corner node of the network) to the mobile sink is typically bounded by two reference distances, e.g., corner node to the ring-canal node, and then to the farthest opposite node around the ring-canal. The longest distance from the corner node to the ring-canal lies along the principal diagonal that is estimated as $\sqrt{a^2 + b^2} - R$. Meanwhile, since the sink visits around the ring-canal, the longest traveling path to the farthest opposite node is estimated as half-perimeter of the ring-canal, i.e., πR. Therefore, the maximum hop-distance H^c_{max} is estimated as $\sqrt{a^2 + b^2} - R + \pi R$, and thus the extreme hop-distance for a packet is bounded by $\lceil (b - R)/r \rceil \leq H^c \leq \lceil (\sqrt{a^2 + b^2} + R(\pi - 1))/r \rceil$, and hereby, Lemma 2 is proved.

Lemma 3. Given that $\overline{\delta}$ is the expected end-to-end data delivery delay of a packet for one hop (including medium access, processing, queuing delay, propagation, transmission, retransmission) in a network, then the worst-case end-to-end data delivery delay $D^c = \overline{\delta^c} \times H^c_{max}$ for a packet traveling H^c_{max} hop in a cycle $c \in C$.

Proof. Since the network contains obstacles, end-to-end delay (i.e., δ) of a packet greatly depends on both hop-distance from the source node to the mobile sink and the number of retransmission(s) at each hop.

To prove the Lemma 3, as motivated from [29], we assume $\rho^{z^c}_{H^c}$ be the inter-hop transition probability of a packet in a Markov chain model for a cycle c, where hop $H^c \in \{1, 2, \ldots, H_{max}\}$ and retransmission attempt per hop till success $z^c \in \{0, 1, 2, \ldots, \phi\}$. Therefore, the expected retransmission attempt for a packet is expressed as $\overline{z^c} = \sum_{z^c=0}^{\phi} z^c \rho^{z^c}_{H^c}$, and the expected delay is expressed as $\overline{\delta^c} = \delta\ \overline{z^c}$ for a packet.

Finally, the average end-to-end data delivery delay for a data packet traveling maximum H^c_{max} hops is expressed as $D^c = \overline{\delta}^c \times H^c_{max}$, which is bounded by extreme hop-distance H^c, as computed in Lemma 2, and thus it is proved.

Lemma 4. Given that $w^c_l \leq w^c_m$, as stated in Eq. (12), the optimal data collection scheduling of a mobile sink in the Starfish routing backbone is sub-cycle free for $l, m \in \mathbb{M}^c_n$ and $c \in C$.

Proof. Suppose, for the sake of contradiction, the hypothesis is not true. Then there exists the constraint $w^c_l \leq w^c_m$ for which there is a sub-cycle between sojourn locations such that $\mathbb{M}^c_n = \{l, l_2, l_3, \ldots, m, l\}$ in a cycle c.

According to the constraint in Eq. (11) of the MILP formulation, the mobile sink travels from l to l_2 that follows $w^c_l \leq w^c_{l_2}$. Similarly, for the sub-cycle through $\{l, l_2, l_3, \ldots, m, l\}$, it also maintains $w^c_l \leq w^c_{l_2} \leq w^c_{l_3} \leq w^c_m \leq w^c_l$.

Now, as on hypothesis, since the mobile sink also travels from m to l maintaining $w^c_m - w^c_l + |\mathbb{M}^c_n| \cdot f^c_{ml} \leq |\mathbb{M}^c_n| - 1$, that gives $w^c_m \leq w^c_l - 1$. However, this contradicts the given fact $w^c_l \leq w^c_m$. Since we have arrived at a contradiction, our original supposition that there exists a sub-cycle between sojourn locations l and m in a cycle c could not be true.

Thus, the optimal data collection scheduling by mobile sink over the Starfish routing backbone is sub-cycle free for a particular cycle c, and hereby the Lemma 4 is proved.

Lemma 5. Given that $\forall c\ \forall \tilde{\mathbb{M}}^c_n\ \sum_{m \in \mathbb{M}^c_n} e^c_m h^c_m / S^c_m < \sum_{m \in \tilde{\mathbb{M}}^c_n} e^c_m h^c_m / S^c_m$, as stated in Eq. (7), the selected set $\mathbb{M}^c_n \in \tilde{\mathbb{R}}^c$ of sojourn locations for a cycle c over the Starfish routing backbone is optimal.

Proof. Suppose, for the sake of contradiction, the hypothesis is not true. Then there exists an $\tilde{\mathbb{M}}'^c_n \neq \mathbb{M}^c_n$ that maximizes the sojourn duration S^c_m.

According to the MILP formulation, the key philosophy of energy efficiency constraint in Eq. (7) is to single out a set $\mathbb{M}^c_n$ from $\mathbb{R}^c$.

Now, as on hypothesis, for the selected set $\tilde{\mathbb{M}}'^c_n$ of rendezvous nodes for a cycle c, it maintains $\sum_{m \in \tilde{\mathbb{M}}'^c_n \in \tilde{\mathbb{R}}^c_n} e^c_m h^c_m / S^c_m < \sum_{m \in \mathbb{M}^c_n} e^c_m h^c_m / S^c_m$. However, this inequality contradicts according to the constraint in Eq. (7) to achieve maximum sojourn duration S^c_m for a particular cycle c simultaneously with $\mathbb{M}^c_n$, since $\tilde{\mathbb{M}}'^c_n \neq \mathbb{M}^c_n$ and $\tilde{\mathbb{M}}'^c_n \in \tilde{\mathbb{M}}^c_n \in \tilde{\mathbb{R}}^c = \{\mathbb{R}^c \setminus \mathbb{M}^c_n\}$. Hence we have arrived at a contradiction, our original supposition that the selected set $\tilde{\mathbb{M}}'^c_n$ of rendezvous nodes is optimal in a cycle c could not be true simultaneously with any other alternative set of rendezvous nodes.

Therefore, the selected set $\mathbb{M}^c_n \in \mathbb{R}^c$ of rendezvous nodes for a cycle c over the Starfish routing backbone is optimal, and consequently, it is true for all cycle $c \in C$, and hereby the Lemma 5 is proved.

C. DATA FORWARDING POLICY

After selection of an optimal set of sojourn locations following the above MILP formulation, the mobile sink (or a central controller) broadcasts both the selected sojourn locations $m \in \mathbb{M}^c_n$ and corresponding sojourn duration S^c_m at the beginning of each cycle $c \in C$. Since the network runs real-time applications, it follows a continuous forwarding policy to send data to the mobile sink over ring-canal and radial-canal nodes of the Starfish routing backbone.

The key philosophy of the continuous forwarding policy employed by backbone nodes is to send data to the mobile sink immediately. If a source node senses data within the transmission range of a ring-canal node, it immediately forwards data to the nearest ring-canal node. Afterward, the ring-canal node takes responsibility to send data to the mobile sink. If any source node is out of transmission range of the ring-canal, it transmits data to the nearest radial-canal node; then the node immediately forwards data to the nearest ring-canal node. As soon as a ring-canal node collects data from the source nodes, or radial-canal nodes, or neighbor nodes, it instantly forwards data over backbone nodes to the

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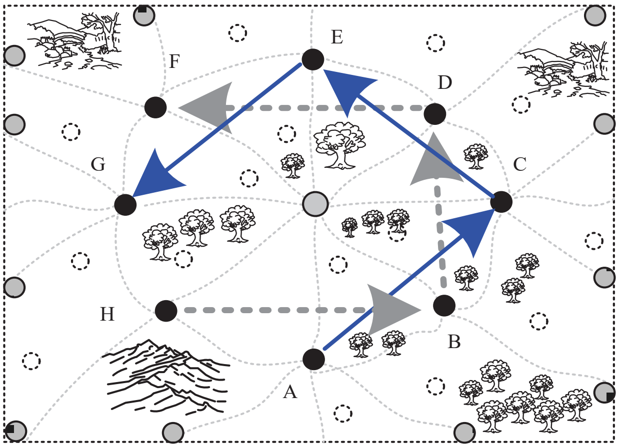


FIGURE 4: Data forwarding in obstructed network environment

TABLE 2: Traveling route matrix for mobile sink

	A	B	C	D	E	F	G	H
A	-	0	1	0	0	0	0	1
B	0	-	0	1	0	1	0	1
C	1	0	-	0	1	0	1	1
D	0	1	0	-	1	1	0	1
E	0	0	1	1	-	1	1	0
F	0	1	0	1	1	-	1	1
G	0	0	1	0	1	1	-	1
H	1	1	1	1	0	1	1	-

TABLE 3: Data arrival rates (packet/sec) and set of sojourn locations

c	σ_A^c	σ_B^c	σ_C^c	σ_D^c	σ_E^c	σ_F^c	σ_G^c	σ_H^c	$\mathbb{M}_n^c$
1	40	7	20	10	30	13	35	17	{A,C,E,G}
2	10	35	16	40	10	45	8	50	{H,B,D,F}
3	40	10	30	50	20	12	45	13	{G,A,C,D}
4	50	10	20	40	12	45	20	38	{F,D,A,H}

current sojourn location $m \in \mathbb{M}_n^c$ of the mobile sink for a cycle c. Here, we consider the shortest routing path in the network that is implemented in [29]. When a ring-canal node runs out of energy, it migrates the role to neighboring node(s) maintaining circular property of the ring-canal. This continuous data forwarding policy minimizes end-to-end delay significantly, even in an obstructed network environment. The simulation results prove the efficiency of the proposed Starfish scheduling to maximize network lifetime, as depicted in Section V.

D. AN ILLUSTRATIVE EXAMPLE

We consider a set of rendezvous nodes $\{A, B, C, \ldots, H\}$ on the ring-canal, as shown in Fig. 4. Due to the presence of obstacles in the network, the mobile sink cannot travel to every rendezvous node from any of those. Table 2 shows the traveling route matrix of the mobile sink among the rendezvous nodes $\{A, B, C, \ldots, H\}$ in the presence of obstacles. When the mobile sink halts at a sojourn location A, it can only travel either to C or H due to obstacles in the network. Similarly, in the case of halting at B, it can travel only to $\{D, F, H\}$. Now, the key philosophy of the proposed Starfish data collection scheduling is to determine the optimal set of sojourn locations based on data arrival rates, energy expenditures at corresponding rendezvous nodes so that the mobile sink can travel through a sub-loop free path. As an example, we consider the maximum delay-deadline of real-time application is $250ms$ and data arrival rates at corresponding rendezvous nodes $\{\sigma_A^c, \sigma_B^c, \sigma_C^c, \ldots, \sigma_H^c\}$ are tabulated in Table 3.

According to the proposed Starfish scheduling, at first, the central controller (or the sink) finds a set $\mathbb{R}^c$ as a power set on the ring-canal nodes $\mathbb{Z}$. When the MILP formulation runs, the central controller selects the most energy-efficient set of sojourn locations $\mathbb{M}_n^c$ for a cycle c to maximize sojourn duration. Meanwhile, it computes energy expenditures over the sets of $\mathbb{R}^c$ based on available traveling paths of the mobile sink in presence of obstacles and data arrival rates, as mentioned in Table 2 and Table 3, respectively. In this example, Starfish scheduling finds a set of sojourn locations $\mathbb{M}_n^1 = \{A, C, E, G\}$, for $c = 1$, and then it determines the sojourn duration at corresponding sojourn locations (using Eq. (3)). For an efficient routing of data packets throughout the network, the central controller acknowledges selected sojourn locations ($m \in \mathbb{M}_n^c$) along with corresponding sojourn duration $\{S_A^1, S_C^1, S_E^1, S_G^1\}$ before starting data collection.

Similarly, Starfish scheduling gets another set of sojourn locations $\mathbb{M}_n^2 = \{H, B, D, F\}$ for the second cycle $c = 2$ satisfying the required constraints in Eq. (6) - Eq. (13), and so on until the network is dead. The lifetime of the network can be estimated when the central controller finds the maximum number of cycles. As soon as the central controller determines the optimal set of sojourn locations, it acknowledges to the ring-canal nodes along with sojourn duration. Afterward, each designated sojourn location broadcasts locally to the neighbors on the radial-canal backbone nodes so as to forward their sensed data up to the sojourn locations.

In continuous data forwarding policy, a source node immediately forwards sensed data to the nearest ring-canal node directly (or via the radial-canal nodes). Since each ring-canal node (or rendezvous node) is aware of the data collection schedule along with sojourn duration, it instantly forwards data to the mobile sink via sojourn location $m \in \mathbb{M}_n^c$. This data forwarding policy minimizes end-to-end packet delivery delay significantly for real-time applications even in an obstructed network environment. The details of simulation results are discussed in Section V.

In the following section, we have carried out an exhaustive experimental analysis to compare the proposed data collection scheduling with state-of-the-art-works.

V. PERFORMANCE EVALUATION

This section presents the performances of the proposed Starfish data collection scheduling compared with recent works such as Viable Path-based scheduling (VPS) [36]

TABLE 4: Simulation parameters

Parameters	Values
Network area	$600 \times 450\ m^2$
Deployment type	Uniform random
Node density	$0.002m^{-2}$
Transmission range	$90m$
MAC	WirelessPhy/802.15.4
Size of data packet	$512\ Bytes$
Channel bandwidth	$512\ Kbps$
Application type	Event-driven
Initial node energy	$6J$
Sensor's transmit power	$-3dBm$
Receive power	$-85dBm$
Pass loss exponent	2-4
d_0	$70m$
Simulation time	$1000s$

TABLE 5: List of events and the burst duration

	Event-A	Event-B	Event-C	Event-D
Burst-1	10s-20s	70s-80s	110s-120s	365s-375s
Burst-2	105s-115s	190s-200s	370s-380s	570s-580s
Burst-3	430s-440s	650s-660s	730s-740s	750s-760s

and Landmark-assisted scheduling (LAS) [37] in network simulator version-2 (NS-2) [39].

A. SETUP ENVIRONMENT

In the simulation setup, a WSN of $600 \times 450m^2$ area is considered, where sensor nodes are randomly deployed following uniform random distribution having node density 0.002 per unit area. In the network, each sensor has a transmission range $90m$, and initial energy of $6J$. In the simulation, constant bit rate (CBR) traffic is modeled while data are transmitted under UDP protocol, 512 $bytes$ of each data packet are transmitted over 512 $Kbps$ of channel bandwidth. The parameters of the simulation-environment setup are listed in Table 4.

B. EVALUATION METRICS

The following six evaluation metrics [29] have been used to gauge the performances of the studied data collection scheduling systems.

- Network lifetime is measured as the time duration from the deployment of the network to the time at which any backbone node has exhausted its energy to transmit data packets in the network.
- Standard deviation of residual energy refers to the distribution of backbone nodes' residual energy when the lifetime of a network is exhausted. This measure is expected to be the smallest so that energy consumption among the backbone nodes is balanced to enhance network lifetime.
- Data throughput refers to the average data rate of successful data that is received by the mobile sink. The higher value of throughput is expected for better network performance.
- Packet delivery ratio (PDR) refers to the ratio between the number of data packets successfully delivered to the mobile sink and the number of packets generated by the source node within certain application delay-deadline. The higher value of PDR represents the reliability of the data routing over the backbone nodes.
- Average end-to-end (e2e) packet delivery delay refers to the difference in time delay from generation time of a packet to its reception time. The lower value of e2e packet delivery delay indicates the effectiveness of data collection scheduling for real-time applications.
- Operational overhead refers to the ratio of network control bytes exchanged to the data bytes received by the mobile sink during experimental evaluation. Performance is better when the operational overhead is lower.

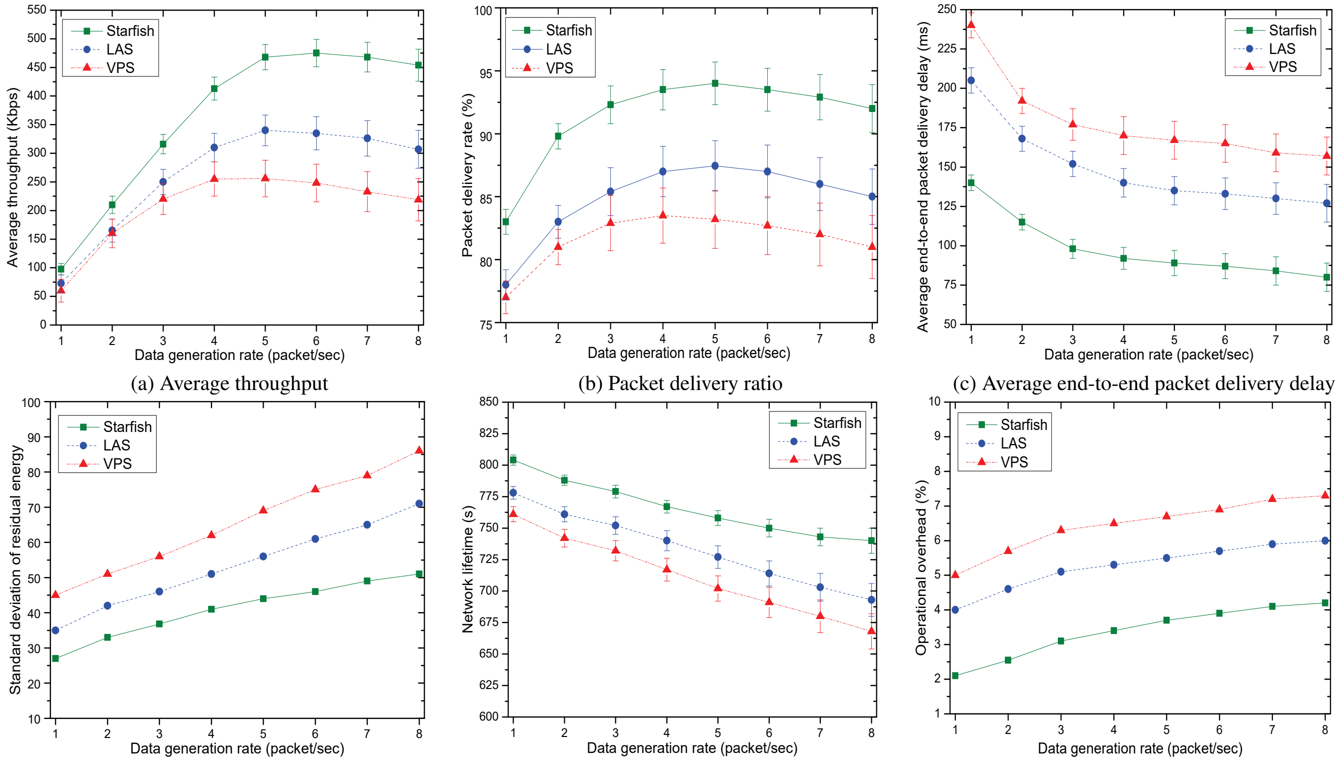
C. EXPERIMENTAL RESULTS

We performed 50 times of simulation experiments with different randomly generated seed values, and the average result is plotted for each data point in the graph. In the network, if there is no direct, line-of-sight path between the transmitter and the receiver due to obstacles, data propagation is bounced off objects and it causes multipath fading with path loss exponent value of 2–4. However, the simulation trace file data depicted that the average value of the path loss exponent used by the transmitters during the experiments was around 2.8. We considered 250 ms for the maximum delay-deadline of application and events in the simulation experiments happened randomly at 30 different locations. Table 5 provides events with corresponding burst duration for the experiment.

1) Impacts of varying data generation rates

This section presents the performances of the studied protocols for varying data generation rates $1-8\ packets/second$. In the experiment, the network size was fixed at $600 \times 450\ m^2$, sink speed was fixed at 6 $meter/second$ and the number of obstacles was fixed at 40 occupying around 15% of the corresponding network area.

The graphs, as shown in Fig. 5(a), illustrate that average data throughput (within delay-deadline) rises sharply with the increasing rate of packet generation in all the studied protocols. This is trivial because of generating more packets and successful reception of these packets by the mobile sink. It is obvious that the proposed Starfish data collection scheduling is effective in terms of bandwidth utilization as the rate of packet generation increases. However, for a higher rate of data generation (e.g., more than 5 packets/second), data throughput decreases steadily due to the exceeding maximum channel bandwidth, buffer overflow, and packet drop, etc. The average throughput for the proposed data collection scheduling over Starfish backbone is significantly higher than those of VPS [36] and LAS [37] strategies because of faster data forwarding is offered over starfish routing backbone and continuous data collection scheduling from the optimal number of sojourn locations on the ring-canal. It is noteworthy that both sojourn location and duration are selected based on corresponding data arrival rates.



(a) Average throughput (b) Packet delivery ratio (c) Average end-to-end packet delivery delay

(d) Standard deviation of residual energy (e) Network lifetime (f) Operational overhead

FIGURE 5: Impacts of varying rates of data generation

For similar reasons, the proposed scheduling over the Starfish routing backbone exhibits higher PDR with progressive data generation rate in the simulation experiments, as depicted in Fig. 5(b), and afterward PDR declines steadily for a higher rate of data generation. These results prove the reliability of using Starfish scheduling for real-time applications in the network.

On the contrary, the average end-to-end packet delivery delay within the application delay-deadline is decreased with the progressive rate of data generation, as illustrated in Fig. 5(c). It occurs because the sink's mobility significantly reduces the vicinity-length from source nodes to the mobile sink. Moreover, the proposed Starfish scheduling performs better than VPS [36] and LAS [37] strategies, because sink's mobility is governed by data arrival rates at rendezvous nodes, and there is no query requirement for sink's fresh location, and finally, forwarding data over pre-constructed routing backbone in the network.

In the experiments, we also computed the standard deviation of residual energy when network lifetime was exhausted. The simulation results show a gradual increase of standard deviation for the higher data generation rates, as illustrated in Fig. 5(d), because of fluctuating energy expenditure from the different corners of the network. The proposed Starfish data scheduling exhibits the lowest standard deviation of residual energy due to balanced energy consumption over the Starfish backbone nodes while forwarding data to the mobile sink. Here, Starfish scheduling finds the optimal path over the least energy-expensive sojourn locations for each cycle. Since energy expenditure and standard deviation of residual energy are increased for higher rates of data generation, as described earlier, the lifetime of the network is inherently decreased for the increasing rate of data generation, as depicted in Fig. 5(e). Finally, with the increasing rate of data generation, it requires more control packets to deliver sensed data to the mobile sink, thus operational overhead increases, as shown in Fig. 5(f). In the case of the proposed data collection scheduling, operational overhead is the lowest among the studied works because of forwarding data packets over preformed Starfish routing backbone in the network.

2) Impacts of varying number of obstacles

Obstacles are an integrated part in a practical network scenario, and thus the efficiency of real-time data collection scheduling in the presence of obstacles should be determined. This section presents the experimental results, as shown in Fig. 6, for the increasing number of obstacles from 10-70, given that obstacles collectively occupied 15 % of a network $600 \times 450\ m^2$. In the experiments, the sink speed was fixed at 6 $meter/second$, and the packet generation rate was fixed at 3 $packets/second$.

The experimental results show that average data throughput within delay-deadline decreases sharply with the increasing number of obstacles, as shown in Fig. 6(a). This happens because sink mobility for visiting sojourn location is hampered due to obstacles, increases path length of the

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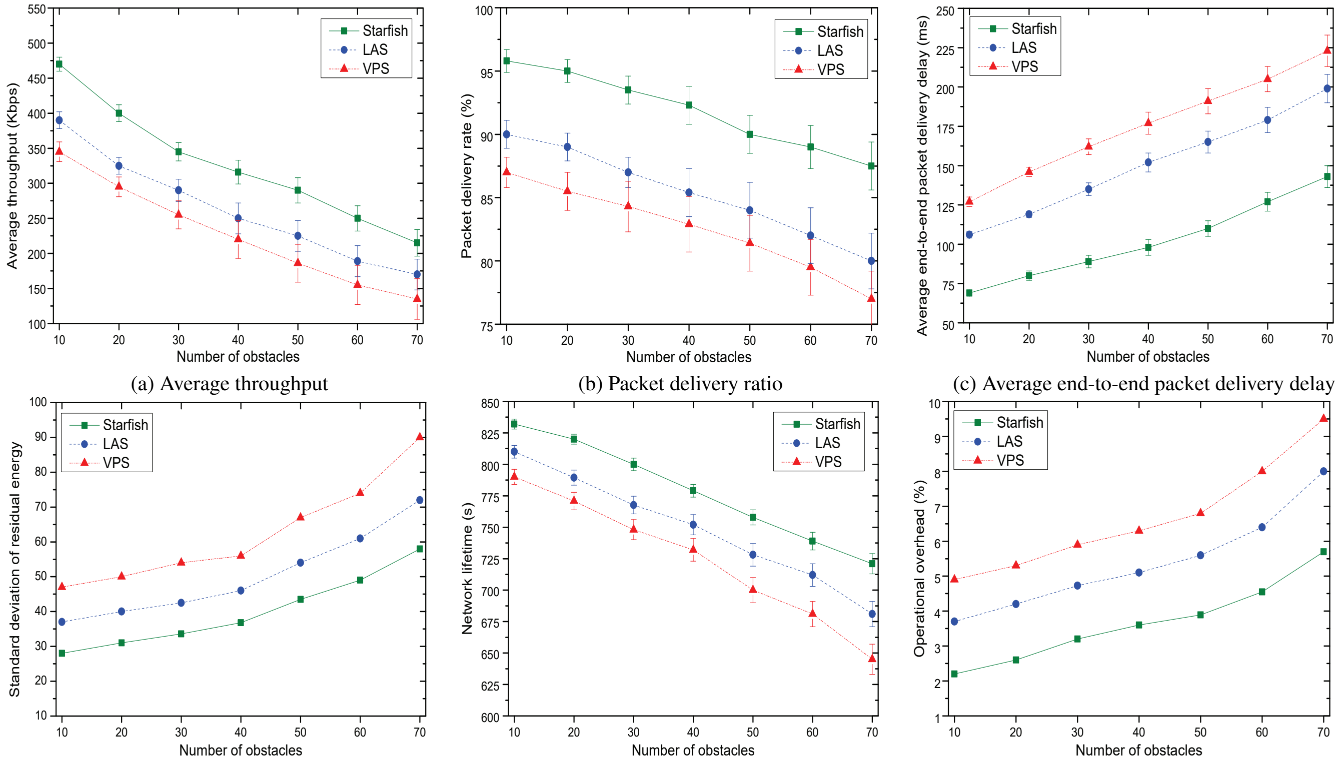

(a) Average throughput (b) Packet delivery ratio (c) Average end-to-end packet delivery delay

(d) Standard deviation of residual energy (e) Network lifetime (f) Operational overhead

FIGURE 6: Impacts of varying number of obstacles

mobile sink, requires more hop distance and increases packet retransmission, etc. These reasons also exhibit decreasing order of packet delivery ratio (PDR) within the delay-deadline, as depicted in Fig. 6(b). However, in the case of Starfish data collection schedule, the performances of average throughput and PDR outperform over VPS [36] and LAS [37] strategies because of faster and continuous data forwarding over obstacle-aware starfish routing backbone in the network.

On the contrary, Fig. 6(c) illustrates that the average end-to-end packet delivery delay sharply increases with a growing number of obstacles. This is mostly due to the increase in the proximity of the mobile sink with the obstacles, consequently increasing the path length and end-to-end packet delivery delay. However, the proposed Starfish scheduling performs better compared to VPS [36] and LAS [37] strategies because mobile sink visits sojourn locations based on the corresponding data arrival rate at rendezvous nodes. Moreover, the mobile sink collects data around the ring-canal and all source nodes forward their data over pre-determined obstacle-aware Starfish routing backbone nodes.

Later, we also evaluated the standard deviation of residual energy among backbone nodes for an increasing number of obstacles, when the network lifetime was exhausted. The graphs, as presented in Fig. 6(d), illustrate that the deviation of energy sharply expands, as the number of obstacles increases. Since obstacles are sporadically distributed in the network and source nodes exhibit fluctuating energy expenditure due to those obstacles, it expands the standard deviation of residual energy. For similar reasons, some of the backbone nodes exhaust earlier, and thus network lifetime decreases with an increasing number of obstacles, as depicted in Fig. 6(e).

Finally, with the growing number of obstacles, more control packets are required to forward data avoiding sporadically situated obstacles in the network, and thus it results in increasing operational overhead, as shown in Fig. 6(f).

3) Impacts of varying size of networks

In a practical WSN application, the network performances and lifetime maximization are not only affected by data generation rate and a number of obstacles but also on the area of a network. Therefore, we evaluated the scalability and efficiency of the proposed Starfish scheduling, varying the network sizes from $400 \times 225\ m^2$ to $900 \times 675\ m^2$, while data generation rate, sink speed, and the number of obstacles are fixed at 3 $packets/second$, 6 $meter/second$, and 40, respectively. In the case of different sizes of network, we considered sporadic size of 40 obstacles that collectively occupied 15 % area of the corresponding size of the network with specific node density as stated in Subsection V-A.

The graphs, as shown in Fig. 7(a), depict that data throughput within delay-deadline steadily decreases with the larger networks for all studied data collection scheduling. This happens because sink mobility for visiting sojourn locations is hampered due to obstacles, increasing path-length of the mobile sink, requiring more hop distance, and increasing

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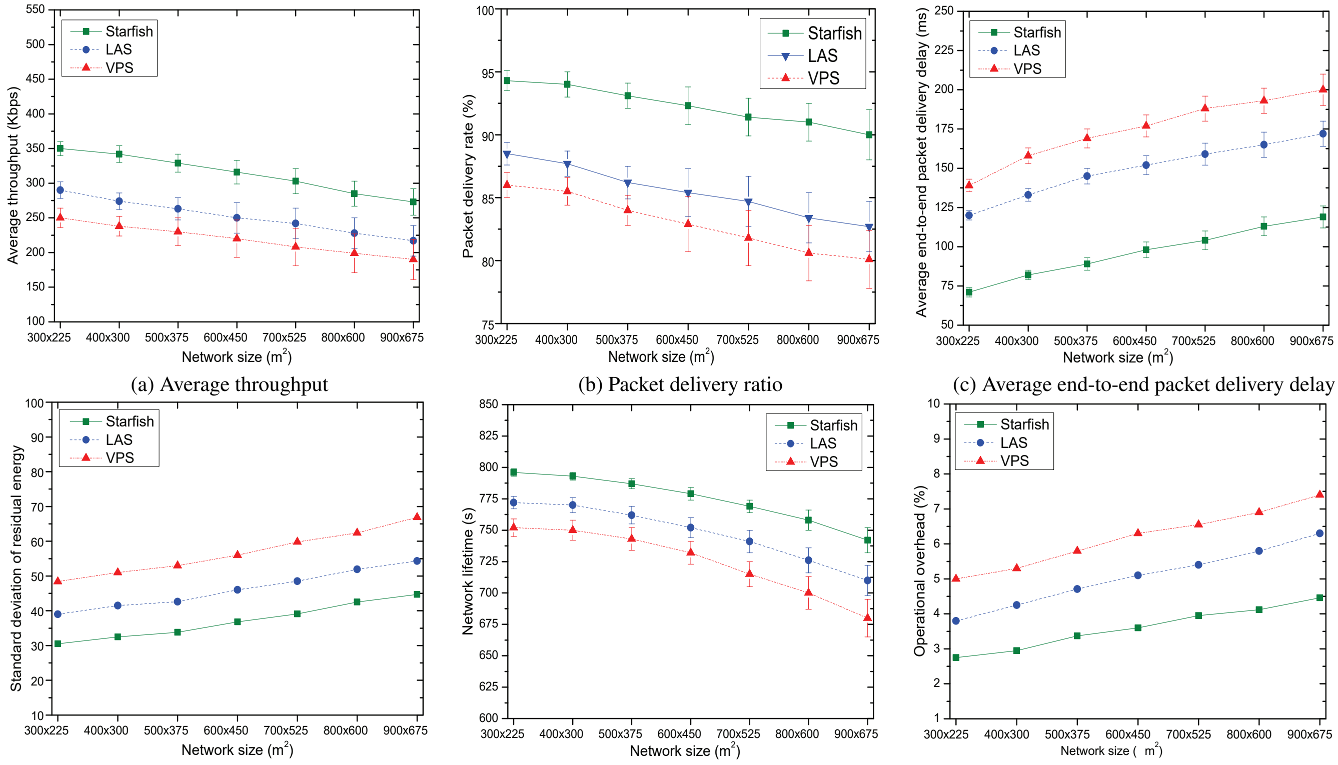

(a) Average throughput (b) Packet delivery ratio (c) Average end-to-end packet delivery delay

(d) Standard deviation of residual energy (e) Network lifetime (f) Operational overhead

FIGURE 7: Impacts of varying size of networks

retransmission of packets, etc. These reasons also reduce event notification as well as the reception probability of data packets by the mobile sink. In the case of Starfish scheduling, average data throughput is higher compared to VPS [36] and LAS [37] strategies because of collecting data over the optimal ring-canal, single hop reachability from any source node and continuous data forwarding over obstacle-aware backbone nodes. For similar reasons, packet delivery ratio (PDR) decreases, as shown in Fig. 7(b). The performances of data throughput and PDR prove the suitability and reliability of the Starfish data collection schedule for larger networks even though there exist obstacles.

On the contrary, the graphs, as presented in Fig. 7(c), depict that end-to-end packet delivery delay within the application delay-deadline is steadily increased for all studied data collection scheduling with increasing network sizes. It is obvious due to the linear increase of hop distance, the larger size of ring-canal with the presence of obstacles. Moreover, experimental results show that the proposed Starfish scheduling outperforms VPS [36] and LAS [37] because of guaranteed single-hop access to at least one backbone nodes by a source node while forwarding data to the sojourn locations, collecting data over the ring-canal nodes, avoiding (re)tracing the mobile sink, etc. End-to-end delay performance of the proposed scheduling proves its suitability for real-time applications maintaining delay-deadline.

In the experiments, we computed the standard deviation of residual energy, when the network lifetime was exhausted. Fig. 7(d) shows that it increases monotonically because of fluctuating energy expenditure for increasing size of networks. Fluctuating energy expenditure occurs for the existence of obstacles at random locations throughout different areas of the network, larger size of the ring-canal, etc. The proposed Starfish data collection scheduling exhibits the lowest deviation of energy among other strategies due to balanced energy consumption of the Starfish backbone nodes during forwarding data to the mobile sink. Since energy expenditure and standard deviation of residual energy increase, inherently the network lifetime is decreased for an increasing rate of data generation, as depicted in Fig. 7(e). Finally, with the increasing size of networks, it requires more control packets due to longer hop distance to collect data that results in increasing operational overhead, as shown in Fig. 7(f).

In a separate experiment, we compared the complexities of the studied scheduling schemes in NEOS optimization [48] server (2 Intel Xeon E5-2698 @ 2.3GHZ CPU and 192GB RAM) for selecting optimal set of rendezvous nodes for each cycle. We find those for both viable path scheduling (VPS) [36] and landmark-assisted scheduling (LAS) [37] are $\mathcal{O}(\mathbb{N}^3)$, where $\mathbb{N}$ is the number of nodes. In the case of Starfish data collection schedule, the mobile sink visits rendezvous nodes that are optimally selected over the ring-canal nodes ($\mathbb{Z}$). According to the MILP formulation, it determines a set of sojourn locations $\mathbb{M}_n^c \in \mathbb{R}^c$ over the ring-canal nodes, instead of overall sensor nodes or all backbone nodes. The constraint in Eq. (7) computes over the power set of the ring

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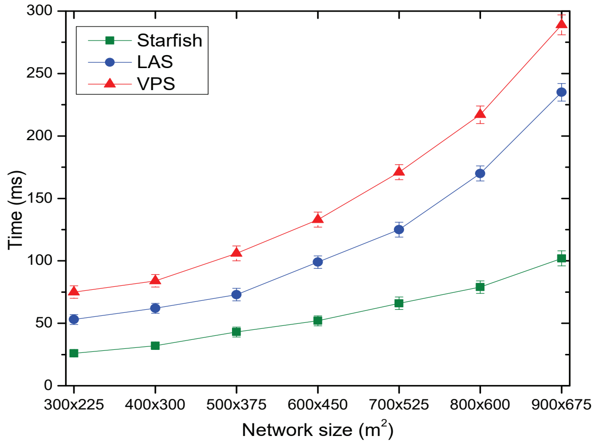

FIGURE 8: Computational complexity

canal nodes $\mathbb{Z}$, and finds out the most energy-efficient set of sojourn locations achieving maximum duration. Therefore, the computational complexity of the Starfish scheduling is estimated as $\mathcal{O}(c \times |\mathbb{Z}| \times 2^{|\mathbb{Z}|})$ which is significantly less compared to those of VPS [36] and LAS [37].

The graphs in Fig. 8 show the computation time required for execution of the studied data collection schedule algorithms for increasing size of networks from 300×225 to 900×675. As VPS and LAS strategies explore all nodes in the network to find out data collection schedules, their computation time increase exponentially compared to a linear graph observed for the Starfish schedule. It is obvious since the Starfish schedule explores candidate power sets on the ring canal nodes only. The problem can be grouped as an NP-complete one [49]. However, the constraints in Eq. (6) - Eq. (13) of the MILP formulation facilitate us to significantly reduce the input sets for selecting the optimal number of sojourn locations, and thus the solution is found in polynomial time.

The above results and discussions conclude that Starfish data collection schedule shows its scalability and efficiency in terms of computational complexity, data throughput, end-to-end data delivery delay, network lifetime, etc. for real-time applications (within certain delay-deadline) in an obstructed network significantly. Moreover, the proposed Starfish schedule is also applicable for an obstacle-free network as well, as was primarily studied in [29]. However, from the simulation trace file data, it is observed that when the data generation rate at a particular node on the ring-canal is superabundant compared to other nodes, the sojourn location is discriminatorily selected for consecutive cycles. This exhibits a quicker partition of the routing backbone than the average network lifetime.

VI. CONCLUSION

This work explored the challenges of data collection and lifetime maximization strategies for real-time applications in an obstructed sensor network with a mobile sink. For real-time data collection, we considered Starfish routing backbone with obstacles, and thereafter, formulated mixed-integer linear programming to find an optimal set of sojourn locations on its ring-canal nodes for a round, corresponding sojourn duration with data collection scheduling so as to maximize network lifetime. The simulation results, performed in network simulator version-2, clearly indicated that Starfish data collection scheduling improved network lifetime as high as 11% while reducing end-to-end data delivery delay by at least 40% compared to state-of-the-art-works.

As a planned study in the future, we envision designing distributed and machine-learning-based algorithms for data collection schedule by multiple sinks in a large-scale network.

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3021623, IEEE Access

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