Flow Based Efficient Data Gathering in Wireless Sensor Network Using Path-Constrained Mobile Sink

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Abstract In energy-constrained wireless sensor networks (WSNs), maximizing the data collection using mobile sink(s) with minimum energy consumption is one of the practical challenging issues. In this article, we consider the problem of efficient data collection along with a pre-specified path using a mobile sink with constant speed. We refer the problem as a Maximizing data gathering with minimum energy consumption (MDGMEC) problem. So far, existing works have heuristic algorithms for MDGMEC problem. Therefore, based on network flow optimization approach, we propose a deterministic algorithm called data gathering using mobile sink for path constraint environment (DGAMSPCE) to handle the MDGMEC problem. The proposed DGAMSPCE scheme runs in polynomial time and is easily scalable for the networks with a large number of nodes. Based on the data receiving models used by the mobile sink, another algorithm called single access based data gathering using mobile sink for path constraint environment (SADGAMSPCE) is also proposed. We evaluate the proposed schemes and compare these with the existing schemes. The simulation experiments in MATLAB show that our proposed schemes outperform other existing schemes in terms of collecting the amount of data and the total energy consumption of the network, significantly.

Keywords Maximizing data collection · Energy utilization efficiency · Mobile sink · Pre-specified path · Deterministic algorithm · Wireless sensor networks.

1 Introduction

Recently, mobile sink based data gathering from wireless sensor networks (WSNs) has been an important research topic in WSNs community. Existing studies have shown that the introduction of mobile sink improves the network performances such as: energy efficiency [1], data throughput [2,3] and network lifetime [4,5,6] etc. A mobile sink could be a mobile robot that can be mounted on animals or vehicles to collect data from sensors [7]. Depending upon the nature of applications, the path of a mobile sink may be random [8] or, pre-specified [9,10] or, controllable [11,12].

In case of the fixed (or, pre-specified) path of a mobile sink, efficient data collection is a major issue for improving the network performances. As, the mobile sink has to traverse only along this path for data collection from the sensors that may result unreachability from some sensors to the mobile sink and if they even reachable, then there may exist longer data forwarding paths to reach at the mobile sink. Consequently, the energy communication cost of the network may very high. If there exists a fixed data communication time between the mobile sink and a sensor, then in some cases, it may also be possible that the sensors close to the path of the mobile sink may not deliver their complete data to the mobile sink which may result poor data collection from the network. Thus, in order to collect data efficiently using a path-constrained mobile sink, the data gathering algorithm should be carefully developed and managed. In this article, our focus is on efficient data collection problem in WSN with a path-constrained mobile sink.

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As an application example, in figure 1, a set of sensors \( N = \{S_1, S_2, \cdots, S_{10}\} \) are deployed in a harsh area network with the probability of having earthquakes. All sensors in set \( N \) are grouped into sub-sinks (or, cluster heads) \( \{S_4, S_6, S_{10}\} \) and far-away sensors \( \{S_1, S_2, S_3, S_5, S_7, S_8, S_9\} \). The sub-sinks \( S_4, S_6 \) and \( S_{10} \) are nearby a pre-specified path \( P \) of a mobile sink \( MS \). The far-away sensors \( S_1, S_2, S_3, S_5, S_7, S_8, S_9 \) are more than one hop away from the path \( P \). They forward their data to the sub-sinks through multi-hop communication. The mobile sink \( MS \) traverses the path \( P \) and collects statistical data only from the sub-sinks to determine the probability of happening an earthquake. The data collection problem in such network is to manage collecting data from the sensors in set \( N \) using a mobile sink \( MS \) in such a way to maximize the data collection with the minimum energy consumption. Obviously, more efficient data collected by the \( MS \) from the sensors in set \( N \) more accurate and efficient event estimation.

In studies [13,14], a mobile sink moves on a pre-specified path and collects data directly from each sensor to improve the energy efficiency of the network, but the data collected from some sensors may infeasible due to the path constraint and the communication power of the sensors. In article [15], a multi-hop sensor network with a fixed-path mobile sink is deployed to improve the energy efficiency and the amount of data collected. In their algorithms, the shortest path tree (SPT) technique is used to identify the cluster heads among sensors and route data, which may cause an imbalance between energy consumption and data traffic. The SPT technique can minimize the total energy consumption, but may not achieve energy efficiency on data collection. In [16], MobiRoute protocol is used by a mobile sink for data collection and to improve the packet delivery ratio, but the protocol can be used in the sensor network with only one mobile sink and each sensor in such network has to be aware of the movement strategy of the mobile sink.

The authors in [9] developed constrained-path based data gathering algorithm. They developed a genetic algorithm based solution called MASP for maximizing the data collection by the mobile sink with minimum energy consumption. When the mobile sink moves around a pre-specified path with a constant speed, it stays for a fixed amount of time at each sub-sink (or cluster head). If the sub-sink has too much data availability and has limited communication time with the mobile sink, then it may not transfer its complete data to the mobile sink. It is due to the uneven distribution of data from the sensors to the sub-sinks based on the limited data communication time of the sub-sinks. MASP tries to make this distribution uniform, but being heuristic may not succeeded forever.

In order to improve the total amount of gathered data by the mobile sink, the data generated by all sensors must be uniformly distributed amongst the sub-sinks. The authors in [10] have also developed improved ant colony based solution for trying to improve the energy efficiency for data collection. But, its’ solution may become more expensive for large scale network.
Kumar et al. [17] proposed heuristic algorithm referred to as MDGOSP for the problem of maximum data collection using a mobile sink on the pre-specified path within the given time deadline. In their algorithm, for the given sub-sinks and the constant speed $V$ of a mobile sink, an optimal sub-path with path-length $VT$ is determined on the given path to collect maximum amount of data within time $T$. However, due to use of SPT in MDGOSP algorithm, the energy consumption of network is minimized, but may not collect maximum amount of data. Also, the problem in their works is defined under the solution that they use heuristic algorithms for developing solutions and also the adjacency between sub-sinks are not considered in their solutions, even though they are neighbors in the proposed communication topology network. Consequently, the unsaturated sub-sinks having larger data delivery capacity may not be well utilized.

Based on the above observations, we focus on developing a deterministic algorithm referred as Data gathering Algorithm using Mobile Sink for Path Constraint Environment (or DGAMSPCE) for maximizing the data collection using path-constrained mobile sink with minimum energy consumption for large scale sensor network that may also exist in real applications, such as structural health monitoring [18], crisis management [19] and traffic monitoring [3] etc.

More specifically, our major contributions in this article can be summarized as follows:

1. By modeling a network flow graph corresponding to the proposed communication topology network with the pre-specified path, formulate maximizing data gathering with minimum energy consumption problem or, in short, MDGMEC problem as a network flow optimization problem.
2. Based on multi-access data receiving model, we propose DGAMSPCE algorithm that exploits min-cost max-flow to solve MDGMEC problem.
3. DGAMSPCE can also be used for exploiting multiple mobile sinks to solve the scalability problem of large-scale network.
4. Based on single-access data receiving model, single access based data gathering algorithm for path constraint environment, in short, SADGAMSPCE is also proposed to investigate the MDGMEC problem under the same assumptions and it is also scalable.

The rest of the article is organized as follows: in section 2, the existed works related to mobile sink based data gathering is reviewed. In section 3, we define the network model, formulate the proposed MDGMEC problem and define an energy consumption model respectively. The design of the proposed solutions, algorithms, and their theoretical analysis are presented in section 4. Furthermore, in section 5, we implement the proposed algorithms and then, further analyze and evaluate their performances through simulation results. Section 6 concludes the proposed work.

2 Literature Survey

Recently, mobile sink based data gathering has been exploiting in a large number of applications. According to existing works, the path of a mobile sink can be broadly classified as random [7,8], pre-specified [9,20], or controllable [21,22,23]. In [24,20], animals or humans act as mobile sinks and collect data from the sensors when they are within the communication range of each other. The sensors in such networks are not usually connected. Therefore, in such type of networks, the movement patterns of moving animals or vehicles are very difficult to predict or control; therefore, the maximum data collection cannot be attained. On the other hand, in case of pre-specified or controllable path mobile sink network, the maximum data gathering efficiency can be ensured. Subsection 2.1 and subsection 2.2 review the existed works related to this, that may use single-hop [3,25] or multi-hop communication [21,22,23] for data collection by one or multiple mobile sinks. These existing studies have shown that controllable path or pre-specified path sink mobility can improve the network performance.

2.1 Pre-specified Path based mobile sink model

In this model, the path of a mobile sink is pre-specified to move on for data collection from the sensors. The sensors send their data to the mobile sink either directly or indirectly. A mobile sink used in [13, 29] can resolve an energy-hole problem by collecting data directly from the sensors to improve the energy efficiency of the network. Jea et. al [20] proposed a load balancing algorithm...
using multiple mobile sinks for improving the network lifetime. The authors in [13] used a queuing model for efficient data collection using a mobile sink. However, the proposed technique has large data gathering delay and it may sometimes in-feasible for large-scale WSNs due to single-hop communication method. In order to reduce the excessive data gathering delay and to collect data from the sensors, the authors proposed multi-hop sensor network with single [15,19] or multiple mobile sinks [9,20], where clustering based shortest path techniques are used for data collection using mobile sink(s).

In [15], a mobile sink uses SPT technique to collect data from some selected cluster heads and remaining other nodes transmit their data to corresponding cluster heads via multi-hop communication. In this method, total energy consumption against data collection may not balance due to mismatch between the number of sensors associated with the cluster heads and their communication time. Thus, it has low data collection efficiency. Zhao et al. [4] have developed a tree-based heuristic topology control algorithm with fixed-path mobile sink for data gathering in WSNs. In this algorithm, a minimum spanning tree is designed to route data from every node to the mobile sink through the multi-hop communication method. Although, it minimizes the energy consumption of the network, but may not attain maximum data collection. Kumar et al. [10] have formulated the problem as an integer linear programming (ILP) and developed an improved ant colony optimization model for calculating the residual energy of a sensor. They developed a solution based on multiple constraints say delay, jitter, data bandwidth and cost for maximizing the network lifetime using a constrained-path mobile sink. However, it has larger delay as compared to mini-delay algorithms. Moreover, being meta-heuristic can’t provide an optimal solution forever.

Gao et al. [9] have presented an improved heuristic algorithm for data gathering using a pre-specified path based mobile sink. They divided the sensors of the network into sub-sinks which are within direct communication area (DCA) and far-away sensors which are within the distance of multi-hop communication area (MCA). All sensors generate data and send to the sub-sinks and, then the sub-sinks cache data and send to the mobile sink when it moves within their communication ranges. They formulated the problem as an ILP and developed MASP algorithm for maximizing the data collection using the path-constrained mobile sink under the constraint that the communication cost energy for transmitting data from the sensors to the sub-sinks must be minimized. However, the solutions proposed in [9] are used for improving the energy efficiency for data collection, but being heuristic do not guarantee the optimal solution all the time. Kumar et al. [17] focused on the same problem of maximum data collection in a fixed-path mobile sink network for a given time constraint. They also divided all sensors of network into sub-sinks and far-away sensors based on their direct reach-ability by the mobile sink. In their heuristic algorithm MDGOSP, they characterize a set of viable sub-paths on the given path and thereafter, find a maximum data gathering sub-path for the mobile sink such that the improved amount of data can be collected. However, due to the use of SPT technique in their heuristic algorithm MDGOSP to route data from the sensors to their nearby sub-sinks, the ratio of data collection and energy consumption may not much efficient.

In order to obtain an optimal solution for maximizing the data collection with minimum energy consumption, it is more realistic and efficient to design a deterministic algorithm. That’ why, to contemplate this maximum data collection ability of the mobile sink in an energy efficient way, a deterministic scheme DGAMFPE is proposed in this article.

2.2 Controllable Path Sink Mobility Model

In this model, the focus of the researches is to design optimal path(s) for the mobile sink(s) to improve the network performance. Articles [27,25,28] have focused on designing the trajectory path for the mobile sink to collect data from sensors using single-hop communication method.

In [27], an improved version of the genetic algorithm is proposed for population generation and thereafter; short-cut technique is applied to improve the tour length. The authors in [25] proposed an approximation algorithm based data gathering method with multiple data mules to reduce the data gathering path-length by minimizing the maximum trajectory length of the data mules. The data mules collect data from the sensors within their neighborhood.

Yogarajan et al. [28] proposed a nature-inspired heuristic discrete firefly algorithm to compute an optimal sequence of sensors for data gathering with minimal travel distance. However, the prob-
lem with these approaches have increased data latency due to single-hop data gathering method which may be impractical when it is used for the dense WSNs. As data gathering from each sensor increases the path-length of mobile sinks trajectory path which may cause buffer overflow due to excessive data gathering delay. Thus, the multi-hop sensor network with mobile sink(s) is used to reduce data gathering delay significantly.

The authors in [21] proposed a rendezvous based heuristic algorithm for data gathering using mobile sink in WSNs. In the proposed method, a set of points are considered as rendezvous points and other nodes transfer their data to these nodes. Then an optimal tour is designed including rendezvous points which is an NP-hard problem. Addressing this issue, a heuristic called weighted rendezvous planning is proposed. Then the mobile sink moves along this tour and receives sensed data from the rendezvous points. The experimental results validate that this method improves and balances the energy consumption. But, due to heuristic does not ensure an optimized tour and this makes the proposed method may have a large delay in some implementations.

Kaswan et al. [22] have also proposed rendezvous based algorithm to design an efficient path for mobile sink that meets the requirement of delay bound applications. In this method, rendezvous points are determined based on the routing load. The mobile sink visits the rendezvous points on a predetermined delay bound trajectory. But, the basic problem with this method is the selection of most suitable rendezvous points which is a NP-hard problem.

Tashtarian et al. [23] proposed a convex optimization technique based on the support vector regression technique. They proposed a data gathering technique for designing an optimal path of the mobile sink without considering the rendezvous points for maximizing the network lifetime in event-driven applications in WSNs. However, they provided substantial increment in the lifetime of the network with single-hop data delivery.

3 Network Model and Problem Statement

3.1 Network Model

In this article, we consider wireless sensor network as an undirected graph $G = (N, E)$, where $N = \{S_1, S_2, \ldots, S_n\}$ denotes a set of uniformly deployed sensors and $E$ represents communication links between them. The communication range of each sensor $R$ is same and treated as a disk model. Furthermore, the location of each sensor in the network is fixed and known beforehand. A mobile sink $MS$ is assumed to have same communication range $R$ with unlimited amount of energy and sufficient memory capacity. It moves with a constant speed $V$ along a given path $P$ to collect data from the sensors. The mobile sink $MS$ traverses the complete path $P$ within time $T = \frac{|P|}{V}$. The sensors whose communication disks intersect the path $P$ are referred to as sub-sinks. These identified sub-sinks can send their data directly to the mobile sink $MS$, when it comes within their communication ranges. Remaining other sensors forward their data to the sub-sinks through multi-hop communication method. Thereafter, sub-sinks finally deliver the received data with their own sensed data to mobile sink. The data received by the mobile sink $MS$ are finally used for further processing. We assume that each sensor continuously generates and transmits its data either directly or indirectly to the mobile sink $MS$. In this work, our focus is to collect the data generated from all sensors for a single round of the path-traversal since the same technique is applied to the succeeding rounds. The data transmission rate of a sensor is greater than its data generation rate. Due to the given path $P$ and the constant speed of $MS$, there is fixed communication time between each sub-sink and the mobile sink $MS$. Based on the fixed communication time of a sub-sink, there is an upper bound of the data that can be delivered by each sub-sink to the mobile sink $MS$ which is referred to as data delivery capacity of the sub-sink.

3.2 Energy consumption model

In this network model, there is no data aggregation. So, the assignment of sensors to the sub-sink is more crucial with respect to energy consumption compared to that of the data aggregated network model. In this article, we consider and optimize the energy consumption of each sensor for only
transmitting and receiving data. So, in this article, the energy consumption model used is as follows.

Let \( q \) be the total data generated by each sensor \( S_i \) for a traversal round time \( T \). Let each sensor \( S_i \) receives \( d_{ir} \) bits and transmits \( d_{it} = d_{ir} + q \) bits within time \( T \). Then, the total energy consumption \( E_i \) of sensor \( S_i \) is expressed as \( E_i \approx (e_r \cdot d_{ir} + e_t \cdot d_{it}) \), where \( e_t \) denotes energy consumption per unit bit transmitting and \( e_r \) denotes energy consumption per unit bit receiving. Therefore, total energy consumption of the network \( E_{\text{total}} \) is as \( E_{\text{total}} = \sum_{i=1}^{n} E_i \).

### 3.3 Problem Statement

**Problem**: A set of sensors \( N = \{S_1, S_2, \cdots, S_n\} \) are deployed over a rectangular area. The path of a mobile sink \( MS \) is a pre-specified trajectory path \( P \). The mobile sink \( MS \) moves at a constant speed \( V \) on the path \( P \) for collecting data from the sensors. Our objective is to maximize the data collection using mobile sink \( MS \) from the sensors with minimum energy consumption of the network. We refer it as MDGMEC problem.

### 4 Network Flow-Based Algorithm

In this section, we describe two different data gathering algorithms for solving MDGMEC problem in two different data receiving models. In the first model, a mobile data sink can receive cached data from multiple sub-sinks simultaneously, while in the second model, a mobile data sink can receive cached data from only one sub-sink at a time. We refer the algorithm for the first model as data gathering using mobile sink for path constraint environment (DGAMSPCE). The algorithm for the second model is referred to as single access based data gathering using mobile sink for path constraint environment (SDGAMSPCE). The following two sub-sections describe our two proposed algorithms for two different models.

#### 4.1 Description of DGAMSPCE algorithm

In this sub-section, we discuss DGAMSPCE algorithm for solving MDGMEC problem based on the first data receiving model. In DGAMSPCE algorithm, the nearby sensors along the path \( P \) are identified as sub-sinks among the sensors in set \( N \). Determine the data communication time \( DCT(SS_i) \) and the data delivery capacity \( DDC(SS_i) \) of each identified sub-sink \( SS_i \). Each sub-sink \( SS_i \) has limited communication time \( DCT(SS_i) \) to deliver its data to the mobile sink \( MS \) due to the constant speed \( V \) of the mobile sink and its fixed position with respect to the path \( P \). The data delivery capacity \( DDC(SS_i) \) of a sub-sink \( SS_i \) is proportional to its data communication time \( DCT(SS_i) \). A network flow graph \( G_f \) is constructed corresponding the communication topology of the sensor network graph \( G = (N,E) \) and with respect to the path \( P \). A cost function is used to assign cost for each link of the network flow graph \( G_f \). Thereafter, maximum data flow from the sensors to the sub-sinks across the network flow graph \( G_f \) is determined. The maximum flow value denotes maximum data collection capability by the mobile sink \( MS \) corresponding to the communication network graph \( G \) with minimum energy consumption in \( \text{Mincost} \). The obtained \( \text{Maxflow} \) and \( \text{Mincost} \) are the solutions of our DGAMSPCE algorithm. In summary, DGAMSPCE algorithm is divided into three phases: namely sub-sink identification phase, determining data delivery capacity of sub-sinks phase and min-cost max-flow phase.

#### 4.1.1 Sub-sink identification:

In this sub-section, we identify sub-sinks among the sensors in set \( N \) and determine their communication start-points and communication end-points. As described in the section, In DGAMSPCE scheme, those sensors which come within the communication range of the mobile sink \( MS \) are referred to as sub-sinks. An example of the process of identifying sub-sinks among the set
of sensors is shown in figure 2. An example of the communication topology of a set of sensors \( N = \{S_1, S_2, \cdots, S_{10}\} \) is shown in figure 1. Due to the intersection of the communication disks of the sensors \( S_4, S_6 \) and \( S_{10} \) with path \( P \) (in figure 2a), the sensors \( S_4, S_6 \) and \( S_{10} \) are identified as sub-sinks and renamed to \( SS_1, SS_2, SS_3 \) (in figure 2b). The intersecting points \( SS_1^a \) and \( SS_1^b \) are referred as communication start-point and communication end-point of a sub-sink \( SS_1 \), where \( SS_1 \in \{SS_1, SS_2, SS_3\} \). In addition, a line segment joining \( SS_1^a \) and \( SS_1^b \) points together is known as secant \( SL_1 \).

In this way, let a set of sub-sinks \( SS = \{SS_1, SS_2, \cdots, SS_m\} \) be identified among sensors in set \( N \) with secants \( \{SL_1, SL_2, \cdots, SL_m\} = \{(SS_1^a, SS_1^b), (SS_2^a, SS_2^b), \cdots, (SS_m^a, SS_m^b)\} \) in the next sub-section, we will discuss how to determine data communication time and data delivery capacity of each identified sub-sink.

4.1.2 Determine data delivery capacity of the sub-sinks:

In this sub-section, determine the data communication time and the data delivery capacity of each sub-sink. Let \( DCT = \{DCT(SS_1), DCT(SS_2), \cdots, DCT(SS_m)\} \) denotes a set of communication time between each sub-sink \( SS_i \in S \) and the mobile sink \( MS \). The communication time of sub-sink \( SS_i \) is determined by \( DCT(SS_i) = \frac{|SL_i|}{dtr}, \forall SS_i \in SS \). The sub-sink with the larger secant length will get bigger communication time. Let a set \( DDC = \{DDC(SS_1), DDC(SS_2), \cdots, DDC(SS_m)\} \) denotes a set of data delivery capacity of the sub-sinks. The data delivery capacity \( DDC(SS_i) \) of a sub-sink \( SS_i \) is determined as \( DDC(SS_i) = DCT(SS_i) \times dtr \), where \( dtr \) is a data transmission rate of each sub-sink.

4.1.3 Min-cost max-flow phase:

In this sub-section, we discuss how to find minimum-cost maximum-data flow from the sensors in set \( (N - SS) \) to the sub-sinks in set \( SS \) through the network flow graph \( G_f \) with minimum cost. The process for finding the minimum-cost maximum-data flow corresponding to graph \( G \) with respect to the path \( P \) is described as follows:

We consider a communication network model based on the fact that a sensor can send any amount of data to its neighbors. We construct a network flow graph \( G_f \) corresponding to the communication graph \( G \) and path \( P \). The network flow graph \( G_f \) is modeled a directed graph such that the vertex set \( N \in G \) remains same in \( G_f \). For each edge \((S_i, S_j) \in E \) in \( G \), we add two directed edges \((S_i, S_j) \) and \((S_j, S_i) \) in the flow graph \( G_f \). Let \( U \) denote capacity matrix and \( C \) denote cost matrix of the flow graph \( G_f \). The capacity and the cost of each edge \((S_i, S_j) \) in graph \( G_f \) are set to \( U(S_i, S_j) = \infty \) and \( C(S_i, S_j) = (e_t + e_r) \). The capacity is set to \( \infty \) because we have assumed that a sensor can send any amount of data to its neighbors. The cost is set to \( (e_t + e_r) \) as it denotes energy consumption per unit bit for transmission and reception.
The mobile sink $MS$ may not collect complete generated data from all sensors as the generated data of all sensors are forwarded through the sub-sinks and the sub-sinks have limited data communication time with the mobile sink $MS$. In order to determine how much data will be forwarded from every sensor $S_i \in N$ to the mobile sink $MS$, we create a virtual source $VS$ and add a directed edge from the virtual source $VS$ to every sensor $S_i$ in the flow graph $G_f$. The capacity and cost of each edge $(VS, S_i)$ are set to $U(VS, S_i) = D = (dgr \cdot T)$ and $C(VS, S_i) = 0$, where $dgr$ is a data generation rate of each sensor. The capacity is set to $D$ because $D$ is the maximum data generation capacity of a sensor within one round of data collection. The cost is set to zero as there is no communication cost overhead for data generation.

In order to satisfy the data delivery constraint from each sub-sink $SS_i \in SS$ to the mobile sink $MS$, we create a virtual sink $VM$ and add a directed edge from every sub-sink $SS_i \in SS$ to the virtual sink vertex $VM$. The capacity and the cost of each edge $(SS_i, VM)$ are set to $U(SS_i, VM) = DDC(SS_i)$ and $C(SS_i, VM) = e_t$, $\forall SS_i \in SS$. The capacity is set to $DDC(SS_i)$ as $DDC(SS_i)$ is the data delivery capacity of a sub-sink $SS_i \in SS$. The cost $C(SS_i, VM)$ for transmitting unit bit data is $e_t$.

An example of a flow graph $G_f$ is shown in figure 3 corresponding to the communication topology of the sensor network in figure 2A with respect to the path $P$. In figure 3 the sensors in set $N = \{S_1, S_2, \ldots, S_{10}\}$ is grouped into $SS_1/S_4, SS_2/S_6$ and $SS_3/S_{10}$ as sub-sinks and $FS = N - \{S_4, S_6, S_{10}\}$ as far-away sensors based on the path $P$ and corresponding to communication topology shown in figure 2A. The vertices $VS$ and $VM$ are virtual source vertex and virtual sink vertex respectively. The capacity and the cost of each edge $(S_i, S_j)$ or $(S_j, S_i)$ are set to $\infty$ and $(e_t + e_r)$, where $S_i, S_j \in FS$. Similarly, the capacity and the cost of each edge $(S_i, SS_j)$ or $(SS_j, S_i)$ are set to $\infty$ and $(e_t + e_r)$ respectively, where $S_i \in FS$ and $SS_j \in \{SS_1, SS_2, SS_3\}$, as shown in figure 3.

The virtual source vertex $VS$ is connected to each sensor in set $N$ with capacity $D$ and cost zero. Furthermore, each sub-sink $SS_i$ is connected to the virtual sink vertex $VM$ by an edge $(SS_i, VM)$ with data delivery capacity $DDC(SS_i)$ and cost zero, for $SS_i \in \{SS_1, SS_2, SS_3\}$.

Thereafter, the minimum cost maximum flow across the network flow graph $G_f$ with source vertex $VS$ and sink vertex $VM$ is found out. The detailed DGAMSPCE algorithm is summarized as follows.

![Network flow graph based on multiple access data receiving model](image)

Fig. 3: Network flow graph based on multiple access data receiving model
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Algorithm 1: DGAMSPCE scheme

**Input:** \( G = (N, E); R; dgr; dtr; V; P; \)

**Output:** MaxFlow as Total data collected; MinCost as Total energy consumption

1. Identify the sub-sinks \( SS = \{SS_1, SS_2, \ldots, SS_m\} \) among sensors in \( N \)
2. for \( i \leftarrow 1 \) to \( m \) do
3. \quad Find \( SS_i^s \) and \( SS_i^e \) of each \( SS_i \)
4. \quad DCT(\( SS_i^s \)) = \( SS_i^s / SS_i^e \)
5. \quad DDC(\( SS_i \)) = DCT(\( SS_i^s \)) * dtr
6. Construct a network flow graph \( G_f \) corresponding to communication topology graph \( G = (N, E) \) and with respect to the path \( P \)
7. Find out maximum data flow in MaxFlow across network flow graph \( G_f \) with minimum cost in MinCost
8. return MaxFlow, MinCost

Complexity analysis

**Theorem 1** Time complexity of the algorithm DGAMSPCE is \( O(\min \{|n|^2 * \text{MaxFlow}, |n|^3 * \text{MinCost}\}) \).

In DGAMSPCE algorithm, finding \( m \) number of sub-sinks from the set of sensors \( N \) takes \( O(n) \) time complexity. Determining the data communication time and the data delivery capacity of all sub-sinks in set \( SS \) require \( O(m) \) time complexity. Therefore, the time complexity from step 1 to step 5 is \( O(n^2) \). In step 6, the construction of the network flow graph \( G_f \) corresponding to the communication topology of the sensor network and with respect to the path \( P \) takes \( O(n^2) \) time complexity. Step 7 finds out min-cost max-flow across the flow graph in \( O(\min \{|n|^2 * \text{MaxFlow}, |n|^3 * \text{MinCost}\}) \) time complexity. Hence, the total time complexity of DGAMSPCE scheme is \( O(\min \{|n|^2 * \text{MaxFlow}, |n|^3 * \text{MinCost}\}) \).

4.2 SADGAMSPCE algorithm

In this sub-section, we discuss our single access based data gathering algorithm in which a mobile sink \( MS \) can receive data from only one sub-sink at a time. We refer it as single access based data gathering algorithm for path constraint environment or, in short, SADGAMSPCE. It also runs in three phases: (1) sub-sink identification (2) Determine data delivery capacity of the sub-sinks (3) Min-cost max-flow phase. The first two phases of this algorithm are similar to the previous DGAMSPCE algorithm, but its last phase is different from DGAMSPCE scheme. In SADGAMSPCE scheme, the last phase is used to find the min-cost max-flow across the network flow graph based on the single access data receiving model. The processes for constructing the network flow graph say \( SG_f \) corresponding to communication topology graph \( G = (N, E) \) and with respect to the path \( P \) are as follows.

A set of sub-sinks \( SS = \{SS_1, SS_2, \ldots, SS_m\} \) in \( N \) are identified with their start-points \( SS^s = \{SS^s_1, SS^s_2, \ldots, SS^s_m\} \) and end-points \( SS^e = \{SS^e_1, SS^e_2, \ldots, SS^e_m\} \). Let \( SS^\text{sort} \) be a sorted sequence of start-points \( SS^s \) and end-points \( SS^e \) and expressed as \( SS^\text{sort} = \{SS^s \cup SS^e\} = \{p_1, p_2, \ldots, p_{2m}\} \), where \( p_1 \leq p_2 \leq \cdots \leq p_{2m} \). Based on the positions of start-points \( SS^s \) and end-points \( SS^e \), the path \( P \) is divided into \( 2m - 1 \) no. of segments. The segments are denoted by a vector \( SG \) and expressed as \( SG = \{sg_1, sg_2, \ldots, sg_{2m-1}\} = \{(p_1, p_2), (p_2, p_3), \ldots, (p_{2m-1}, p_{2m})\} \). For exemplification, in figure 2, there are three sub-sinks \( SS_1, SS_2 \) and \( SS_3 \). The set of possible segments with respect to the path \( P \) are \( SG = \{sg_1, sg_2, \ldots, sg_6\} = \{(p_1, p_2), (p_2, p_3), \ldots, (p_5, p_6)\} \), as shown in figure 3.

All segments in set \( SG \) are grouped into void segments and data segments. A segment \( sg_i \in SG \) is said to be void, if it is not under the communication region of any sub-sink. But, if a segment \( sg_i \in SG \) is under the communication range of at least one sub-sink, then it is called data segment. Let \( MDDC(sg_i) \) denote maximum data delivery capacity of a segment \( sg_i \in SG \) and expressed as \( MDDC(sg_i) = \frac{|sg_i|}{dtr} \). In case of a void segment \( sg_i \in SG \), the maximum data delivery capacity \( MDDC(sg_i) \) is assumed to be zero. Compute maximum data delivery capacity \( MDDC(sg_i) \) of each segment \( sg_i \in SG \) for \( i = 1 \) to \( 2m - 1 \). Find maximum data flow from the sensors in set.
Fig. 4: A set of segments $SG = \{sg_1, sg_2, \cdots, sg_5\} = \{(p_1, p_2), (p_2, p_3), \cdots, (p_5, p_6)\}$ within the path $P$.

$(S - SS)$ to the sub-sinks in set $SS$ with minimum cost corresponding to network graph $G = (N, E)$ and with respect to the path $P$ as follows.

In this scheme, we also consider a communication network model where a sensor can send/receive any amount of data to/from its neighbor. Based on this model, we define a network flow graph $SG_f$ corresponding to communication topology graph $G = (S, E)$ and with respect to the path $P$. Let $SU$ denote capacity matrix and $SC$ denote cost matrix of the network flow graph $SG_f$. The capacity and the cost of each adjacent edge $(S_i, S_j)$ in $SG_f$ are set to $SU(S_i, S_j) = \infty$ and $SC(S_i, S_j) = (e_t + e_r)$. The capacity is set to $\infty$ because in this model we have already assumed that a sensor can send any amount of data (unrestricted) to its neighbor. The cost is set to $(e_t + e_r)$ as it denotes energy consumption per unit bit for transmission and reception.

In order to determine how much data from each sensor will be transferred to the mobile sink $MS$, we create a virtual source $VS$ in graph $SG_f$ and, then add directed edges from $VS$ to all sensors $S_i \in S$ in the network flow graph $SG_f$. The capacity $SU(VS, S_i)$ is set to the maximum data generation capacity $D$ of sensor $S_i$ and the cost $SC(VS, S_i)$ is set to 0 as there is no communication overhead for data generation.

Fig. 5: Network flow graph based on single access data receiving model.
In order to satisfy the data delivery capacity constraints for the sub-sinks from each data segment \( s_{gi} \) to the mobile sink \( MS \), we create a virtual sink vertex \( VM \) in the flow graph \( SG_f \) and, then add a virtual vertex \( ds_i \) to the flow graph \( SG_f \) for each data segment \( s_{gi} \). Thereafter, add an edge \((ds_i, VM)\) from each virtual vertex \( ds_i \) to the virtual sink vertex \( VM \) with capacity \( SU(ds_i, VM) \) set to \( MDDC(s_{gi}) \) and cost \( SC(ds_i, VM) \) set to \( e_i \). This is because \( MDDC(s_{gi}) \) is the maximum amount of data that can be delivered from the data segment \( s_{gi} \) to \( MS \) and the energy cost for transmitting unit bit data from a sub-sink is \( e_i \). Furthermore, each sub-sink \( SS_i \) is connected to all the data segment vertices \( ds_j \) which are within its communication region with capacity \( \infty \) and the cost 0.

An example of a network flow graph is shown in figure [1] with respect to the path \( P \) and corresponding to the communication topology graph shown in figure [2]. The sensors are grouped into sub-sinks \( SS_1/\bar{S}_1, SS_2/\bar{S}_2 \) and \( SS_3/\bar{S}_3 \) and far-away sensors \( FS = N - \{S_4, S_5, S_{10}\} \). \( VS \) and \( VM \) are virtual source vertex and virtual sink vertex respectively. The capacity and the cost of each edge \((S_i, S_j)\) or \((S_j, S_i)\) are set to \( \infty \) and \((e_i + e_r)\), where \( S_i, S_j \in FS \). Similarly, the capacity and the cost of each edge \((S_i, SS_j)\) or \((SS_j, S_i)\) are set to \( \infty \) and \((e_i + e_r)\) respectively, where \( S_i \in FS \) and \( SS_j \in \{SS_1, SS_2, SS_3\} \), as shown in figure [5].

The virtual source vertex \( VS \) is connected to each sensor in set \( N = \{S_1, S_2, \ldots, S_{10}\} \) with capacity \( D \) and cost zero. The set \( SG = \{s_{g1}, s_{g2}, s_{g3}, s_{g4}, s_{g5}\} \) is a set of segments with respect to the path \( P \) and among them \( s_{g1}, s_{g2}, s_{g4} \) and \( s_{g5} \) are data segments. Let \( DS = \{ds_1, ds_3, ds_4, ds_5\} \) denote a set of virtual vertices for denoting the data segments \( \{s_{g1}, s_{g2}, s_{g4}, s_{g5}\} \).

Furthermore, each sub-sink \( SS_i \) is connected to all the data segment vertices \( ds_j \in DS \) which are within its communication region with capacity \( \infty \) and the cost 0, where \( SS_i \in \{SS_1, SS_2, SS_3\} \). To satisfy the data delivery capacity constraint for each data segment \( s_{gi} \), add edges from each virtual vertex \( ds_i \) to the virtual sink vertex \( VM \) with capacity \( MDDC(s_{gi}) \) and cost \( e_i \). Thereafter, the minimum cost maximum flow from \( VS \) to \( VM \) is determined across the flow graph \( SG_f \). The obtained max flow value is the maximum data collection capability by SADGAMSPCE algorithm.

5 Experiment Analysis

In this section, we evaluate the performances of DGAMSPCE algorithm using simulations in MATLAB. We compare the performance of DGAMSPCE algorithm with Static-Sink approach, SPT method [15], MASP protocol [9] and MDGOSP protocol [17] which will be discussed in the next section. The sensor networks with the uniformly deployed sensor nodes 200, 220, 240, 260, 280 & 300 within 400 m x 600 m rectangular area are used in the simulations. The results are the average of 50 different random topology of sensors for each specific size of network.

In this experiment, each sensor / sub-sink has communication range of 52 m and has initial energy of 20 Joule. A mobile sink moves at constant speed of 5 m / sec on the left border of the communication network as its movement trajectory for collecting data from the identified sub-sinks. However, the selection of movement path may influence the total data collection and energy-efficiency of the network, but may not affect the network performances significantly for each specific algorithm. The data transmission rate of a sub-sink is set to 20 Kbps. And, the data generation rate of a sensor is set to 0.2 Kbps. The energy consumption per unit bit transmitting \( e_t \) and energy consumption per unit bit receiving \( e_r \) are set to \( e_t = e_r = 0.5 \) \( \mu \)joule/bit. By simulations, we explore the impact of the data collected, total energy consumption and total energy utilization efficiency metrics as network performances.

- The total amount of data collected is the amount of data received by a mobile sink along with the fixed path from each sub-sink in one round of data collection.
- Total energy consumption is the sum total of energy consumed by all sensors and sub-sinks in one round of data collection.
- Total energy utilization efficiency is the ratio of the amount of data collected and total energy consumption in one round of data collection.
5.1 Analysis of DGAMSPCE Algorithm

DGAMSPCE is a centralized algorithm which is not self-adjustable in itself according to the dynamic topology change. Therefore, the mobile sink must be aware of the changes in the system dynamics. In this algorithm, we have considered energy consumption of each sensor for only transmitting and receiving data. So, the total energy consumed by all sensors is the sum total of energy consumed by them in the network data communication (transmitting and receiving). The DGAMSPCE can be adapted to the wireless sensor network employing more than one mobile sink. Intuitively, a wireless sensor network with multiple mobile sinks provides better scaled output than a single mobile sink. In DGAMSPCE protocol, the far-away sensors don’t communicate directly with the mobile sink. They only need to transfer their data to the sub-sinks. In other words, the mobile sink is transparent for the far-away sensors that even need not know the location of the mobile sink. Consequently, the DGAMSPCE protocol can also employ multiple mobile sinks. With the increment in the number of the mobile sinks, the energy communication cost of the network is relatively reduced due to the selection of a larger number of sub-sinks among the sensors.

5.2 Performance of DGAMSPCE Algorithm with a Single Mobile Sink

In this sub-section, we compare the performances of the proposed DGAMSPCE algorithm with MASP and MDGOSP methods. The latter two are used for assigning the members to the individual sub-sinks that have different scenarios with ours. In MASP and MDGOSP, due to the construction of a forest of routing trees rooted with individual sub-sinks, two adjacent sub-sinks in the topology network cannot send or receive data to each other. In addition, a sensor can transfer its data to a specific sub-sink for a single round of data collection, whereas in DGAMSPCE, two adjacent sub-sinks can communicate to each other and a sensor may transfer its data to more than one sub-sink by one for a single round of data collection. First, for making intuitive comparison, consider the case with only one mobile sink moving along the left border of the deployment area. As in the case with two mobile sinks, the second mobile sink is allowed to move on the right border of the area without any change in the trajectory path of the first mobile sink, so that the performance improvement with one more mobile sink can be observed more intuitively. Although, a center line of the deployment area as a trajectory path may get better performances with the case of a single mobile sink. The optimal selections of trajectory paths for the mobile sinks are out of scope of this article.

Based on the results of the simulation experiments, we validate that DGAMSPCE has better energy efficiency on data collection compared to the existed protocols. In figure 7a, we find that DGAMSPCE collects the largest amount of data that any other existing protocols for a single round of the data collection. The DGAMSPCE collects data about 0.5 times more than MASP and MDGOSP methods due to the use of max flow approach for the maximization of data forwarding from the sensors to the sub-sinks such that a sensor may forward its data to more than one sub-sinks one by one during the traversal round of the mobile sink.

Minimizing energy consumption of the network is one of the most popular problems in WSNs. We now evaluate total energy consumption employed by Static sink, MASP, MDGOSP and DGAM-
SPCE. The static sink is deployed in the middle point of the path of the mobile sink. Figure 7 makes the comparison between energy consumption under Static sink, MASP, MDGOSP and DGAMSPCE. We find that the energy consumption with MASP, MDGOSP and DGAMSPCE are very less compared with static sink. The energy consumption with MASP is larger than MDGOSP in one round of data collection. Moreover, the energy consumption with DGAMSPCE is less (about 0.05 times less) than MASP, but is larger (about 0.075 times) than MDGOSP in one round of data collection. As, to route data from the sensors to the sub-sinks, the MDGOSP method uses SPT and the MASP method uses modified SPT, where the ratio of data collection and energy consumption may not optimal due to heuristic implementation. The deterministic implementation based DGAMSPCE method uses minimum cost maximum flow technique to route data. Therefore, considering the amount of data collection and the energy consumption together, we can say that DGAMSPCE collects a larger amount of data efficiently and effectively as compare to MASP and MDGOSP methods. The energy efficiency utilization with MDGOSP is about 0.85 times more than MASP and MDGOSP methods.

5.3 Performance of DGAMSPCE protocol with Multiple Mobile Sinks

In this sub-section, we evaluate the performance of DGAMSPCE scheme with multiple mobile sinks. We position and increment the number of mobile sinks from 1 to 2 sinks along with the rectangular region of the deployment area of the network, as shown in figure 6a and figure 6b. With the help of multiple mobile sinks, as shown in figures 8, the energy utilization efficiency of DGAMSPCE is always better than MASP and SPT with the multiple mobile sinks, as shown in fig. 8. It is so because unlike SPT or MASP, it is not based on the construction of the spanning forest.
of trees of sub-sinks obtained using heuristic implementation. In this article, we have eliminated
the need of creating a spanning forest of trees of sub-sinks for efficient data communication and
have used min-cost max-flow network flow model instead of it.

![Graph showing energy utilization efficiency](image)

Fig. 8: Total energy utilization efficiency using 2 mobile sinks in one round

5.4 Performance of SDGAMSPCE Protocol

In this sub-section, we study the performances of SDGAMSPCE Protocol shown in figure 9. We
observe that SDGAMSPCE Protocol affects the performance of MDGMEC problem. In figure 9, it
is noticeable that SDGAMSPCE efficiently collects more data (about 0.025 times) than ShareOT
(Sharing Overlapping Time) [9] and MinOT (Minimum Overlapping Time) [9], for about the same
energy consumption.

Figure 9c illustrates that SDGAMSPCE yields more efficient output (about 0.12 times) in
terms of energy efficiency utilization as compare to others. This is so because in MinOT method,
the allocation of the communication time of a mobile sink is based on the arrival time of a new
sub-sink. In ShareOT method, this communication time is allocated among the sub-sinks based
on the segments’ lengths and number of contributing sub-sinks within those segments. But, in
SDGAMSPCE protocol, the allocation of the proportion of the data communication time of a
mobile sink among the sub-sinks are based on the concerning segments of the sub-sinks and the
data out-flows of the respective sub-sinks.
In this article, based on two different data receiving models, we presented two efficient data gathering algorithms, DGAMSPCE and SDGAMSPCE for maximizing the data collection using fixed-path mobile sink(s) for WSNs. We first provided a definition of our proposed MDGMEC problem, then we formulated the MDGMEC problem into a network flow optimization problem. Thereafter, based on multi-access data receiving model, we devised a deterministic polynomial running time algorithm, DGAMSPCE for the said problem that uses min-cost max-flow approach and exploits the resulting flow information to collect maximum amount of data with the minimum energy consumption. Furthermore, we analyzed the effects of single access data receiving model in the data collection process for this network scenario and presented SDGAMSPCE protocol that efficiently collects more data among all the existing ones. Finally, we evaluated the performance of the DGAMSPCE and SDGAMSPCE algorithms through experimental simulation. We used MATLAB as a tool for conducting simulation experiments. The result obtained through experiments proved that DGAMSPCE has high energy utilization efficiency and is better than MDGOSP, MASP and other SPT protocols in terms of the total amount of data collection at the cost of total energy consumption.

In the future, we plan to find an unconstrained path for a mobile sink, moving with a constant speed to collect maximum data throughput with minimum energy consumption. In addition, we also plan to find a distributed algorithm for solving this problem.
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