

ONLINE DRONE-BASED DATA GATHERING STRATEGIES FOR GROUND SENSOR NETWORKS

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ABSTRACT. This paper proposes two path-planning schemes for data collection in WSN using a drone flying over the sensor nodes to collect their data. We assign a weight to each sensor node corresponding to its priority in the collection process. When the drone selects its destination node, it will choose the one having the highest weight. We have defined utility functions based on the sensor nodes' information disseminated in the Wireless Sensor Network (WSN) using the Optimized Link State Routing protocol (OLSR). The information required to compute the nodes' weight is added to the exchanged packets during the execution of OLSR. The first proposed strategy is Data-driven Data Gathering Strategy (DDG) which uses the amount of stored data in each sensor node buffer. A priority is given to the nodes having the most significant data amount to collect. The second strategy is called Time-driven Data Gathering Strategy (TDG) where the age of the data is considered.

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1 Introduction

In recent years, technological advances in wireless communications have enabled the development of sensors characterized by low production cost, low power consumption, and great flexibility. These small devices are interconnected to form networks of wireless sensors that can be deployed in an area of interest to meet specific needs. Wireless Sensor Networks (WSNs) have become an established technology for a large number of real-world applications, ranging from monitoring (Garcia-Sanchez et al., 2011; Hejlova and Vozenilek, 2013; Kallur and Kulkarni, 2016) (pollution, agriculture, structures, and buildings) to event detection (Salman et al., 2019; Piera and Salva, 2019) (e.g., intrusions, fires, and floods) and target tracking (Parvin and Vasanthanayaki, 2019; Adhami et al., 2020).

Typically, many small devices (nodes) compose a WSN, where the nodes are considered limited resources, i.e., with limited on-board memory, short-range radio transceivers, and battery-powered. These devices perform three basic tasks: (i) sample a physical quantity of the surrounding environment, (ii) process (and possibly store) this data, and (iii) transfer it via embedded wireless technology to a central point called collector node, base station or *sink*. These sensor nodes can be disseminated over a large or hostile area. In this case, Data collection becomes one of the significant problems; thus, connecting to each sensor node and retrieving information on time introduces new challenges.

The classical approach is to deploy static sinks, and the data is transmitted to the central point using multi-hop wireless communications. These are called converge cast or, in other words, many-to-one communications. In this case, it is necessary to set up routing protocols that help route the packets to the destination nodes. This task is complicated due to the dynamic nature of the network topology. Indeed, when a sensor node runs out of its energy or is deteriorated by environmental conditions, this latter becomes unreachable, leading to a loss of connectivity in the network.

Many routing solutions for wireless sensor networks use static sinks for data collection (Lee et al., 2011; Manisekaran and Venkatesan, 2010). In these approaches, the sensor nodes near the sink are subject to a high traffic. In fact, they are more often used than the other sensor nodes and therefore consume more energy because they take care of packet re-transmission towards the sink.

To overcome this problem, more recent studies have considered using a mobile sink for data collection in wireless sensor networks (Vijayashree and Suresh Ghana Dhas, 2019; Fella and Kechar, 2020). In fact, considering these approaches, the sink moves inside the network to be within the sensors' communication range, allowing it to collect the data from each node directly. Most of the state-of-the-art works consider a ground-based data collection where the sinks are placed on robots or people (Yogirajsinh et al., 2016) and even fixed on animals (Juang et al., 2002).

More recently, with the development of new, low-cost flying equipment (also known as drones or UAVs), researchers have considered using them as mobile sinks to collect data from wireless sensor networks (Luo et al., 2021; Mazayev et al., 2016). This type of WSN is part of the mobile wireless sensor networks (MWSN) family, where the sensor nodes are placed on fixed locations and the sink move around to collect the sensed data.

The use of mobile sinks in the WSN brings a lot of improvements but also a lot of challenges. This method reduces the transmission and communication delays in the whole network and contributes to decrease the energy consumption of the nodes located near the sinks, which extends the network lifetime. Although mobile sinks have many advantages, there are still difficult issues to solve, such as dynamic network topology and reliability. One of the crucial challenges in collecting data in WSNs with mobile sinks is *the sinks' path planning* (Chatzigiannakis et al., 2008).

The use of drones as a mobile sink for collecting data from a ground wireless sensor network has been widely considered in the literature (Liu et al., 2018) (Yang and Yoo, 2018). Unfortunately, most of these works propose offline centralized path planning strategies with almost perfect knowledge of the sensors' location or state (i.e., energy, amount of data, frequency of data gathering, etc.). In this case, the drone's path is calculated in advance and subsequently followed by the drone. On the other hand, and to the best of our knowledge, only Na and Yoo (2019) adopted an online strategy. However, as we will see in the next section, they do not consider the same objectives as we are considering in this paper.

In this work, we propose two path-planning strategies to help the drone moving inside the WSN and collect the sensed data. Precisely, to select the different nodes to visit, the drone assigns a priority weight to each node of the network. This weight is calculated using a utility function based on the information transmitted by the sensors to the drone and is propagated in the WSN using OLSR (Optimized Link State Routing) routing protocol. The first strategy is Data-driven Data Gathering Strategy (DDG), and it gives priority to the nodes having the most considerable amount of data in their buffer. This strategy is more suited to applications where the more data we collect, the more beneficial this is of the application. No matter if the collected information is old or new. In the second strategy, called Time-driven Data Gathering Strategy (TDG), we use

the amount of stored data in the sensors and the age of this data to select the order in which the sensors will be visited. This second strategy is more suited for applications for which the freshness of the collected information is essential. We've implemented our two strategies in the OMNeT++ simulator using INET-MANET framework.

In short, we define our contributions as follows:

- We give a brief overview of the advantages and the challenges of using a UAV as a mobile data collector. Then, we review some related works of different path planning strategies for UAV data collection in WSN.
- We describe our two proposed path planning strategies presenting both the energy consumption and the communication models. We also outline the utility functions used with the different constraints to consider in terms of quantity and age of data.
- We present the different simulation settings, enumerating the simulation scenarios and giving the results of the DDG and TDG strategies. (section 5);
- We evaluate the proposed framework via extensive OMNeT++ simulations. We compare our proposed strategies DDG and TDG against basic path-planning strategies. We compute the gain of our frameworks in terms of the amount of collected data for the first one and the validity of this data with the second strategy.

2 Related works

Traditionally, data collection in wireless sensor networks was done through multi-hop communications. Thereby, the nodes close to the sink node will see their energy rapidly exhausting since they concentrate all the traffic to the sink, reducing the network efficiency and lifetime. One first alternative solution is to use more than one sink node. Unfortunately, this approach is not feasible for larger networks because of the implied financial cost. The second alternative is to use a mobile sink. Several research works have used different types of ground mobile sinks such as mules (Chehbour et al., 2019; Prince and Gupta, 2016), robots (Arezoumand and Mashohor, 2014; Wang et al., 2016), animals (Ozturk et al., 2004; Juang et al., 2002) or even buses (Huang and Savkin, 2017). However, the use of such a ground mobile sink has shown some drawbacks, including long latency in data collection because of the low mobility speed, besides the inability of this mobile sink to access damaged or obstructed areas.

More recently, drones have been widely used for data collection in WSNs as they offer a solution to the various drawbacks of ground mobile sinks. The emergence of drone technology has allowed them to be used to perform multiple tasks in several fields such as transport (Outay et al., 2020), agriculture (Maddikunta et al., 2020), health (Islam and Shin, 2019) and industry (Zhang et al., 2016). They are characterized by their flexibility, portability, reduced cost, and practicality of use. Some additional features such as being wireless, unmanned, and operating remotely make them suitable for use in dangerous zones or challenging to access for humans. However, the use of drones also suffers from some limitations (Mekki et al., 2019) since they are powered by batteries, which reduces their autonomy and thus, reduces their range of action.

The use of drones in WSN brings many improvements but also many challenges. In truth, it reduces the delays for data collection and the power consumption of the sensor nodes located near

the sinks, which leads to an increase in the network lifetime. However, there are still issues to solve. One of the most critical challenges is path planning, and the drone must consequently follow an optimized trajectory to collect as much data as possible in one flight because of the limited flight autonomy.

In table 1, we summarize the different approaches and strategies proposed in the literature for path planning with mobile sink. Hereafter, we classify thaws strategies into three main categories.

2.1 Random Mobility Models

In this model, the sink node follows a random path inside the sensing area. This mobility type is considered highly unpredictable regarding the next mobile sink position. Juang et al. (2002) proposed an efficient energy path determination strategy for wildlife tracking; they used animals as mobile data collectors in a wild environment. The author in (Johnson and Maltz, 1996) proposed a random mobility model that uses random directions and speeds. Both speed and direction are updated at each step. However, too frequent random changes can lead to effortless travel.

2.2 Predictable Mobility Models

Predictable mobility models refer to models where the mobile sink follows a pre-computed path. The trajectory is calculated in advance and, most of the time, offline. As a result, the sink follows the defined points until reaching the final destination.

The first solutions proposed in the literature suggest path-planning strategies where the sink follow simple geometric shapes such as straight lines, circles, squares, rectangles, or zigzag. For example, authors in (Mathur et al., 2016) proposes a data collection process based on a straight-line path. Cluster heads are chosen among the deployed sensors to form a straight line. The sink will then follow these points to collect sensed data. In (Khan et al., 2013), the authors deployed a wireless sensor network on a circular field, and the sink moves around the center with a fixed centered circular path. They consider a routing protocol based on the shortest path from sensors to the sink. The authors of (Zhan et al., 2018) consider a drone as a mobile sink and propose to use a zigzag path. In (Wang et al., 2015), the authors proposed a path planning algorithm named FPPWR (i.e., Fast Path Planning With Rules). They divide the targeted area into grids. They elected the minimum of grid points as cluster heads to cover all the sensor nodes by at least one cluster head. The obtained set of cluster heads is used to derive the drone’s path. The visiting order is obtained by solving the classic traveling salesman (TSP) problem where horizontal grids take precedence in path planning. This work was extended by Yue and Jiang (2018) and proposed a spiral-based path planning algorithm, which can quickly compute the shortest possible path. Similar to the previous work, Nitesh et al. (2017) propose a path planning strategy based on the Minimum Spanning Tree-based method to reduces the path length and the sensors’ energy consumption. A Rendez-vous Points are selected by choosing the nodes having the maximum cost function. After that, the mobile sink visits these selected nodes based on the TSP problem.

In (Valente et al., 2011), the authors use a drone for data gathering for precision agriculture and propose an iterative genetic algorithm to compute the path for maintaining the connectivity among the sensors and the drone. They first select points as hover positions to have a maximum of covered ground nodes. After that, they calculate a route that passes through this set of drone hovering positions. Yang and Yoo (2018) defined a path planning mechanism using a multi-objective bio-

Table 1: Related work and their main contributions.

reference	sinks	mobility model	path computation	Objective
Juang et al. (2002)	1	Random	Random	Network lifetime
Johnson and Maltz (1996)	1	Random	Random	Energy
Mathur et al. (2016)	1	Predictable	straight Line	Energy
Khan et al. (2013)	1	Predictable	Cycle	Energy
Zhan et al. (2018)	1	Predictable	zig-zag	Energy
Wang et al. (2015)	1	Predictable	Grid	Energy
Yue and Jiang (2018)	1	Predictable	Cycle	Data collection time
Nitesh et al. (2017)	1	Predictable	MST	Energy
Valente et al. (2011)	1	Predictable	GA	Connectivity
Yang and Yoo (2018)	1	Predictable	GA+ACO	Flight time and Energy
Raj et al. (2020)	1	Predictable	GT+ACO	Energy and Delivery delay
Liu et al. (2018)	1	Predictable	GA+DP	Age of data
Kong et al. (2018)	1	Predictable	SFLA	Path length
Bouhamed et al. (2020)	1	Predictable	DDGD+QL	Data collection time
Albu-Salih and Seno (2018)	1	Predictable	MILP	Path length and Energy
Pereira et al. (2004)	1	Dynamic	APF	Amount of collected data and Energy
Tazibt et al. (2018)	1	Dynamic	APF	Amount of collected data and Energy
Kinalis et al. (2014)	1	Dynamic	/	Latency
Yin et al. (2017)	1	Dynamic	/	Avoid obstacles
Wen et al. (2015)	1	Dynamic	IFS+RRT	Avoid obstacles
You and Zhang (2020)	1	Dynamic	/	Path length
Na and Yoo (2019)	> 1	Dynamic	PSO	Data collection time

inspired algorithm. As in the previous work, the objective is to collect the maximum amount of data while minimizing the total cost in terms of flight time, power consumption, and risk of operation of the drone according to some environmental conditions. They presented an algorithm that jointly uses the Genetic Algorithm and Ant Colony Optimization algorithms. The algorithm has two parts: first, the optimal detection points are derived from the information available at different types of sensors on the ground, then tIn this model, the sink node follows a random path inside the sensing area. This mobility type is considered highly unpredictable regarding the next mobile sink position. Juang et al. (2002) proposed an efficient energy path determination strategy for wildlife tracking; they used animals as mobile data collectors in a wild environment. The author in (Johnson and Maltz, 1996) proposed a random mobility model that uses random directions and speeds. Both speed and direction are updated at each step. However, too frequent random changes can lead to effortless travel. Other works of the literature have focused more specifically on reducing energy consumption. For example, in (Kong et al., 2018) the authors propose to reduce the drone’s trajectory length in order to decrease its energy consumption. The selection of the points forming the drone’s path is formulated as a weighted set coverage problem and solved by a greedy algorithm. In (Raj et al., 2020) a data-gathering scheme was proposed to reduce both energy consumption and data delivery delays. The solving methods are based on Game Theory to select the best set of Rendez-vous points. Enhanced Ant Colony optimization is used to compute the shortest path following the selected Rendez-vous points.

In another work, Liu et al. (2018) considered the age of the data and proposed two trajectory schemes. The first scheme consists of minimizing the age of the oldest information detected by the sensor nodes, and the second one minimizes the average age of the collected data. Both methods use dynamic programming and genetic algorithm to compute the paths. Similarly to the previous work, Bouhamed et al. (2020) consider the minimization of the data collection time as an objective. They first used the gradient descent-based algorithm to find the drone’s path, which allows him to avoid obstacles. Then, they compute the shortest path using the Q-Learning approach. The order of nodes to visit is chosen based on the drone’s battery constraints, the delay constraints, and some nodes’ priority. Finally, authors in (Albu-Salih and Seno, 2018) focus on the age of the data and uses a Mixed Integer Linear Programming approach to find the best stop locations, and the drones’ path helps to minimize the traveled distance and reduce the energy consumption.

2.3 Dynamic Mobility Models

Dynamic mobility models refer to models where the sink has no prior knowledge of the network or the topology. The mobile data collector computes its path according to its current state and based on information received from the sensor network. This trajectory generation method is also called "*online path planning*". Several works in the literature have focused on online path planning for mobile sink data collection in WSN. For instance, Pereira et al. (2004) proposes an Artificial Potential Field (APF) approach for collecting data from sensor networks using mobile robots. The authors consider that each sensor node is a source of an attractive potential function, which leads to choosing the radial basis function (RBF) centered on each sensor node. The used cost function is based on the amount of harvested data; specifically, the robot goes toward the nodes with the least available space in the buffer. Once the forces have been calculated, the direction vector to be followed by the robot is obtained by adding all the vectors to the same vector of the strongest attractive force. However, the mobile sink has more than one sensor node within its communication range. Using only the sensors as a source of attraction can lead to data loss.

These issues were studied in (Tazibt et al., 2018), they used a mobile sink to collect the sensing information and the same cost function based on the amount of collected data. The main difference is that the RBF is centered on cells containing several sensors, and they used a drone as a mobile data collector. Unfortunately, both works assume that the robot/drone knows sensors' positions and their collection frequencies.

Kinalis et al. (2014) proposed a path planning approach with adaptive stop & pause times. They supposed that some nodes might not complete their data transmission to the sink because of the sink mobility. Thus, they have to wait until the sink comes back in their communication range, leading to high data delivery latency and potential data loss. The proposed crossing process is carried out region by region. The sink visits the regions one by one and stops and stays at each region for a certain period to give sensor nodes enough time to transmit their data. They proposed two different path planning schemes. In the first scheme, the sink visits the regions from left to right and vice versa when a boundary is reached. This way, it ensures that the sink follows a trajectory without overlap. The second path planning scheme proposed is dynamic. This method favors areas with a high density of sensor nodes and the less frequented regions for the next move of the sink by recording the visited regions.

In (Wen et al., 2015) and (Yin et al., 2017), authors were interested in the path planning problem in a low-altitude urban environment. This environment is characterized by the presence of both static and dynamic (unexpected) obstacles. The objective is to reduce the collection time while avoiding obstacles. An offline path planning algorithm is used to find the shortest path to collect the data avoiding static obstacles. In contrast, an online path planning algorithm is exploited to bypass unexpected obstacles based on the dynamic map.

Similar to the previous works, You and Zhang (2020) also proposed offline/online, hybrid schemes. A first offline phase is executed before the drone begins its flight, and a second online step is completed during the collection process. The drone's trajectory is first determined based on the probabilistic LoS (Line of Sight) channel model during the first step. It is then online adjusted by controlling the drone's flight speeds along the optimized offline trajectory and the communication planning based on instantaneous information on the channel state and the individual quantities of data received cumulatively.

Finally, the authors of (Na and Yoo, 2019) proposed a pure online solution for data collection using multiple drones. This solution aims to identify the drones' positions where the utility value is maximized. The proposed approach uses a multi-objective utility function based on sensors' priority, the spatio-temporal distribution of the information to collect, and the drones' connectivity. The drones' locations are readjusted at each step using the Particle Swarm Optimization algorithm.

2.4 Discussion

The main common point among the state-of-the-art works is that they consider a centralized approach, which means that the drone's path is computed in advance. Indeed, they assume perfect knowledge of the coordinates, the quantity of data, and the energy available at each deployed sensor node, which is not realistic in real applications. Most of these approaches focus on the mobile sink's path length reduction to decrease energy consumption without considering the value of gathered data or their validity.

The obtained results by these approaches are optimal, but, on the other hand, they are not dynamic

and are not flexible to the eventual changes that may occur in the network. Indeed, in those cases, the drone cannot be interrupted during its data collection process to take over a new event.

Similar to the offline approaches, in our solutions, the drone uses a map containing the network's topology to choose its next destination point. The drone receives the necessary information to build this map by flying over a sensor node. However, the main difference is that the drone is learning the sensed area, including the topology of the wireless sensor network and sensors stats in an online manner by regularly updating this information to allow the drone to adapt to possible changes in the network (sensing frequency modification, nodes' failure, etc.).

In our paper, we address the problem of pure online path planning for mobile data gathering. We used an Unmanned Aerial Vehicle as a mobile sink to maximize the acquired sensor information and ensure the freshness of data.

3 Problem Statement and Formulation

In this paper, we are interested in using a drone as a mobile sink for data gathering from a ground wireless sensor network. In a first step, our system is presented, then the considered energy consumption models at both the sensors and the drone are defined; finally, the communication model relating the sensors and the communication model used between the sensors and the drone are detailed.

3.1 System Overview

As we can see in Fig. ??, a data-gathering application using a drone as a mobile sink is considered. Let us consider a square geographical area denoted as A , and a set of static wireless sensor nodes N deployed within A . Each sensor node has a perfect knowledge of its GPS coordinates. We consider that the sensor nodes are equipped with a certain number of physical sensors (temperature, humidity, etc.), enabling them to collect data relating to their immediate environment. These data are collected according to a capture frequency noted as $f_i : \forall i \in N$. We denote by $d_i(t)$ the maximum amount of data that could be collected by a given sensor node i during a period of $\Delta(t)$. Each sensor node has a limited storage capacity noted as C_i . In addition to sensing capabilities, sensor nodes are also equipped with a wireless interface to communicate with each other. We denote by r_i the communication range for both the sensor nodes and the drone. Finally, we assume that the density of the sensors and the communication range are high enough so that the obtained network forms a connected graph.

The data collection is realized using a drone acting as a mobile sink; it is deployed and can move freely within A . Besides, each time it flies over one or more sensors, it can communicate with them and collect the available data. The battery constraint of the drone is taken into account by limiting the flight length. This last should not exceed the flight autonomy limit. Finally, as for the sensor nodes, the drone is also equipped with a wireless interface to communicate with the sensor nodes deployed on the ground.

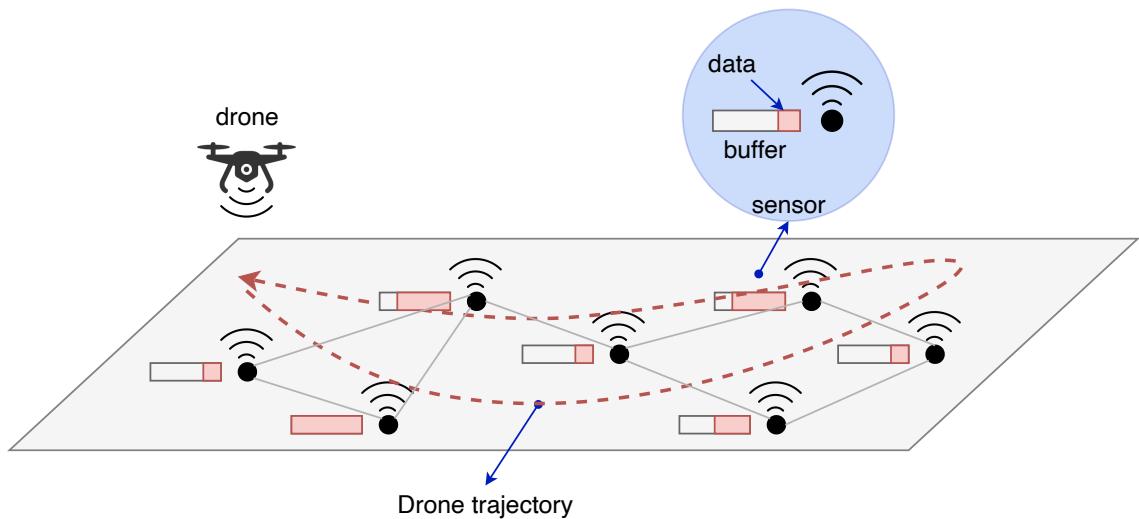


Figure 1: System overview

Table 2: Power consumption of Node's transmitter/receiver.

Node State	Value (mW)
Switching off-on	1
Idle	2
Busy	5
Receiving	10
Transmitting	100

3.2 Energy Consumption Model

3.2.1 Modèle de consommation d'énergie du capteur sans fil

Similarly to the existing literature on sensor energy consumption models, in this paper, we consider that the sensor nodes' power consumption is determined by the radio model and the transmitter/receiver state using constant parameters. We define the energy at each node as the sum of the energies expended when a sensor node is being in each of the following states: *Idle*, *Busy*, *Switching*, *Receiving*, and *Transmitting*. For example, when a sensor node begins to receive a data packet, the energy consumed in this case corresponds to the energy expended for switching the radio from *Idle* state to *Receiving* state plus the energy corresponding to the *Receiving* state until the reception of the packet. Similarly, when a sensor nodes start transmitting a data packet, the consumed energy corresponds to the energy expended for switching the radio from *Idle* state to *Transmitting* state plus the energy corresponding to the *Transmitting* state until the transmission of the packet. Table 2 summarize the energy consumption parameters considered in this paper.

3.2.2 Drone's Energy Consumption Model

Rotary-wing drones have generated tremendous interest in industrial and scientific circles. They have exclusive capabilities like hovering, vertical take-off and landing, limited launching space, and good maneuvering. The main challenge for constructing rotary-wing drones is to maximize their autonomy for a given mass while providing the power needed for propulsion and the embedded instruments. Therefore, it is essential to carefully manage the available energy and path planning in order to have the most prolonged flight duration. Recent progress achieved on Lithium battery type allowed the electric flight to accomplish an important autonomy for entertainment or local missions, but still far from being sufficient for longer trips and assignments.

In our study, we consider a quad-copter. The four rotors provide the vertical force (Thrust) that allows the unit to rise. The quad-copter may evolve following its roll, pitch, and yaw axes and in translation in all directions in flight. The dynamic model of a quad-rotor can be thought of as a system where the drone's spatial evolution (i.e., outputs) is due to the voltage applied to each of the four motors (i.e., inputs). Moving the drone in a specific direction is obtained by changing one or more rotor's rotation speeds. Several methods exist in the literature, allowing us to estimate a propeller's required power, such as the blade element theory (BET) and the Froude theory. Even if these methods can provide a more precise result, they assume a certain number of coefficients, which cannot be computed only after empirical tests, such as Thrust, Torque, and Power coefficients. Moreover, the obtained coefficients are specific to the tested propeller at a specified rotation speed and cannot be generalized for other types of propellers. Basic drone maneuvers include take-off, hovering, changing altitudes, and landing, which require different rotors and propeller rotation speeds. In this case, and to the best of our knowledge, the most suited method to approximate drones' power consumption is to use the model proposed by Abbott. Considering this model, the power consumption of a drone can be expressed as follows:

$$P = 5.33 \times 10^{-15} \times Diam^4 \times Pitch \times N_t^3 \quad (1)$$

where P is the power in Watt, $Diam$ and $Pitch$ in inch, and N_t in tr/mn.

Thereafter, we can easily derive the energy consumed by the drone according to the flight duration as follows:

$$E_{drone} = \int P(t) dt \quad (2)$$

Since a constant speed is considered, the equation 3 simplifies to:

$$E_{drone} = P \times \frac{l}{s} \quad (3)$$

where l is the path length and s the drone speed.

In addition to the energy consumed for the mobility of the drone, the latter is also equipped with a communications interface allowing it to communicate with the sensors on the ground and which also requires energy. In what follows, we assume that the drone's communication energy model follows the same model as that of the sensors described above.

3.3 Communication Model and Protocols

As introduced earlier, a gathering utility function that corresponds to the priority of collecting data from a given sensor node in the collection process is defined. Each sensor node computes a weight used by the drone to select its next destination node. Basically, it chooses the destination sensor node with the highest weight. As we can notice, the drone needs to be informed of the weights associated with all the sensor nodes to make its decisions. To provide this knowledge, the OLSR protocol and, more precisely, its signaling messages are used to efficiently disseminate the weights of each sensor node to all the networks, including the drone.

Optimized Link State Routing (OLSR) Clausen and Jacquet (2003) protocol is a proactive routing protocol initially developed for ad-hoc networks. One of its main advantages is that it inherits the stability of link-state algorithms family and the fact that the routes are immediately available when needed, thanks to its proactive nature. In OLSR, each node periodically sends signaling messages to discover the entire topology of the network. Two types of signaling messages are used: the HELLO messages and the TC (*Topology Control*) messages. The objective of the HELLO messages is to discover all 1-hop neighbors of a node. From this information, each node can elect its MultiPoint Relays (MPR) nodes list, which consists of a list of 1-hop nodes that offers the best routes to the 2-hop nodes. The next step is to disseminate this list of MPR within the TC messages using only the MPR nodes to all other network nodes. Finally, each node can then use Dijkstra's shortest path algorithm to find each reachable node's best route. In the standard version of OLSR, the metric used to find the shortest path between a source and a destination is the number of hops.

In this paper, we propose to take advantage of one of the strengths of OLSR, which is an optimized broadcast of signaling messages within the network. Basically, each sensor node integrates into the HELLO and TC signaling messages information about its current state, such as its GPS position as well as the amount of data currently available in its buffer. This will allow each sensor node within the network to build the topology of the network by including these information. After that, when the drone starts its data collection process, it periodically sends beacon messages to signal its presence in an area. If a sensor node on the ground receives one of these beacons, that indicates that the drone is in its communication range. Consequently, the sensor node starts transmitting both the data stored in its buffer to the drone and its network map view, which corresponds to the network topology built using the OLSR's signaling messages.

4 Data Gathering Strategies

In this study, we propose to follow a purely online approach, which means that the drone must iteratively build its path as it evolves within the targeted area. In this case, it is essential to give the drone the possibility to select the order to visit the sensor nodes. To do so, the drone starts by assigning a weight corresponding to the priority of each sensor node in the collection process. Hence, the drone selects the next destination node with the highest weight. This weight is obtained according to a utility function that uses the sensor nodes' information and propagated in the network, including the drone, using the OLSR's signaling messages. In the following, we propose two strategies: a.) **Data-driven Gathering Strategy – DDG**, and b.) **Time-driven Gathering Strategy – TDG**. In this section, we introduce both strategies, and details how we formulate the utility function and modify OLSR signaling messages to disseminate both approaches' required information.

4.1 Data-driven Gathering Strategy – DDG

In Data-driven Gathering Strategy – DDG, we consider a utility function derived from the amount of data stored in each sensor node buffer. A priority is given to the sensor nodes having the most significant amount of data to collect. In the following, we provide more details on our utility function and on the information dissemination using OLSR signaling messages.

4.1.1 Utility function

As introduced earlier, the drone periodically transmits a beacon message to announce its presence in the area. When a sensor node receives this beacon, it starts sending to the drone the data stored in its buffer and a copy of the map representing its view of the network topology. The later ones are then merged and updated with the topology map locally available at the drone. The resulting map is then used to compute the weight associated with each sensor node. This weight is called the *attractiveness weight* and is used to determine the advantage (or disadvantage) of flying to a specific sensor node in the network. In Data-driven Gathering Strategy, we propose to compute the *attractiveness weight* as follows:

$$A_i^t = \alpha_t \times \ln\left(\frac{Q_i^t}{C_i}\right) + (1 - \alpha_t) \times \ln\left(\frac{1}{\frac{d_i^t}{S_{max}}}\right) \quad (4)$$

where Q_i^t the amount of data present in the buffer of the sensor node i at time t , C_i is the maximum buffer capacity of the sensor node i , d_i^t is the distance between the drone D and the sensor node i at the time t , S_{max} is the maximum distance allowed per step for the drone, finally, α is weight factor.

As we can see, a sensor node’s attractiveness is deduced from the amount of data available in the buffer of a sensor node counterbalanced by the traveling distance needed to reach that sensor node. Indeed, the first part of the formula ($\ln(\frac{Q_i^t}{C_i})$) attribute a greater value to the sensor nodes having the largest amount of data in their buffer. While the second part ($\ln(\frac{1}{\frac{d_i^t}{S_{max}}})$) assigns a greater value to the sensor nodes that are the closest to the drone.

The parameter α is used to define the importance of the amount of collected data compared to the distance traveled by the drone to collect that data. Given that the drone’s autonomy is reduced over time, the choice between the amount of data to collect and the distance to collect it becomes crucial. In this case, we propose to dynamically adjust α according to the remaining maximum distance that the drone can accomplish. More precisely, we propose to compute α as follows:

$$\alpha_t = 1 - \frac{D^t}{D_{max}} \quad (5)$$

where D^t is the total distance traveled so far by the drone and the D_{max} is the maximum distance that can be traveled by the drone, which relates to its maximum autonomy.

As we can see, when the drone starts its data collection process, the traveled distance is small, which means that α tends to be equal to 1. This value gives more importance to the first part of the formula 4, related to the amount of data. The drone can then move to the sensor nodes having the largest amount of data stored in its buffer even if it is at a large distance from the drone.

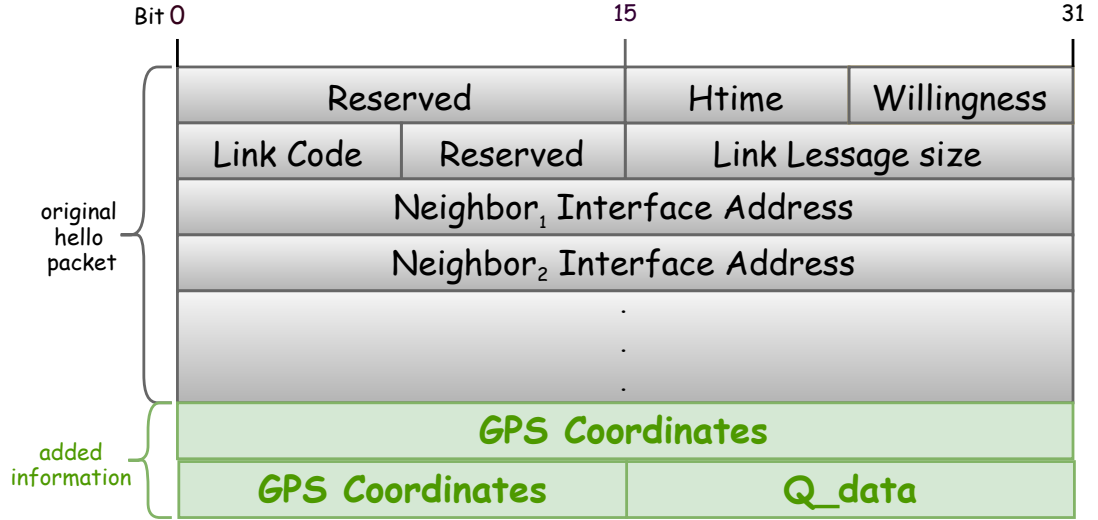


Figure 2: DDG HELLO packet format.

On the other hand, when the drone continues its collection path, the distance traveled increases, and the value of α is automatically adjusted accordingly. Therefore the importance of the amount of data becomes less important compared to the distance. This leads to the introduction of the distance factor when choosing the target.

4.1.2 Information Dissemination

As mentioned above, based on the information disseminated by the sensor nodes, the drone can build its path iteratively by choosing the next sensor node to serve. In DDG, this information consists of the amount of data currently contained in each sensor node buffer and the distance separating the drone from that sensor node. To disseminate the required information, we enrich the classical OSLR protocol messages. In a first step, each sensor node periodically broadcast in its HELLO message both the amount of data and its GPS coordinate as denoted in fig. 2. In a second step, once the MPR nodes have been selected, they periodically broadcast their TC message to all network nodes. Because the MPR nodes are now aware of the information of all the sensor nodes that selected them as MPR, they can include that information in TC message as illustrated in fig. 3. The reception of these TCs messages allows each sensor node to maintain a database containing the topological of the network, including the GPS coordinate and the amount of data for each sensor.

4.2 Time-driven Gathering Strategy – TDG

In Time-driven Gathering Strategy – TDG, we assume that a deadline is associated with each sensor’s data. This deadline is a time value after which the data is no longer considered valid or useful. In this case, the objective is then to collect as much data as possible before they become

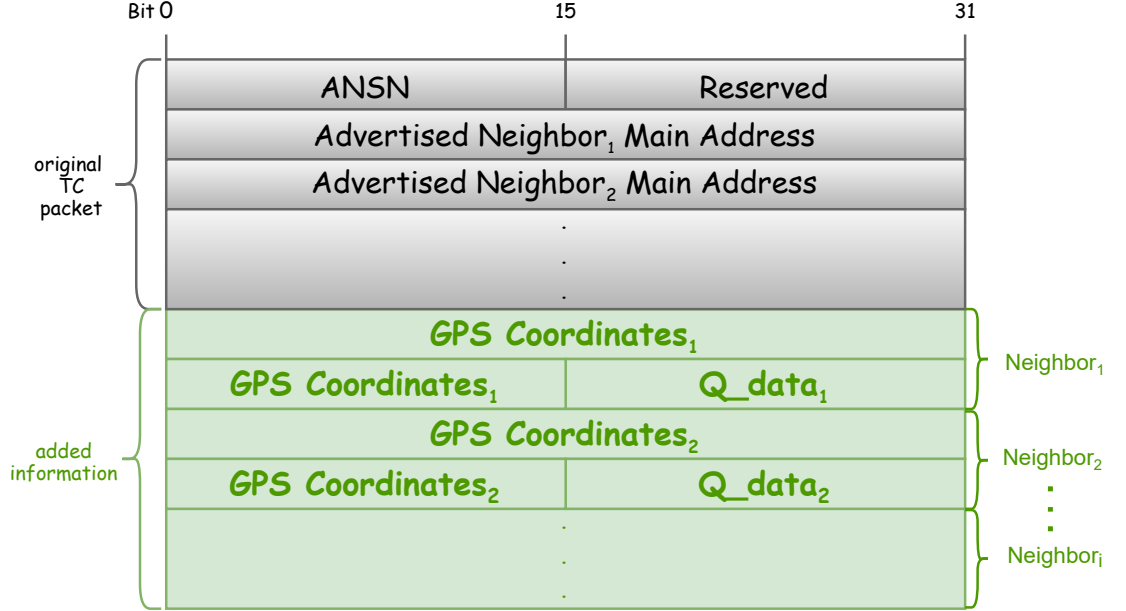


Figure 3: DDG TC packet format

unusable, which means that a priority is given to the sensor nodes having data in their buffers that are the closest to their deadlines. In the following, we provide more details on our utility function and on the information dissemination using OLSR signaling messages.

4.2.1 Utility function

Similarly to the previous strategy, the objective of the utility function is to associate an *attractiveness weight* to each sensor node. However, instead of using the amount of data available at the buffer of each sensor node, we consider the age of the data and taking into account the time needed to reach the targeted sensor. Because, a data can be valid at the decision time, but its validity can expire when it is waiting for the drone's arrival. Basically, we propose to compute the *attractiveness weight* as follows:

$$A_i^t = \alpha_t \times \ln\left(\frac{a_i^t + \frac{d_i^t}{Sp_d}}{T_i}\right) + (1 - \alpha_t) \times \ln\left(\frac{1}{\frac{d_i^t}{S_{max}}}\right) \quad (6)$$

where a_i^t is the age of the oldest valid data present in the sensor node i at time t , T_i is the age at which the data is no longer considered as valid for sensor node i , d_i^t is the distance between the drone D and the sensor node i at the time t , Sp_d is the drone's speed, S_{max} is the maximum distance allowed per step for the drone. Finally, α is a weight factor.

As we can see, this utility function is based on the age of the data stored in the sensor nodes' buffer and on the distance separating these sensors from the drone. The first part of equation 6

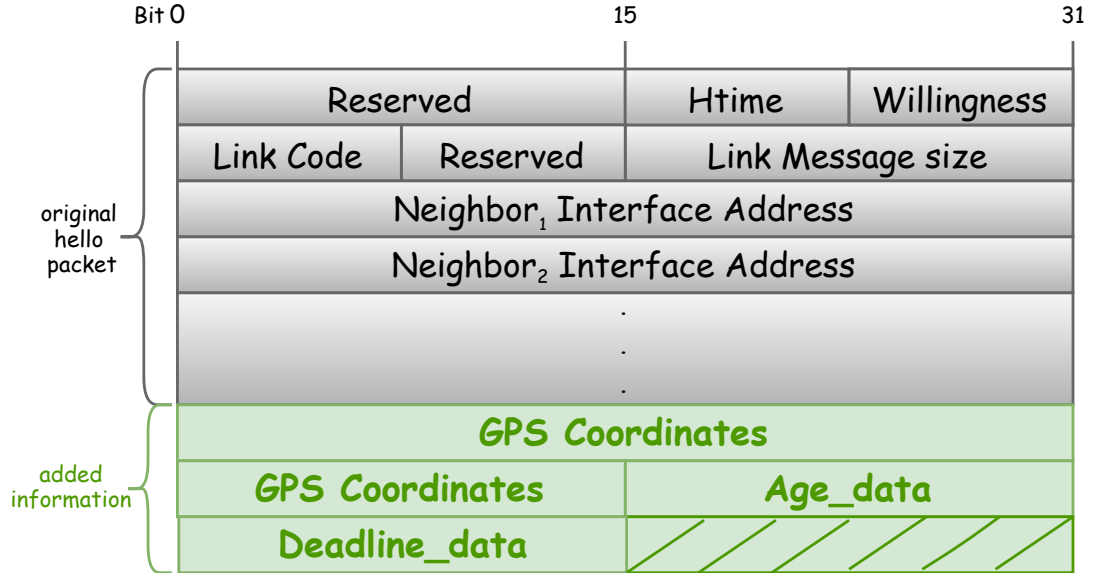


Figure 4: TDG HELLO packet format

aims to assign a high score to the nodes having the data approaching their deadline. While the second part assigns a greater value to the sensor nodes that are the closest to the drone. Finally, we propose to compute the weight factor α similarly to the previous strategy, using the formula 5. Indeed, following the same logic, when the drone begins to collect the data, a priority is given to the sensor nodes having the oldest data. However, the more the drone progresses in its path, the more priority is given to nodes that are closest sensor nodes.

4.2.2 Information Dissemination

The information dissemination method adopted in TDG is alike the previous strategy except for the fact that instead of considering the amount of data, we are adding the deadline and the age, as illustrated in fig. 4 for the HELLO messages and fig. 4.2.2 for the TC messages.

TDG TC packet format

5 Performance evaluation

In this section, we evaluate the performances of the proposed approaches. As presented above, two data collection schemes have been proposed. The first one aims to collect as much data as possible, the second aims to collect data before its deadline expires. In this purpose, several series of simulations have been conducted. The next section will describe the environment where our simulations were performed and then the obtained results are presented and commented.

Table 3: Simulation Parameters.

Parameter	Value l
Number of sensors	50-100
Sensing frequencies	10-15 Byte/s
Buffer size	5000 Bytes
Communication range	200 m
Deadlines	500-700 s
Drone’s speed	4 m/s
HELLO send interval	2 s
TC send interval	5 s

5.1 Simulations Settings

We carried out a set of performance evaluations using OMNeT++ simulator (Varga, 2001). Also, we used the INETMANET framework Ariza and Inzillo (2019), an open-source model library for the OMNeT++ simulation environment that provides protocols, agents, and other models for Mobile Ad Hoc Networks. We have considered that the sensor nodes and the drone are equipped with IEEE 802.15.4 communication interfaces, allowing them to communicate. All the sensor nodes have the same capabilities in buffer size and communication radius. Finally, we modified the OLSR protocol of OMNeT++ /INET-MANET to match our signaling needs. More precisely, we have changed the format of both HELLO and TC OLSR signaling messages. Table 3 summarize our simulation parameters that we are considering in our evaluations.

Due to the strong constraints on the autonomy of the drones, it is not possible to consider areas of huge sizes. Consequently, it is not possible to consider a large number of sensors that could be deployed in the area. We have, therefore, considered an area of 2km x 2km with a density of sensors between 50 and 100 sensors. We have fixed the sensor nodes’ buffer size to 5K bytes, because they have limited capacities in terms of computation and storage. The communication range of the sensors is set to 200 m to guarantee a connected graph since the sensors need to disseminate their information in the network. We explore three categories of applications: i) applications with a low collection rate, ii) applications with a moderate collection rate, iii) and finally, applications with a high collection rate. We have assumed a collection rate of between 1 and 5 bytes/s for the first category of applications, corresponding to an amount of data between 6k and 18k bytes per hour. For applications with a moderate collection rate, we set the collection rate between 5 and 10 bytes per second (from 18k bytes to 36k bytes per hour). Finally, we set a collection rate between 10 and 15 bytes per second (36k bytes to 54k bytes per hour) for applications collecting a large amount of data. We believe that our choices allow us to cover a wide spectrum of applications.

In this paper, we considered a drone with the characteristics of the drones currently available in the market in terms of speed and flight autonomy . We considered a drone with an autonomy of 20 minutes; therefore, we decided to set the deadline to half this duration, which is 10 minutes.

Finally, both HELLO and TC message intervals were set to the values recommended by the standard.

Following state of the art presented in the section 2, we consider that the closest works to our

proposed approaches are those presented in (Liu et al., 2018), (Yang and Yoo, 2018) and (Na and Yoo, 2019). As for our solution, the proposed work in (Liu et al., 2018) uses the age of data to optimize the drone’s trajectory. However, unlike our approach, they did not define a deadline for this data, which makes the comparison of the two propositions difficult because they do not aim to evaluate the same utility value. The authors of (Yang and Yoo, 2018) defined a utility function that assigns a weight to each sensor node of the network to optimize the drone’s trajectory. The parameters considered in their solution are the node’s priority, sensors and drone’s energy, and forbidden areas. These parameters are, therefore, different from those we used. This difference means that our two solutions cannot be compared because they do not have the same objective.

Unlike the solutions presented in this paper, which are dynamic approaches, the two approaches mentioned above are static and not flexible to an eventual network’s change. The comparison with our solutions cannot be made because they do not start from the same assumptions. Finally, the work presented in (Na and Yoo, 2019) is a similar approach to the solutions presented in our article. They present an online solution that uses a utility function to adjust the drone’s trajectory during its data collection process. However, their function is based on different parameters from those we used. Therefore, it is impossible to compare our results because the methods do not aim to assess the same utility value.

Because of the wide diversity of approaches and the variety in experimental and evaluation criteria, there are no approaches in the literature that can be considered a highly relevant state-of-the-art baseline. We have, therefore, chosen to implement two additional methods apart from the proposed ones.

In the first approach, named NDG (i.e., Nearest Data Gathering Strategy), the drone moves and collects the data from the closest sensor node at each step. In other words, the utility function used to select the next sensor node to visit is based only on the distance separating the drone and the sensor nodes. The other approach that we compared with, named DDG-WIC (i.e., *Data-driven Gathering Strategy–Without Intermediate Collection*), is derived from our proposed strategy DDG. Basically, in DDG-WIC, we consider the same utility function as in DDG, except the fact that the drone does not collect any data from intermediate sensor nodes being in its path to the targeted destination. This approach correspond to use case where the drones’ altitude does not allow him to communicate with the sensors on the ground during its movement to reach the destination.

5.2 Results

In our first performance evaluation, we focused on comparing all strategies in terms of data gathering speed. In this case, we deployed a set of 75 sensor nodes over an area of 2000 m by 2000 m . We consider that the drone is initially deployed at the position (0,0) and an altitude of 20 m . Fig 6 depicts the data collection speed obtained when the drone uses the strategies DDG, NDG, TDG, and DDG-WIC. The data collection speed is computed as the amount of data in Byte collected by the drone per traveled distance in meters.

In Fig. 6 the data collection speed when using the DDG strategy outperforms the data collection speed of all other strategies. For instance, at a traveling distance of 2000 m , the drone’s collection speed when using DDG is almost equal to 25 *byte/m*, whereas it is only around 20 *byte/m* for NDG and TDG and drops to less than 10 *byte/m* for DDG-WIC. We also notice that both NDG and TDG give similar results when the traveled distance is less than 8000 m . However, starting from that distance, the NDG strategy outperforms TDG.

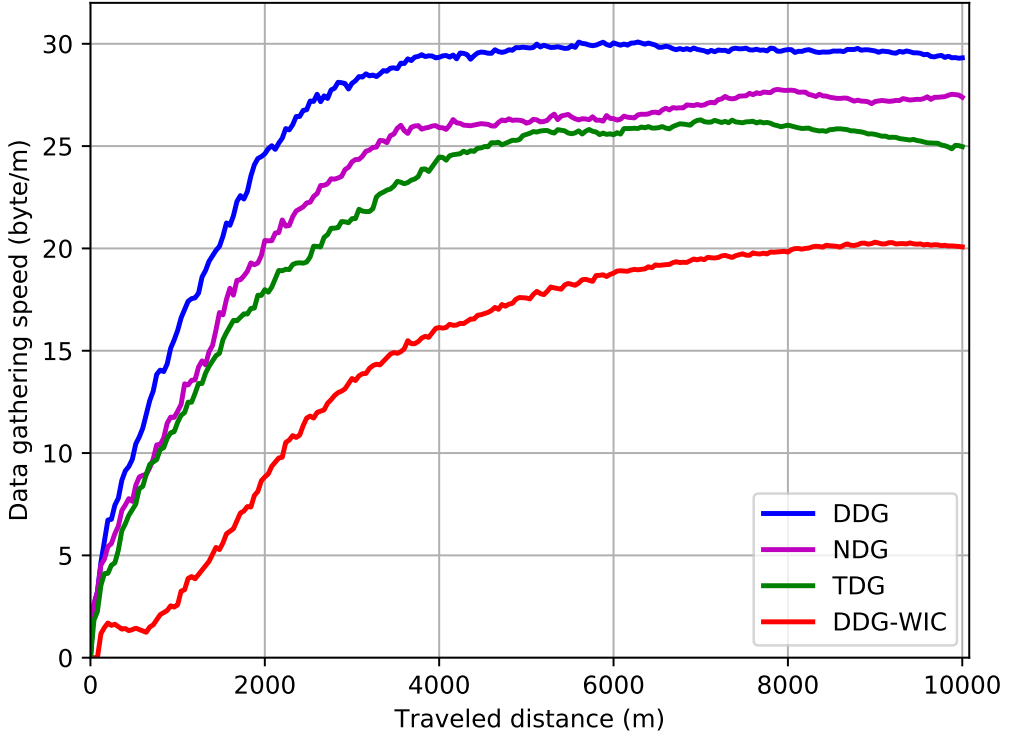


Figure 6: Data gathering speed

We can also notice that when more distance crossed by the drone is realized, the gap between the collection speeds of DDG and NDG is reduced. This trend could be explained by the fact that the parameter α is progressively updated as the distance crossed by the drone increases. Indeed, in the early steps, the drone favors the nodes having the most data in their buffer even if these nodes are at a large distance. The drone is allowed to make longer trips if, in return, it collects more data. From this curve, we can conclude that DDG improves the drone’s performance in terms of the amount of data collected per traveled distance.

In Fig. 7, we consider the same configuration as before, and we plot the percentage of collected data for all four strategies. As expected, the DDG strategy outperforms all other strategies. We can also observe that NDG and TDG give similar performances except when the drone starts to cover significant distances.

We can also notice that allowing the drone to collect data from intermediate sensor nodes leads to collect a more significant amount of data. For instance, in DDG, after a traveling distance of 10000 m, the amount of data collected by the drone is almost equal to 80% of all data present in the network. At the same time, this amount is slightly less to 60% for DDG-WIC. This is because, in the DDG-WIC strategy, the drone cannot collect data from intermediate sensor nodes along

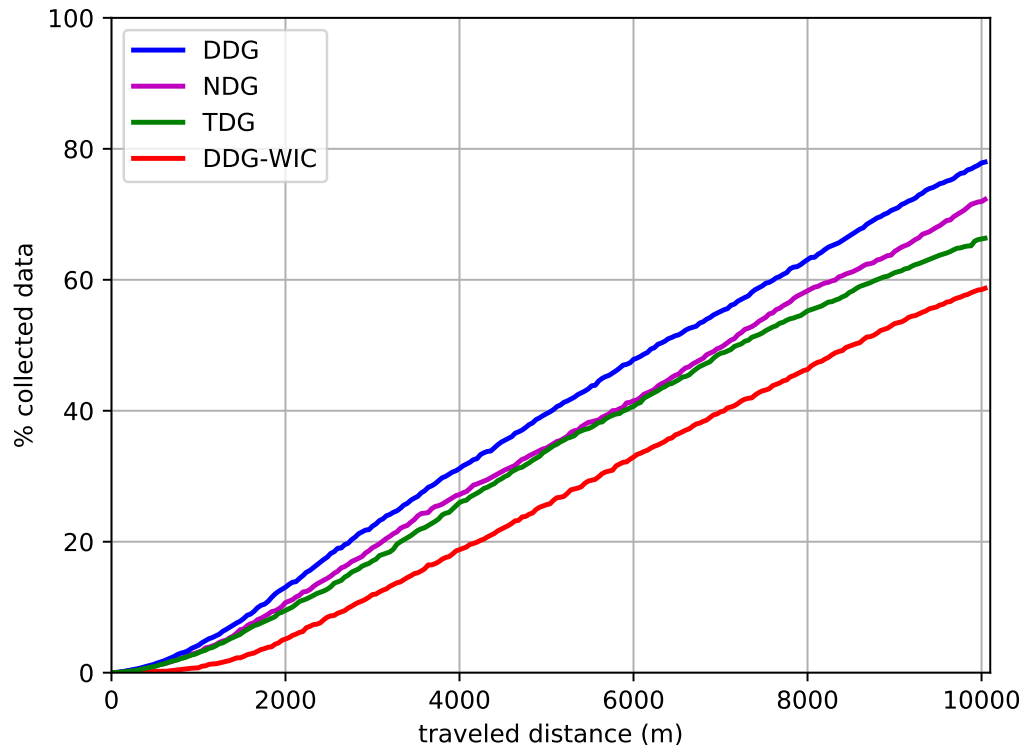


Figure 7: Amount of collected data per traveled distance

its path. As introduced earlier, this may correspond to situations where the drone cannot move straight to a specific destination. In this case, to reach the next sensor node, the drone must gain altitude to avoid any obstacles, such as in a forest. Therefore, it may lose connection with the sensors on the ground. In conclusion, it is more interesting to allow the drone to collect data from intermediate nodes when possible, even if the amount of data within that node is insufficient to attract the drone.

In fig. 8, we depict the percentage of collected data when we varied the number of sensor nodes in the area. As we can see, the DDG strategy offers better performances than the other methods. For example, when we deployed 50 sensor nodes, the drone can collect almost 72% of the total amount of data present in the network, while both NDG, TDG, and DDG-WIC collect 65%, 62% and 60% respectively. The same trend is observed when we set the number of sensor nodes to 100. It is interesting to notice that when the number of deployed sensor nodes is increased, a higher percentage of data can be collected. This is mainly due to the fact that more density brings more opportunities for the drone to fly over several sensors and collect more data simultaneously.

Fig. 9 represents the percentage of outdated collected data for a different number of deployed sensor nodes. The data validity period is randomly set from 500s to 700s within each sensor node. As

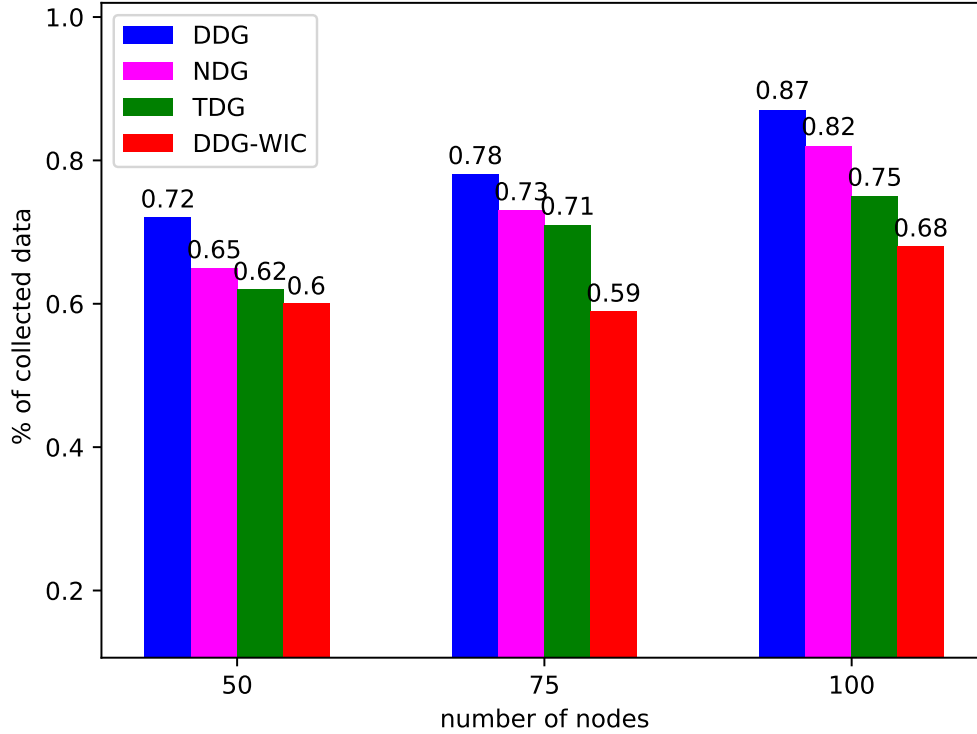


Figure 8: Amount of collected data VS number of nodes

we can see, the TDG strategy outperforms all other approaches. This is because when assigning attractiveness scores to each node, the drone gives high importance to the age of the data. This means that the nodes with the oldest data stored in their buffers are given higher priority and therefore visited first.

The Fig. 10 shows the amount of valid collected data as a function of data sensing frequencies. In this figure, we varied the sensing frequency of the sensor nodes in order to study the impact of this parameter on the quantity of valid data collected using the TDG and DDG methods. As we can see, the TDG method outperforms the DDG method for the different ranges of values. For example, for data capture frequencies ranging from 1 to 5 *byte/s*, the TDG method collects nearly 98% of data before it expires. While for the DDG method, this quantity drops to 61%. Likewise, for the other capture frequency ranges, the amount of data collected using TDG is much greater than that of DDG.

Finally, it is essential to evaluate the proposed approaches in terms of consumed energy. Indeed, one of the primary purposes of using a drone is to extend the network lifetime. In addition to the strategies mentioned above, we also measured the energy consumed by the network when considering a classical data routing strategy between the sensor nodes and a well that we place

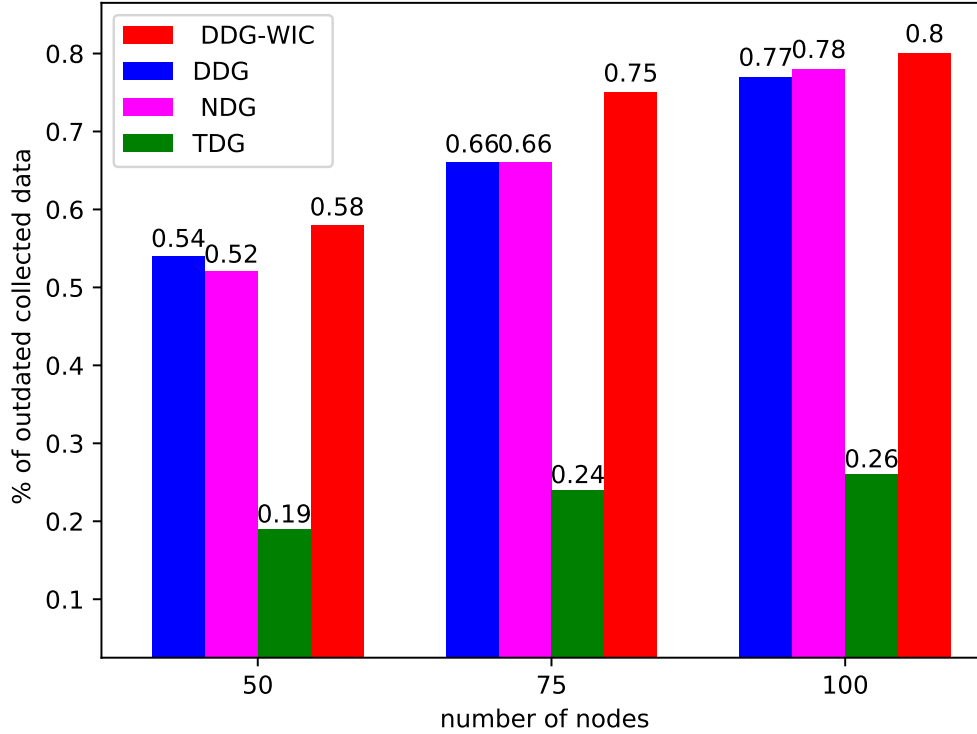


Figure 9: Amount of outdated collected data VS number of nodes

at the drone’s initial coordinates. We choose OLSR as a data routing protocol. As we can see in Fig. 11, the sensor nodes consume much more energy when the data collection strategy is based on OLSR. For example, at $t = 1000s$, the average power consumed by the sensor nodes is slightly greater than $1 j$. In contrast, when we use one of our drone-based strategies (DDG or TDG), the energy consumption is less than $0.4 j$, which leads to an improvement of more than 60%. This improvement is due to the fact that the sensor nodes are no longer required to periodically transmit their data to a central point using a multi-hop communication protocol, which leads to high energy consumption. On the other hand, in DDG and TDG, the sensor nodes transmit their data only after detecting the drone.

6 Conclusion:

This paper has presented two dynamic strategies for data gathering from a ground wireless sensor network. Compared to previous studies that aim to reduce the mobile sink’s path or even on obstacle avoidance, we propose to focus on the amount of gathered data and their validity. The first strategy, named Data-driven Gathering Strategy – DDG, aims to collect the maximum amount

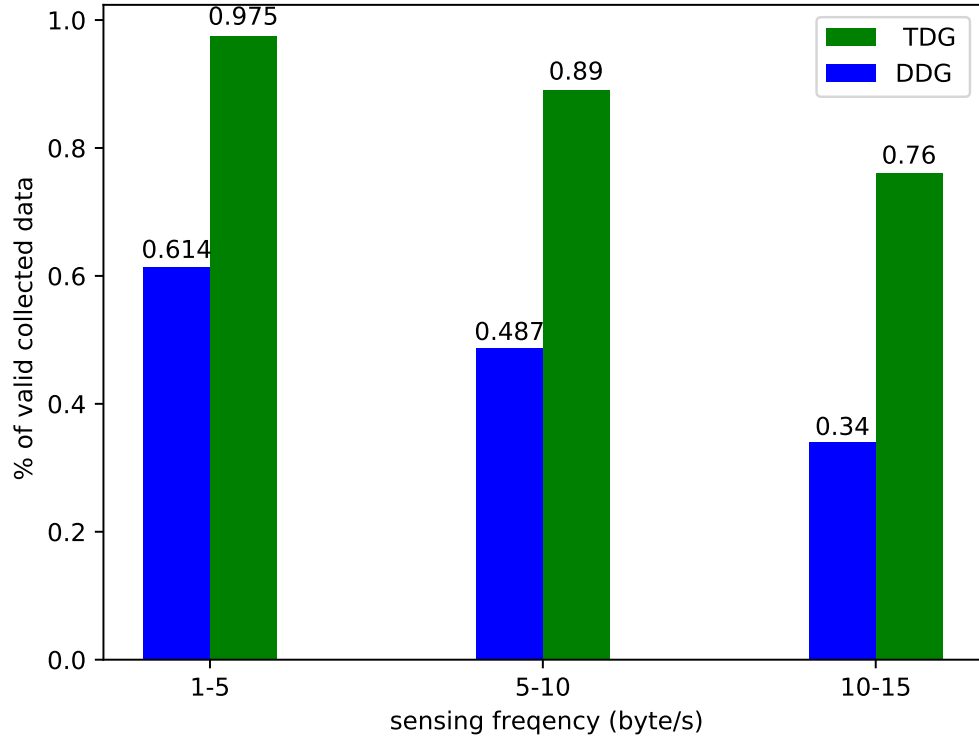


Figure 10: Amount of valid collected data VS sensing frequency

of data stored by the sensors. We have proposed a cost function that assigns a score to each sensor node based on the amount of data each sensor node buffer is carrying and on the distance separating that node from the drone. We have also proposed a second strategy, named Time driven Data Gathering Strategy – TDG, which aims to collect as much as possible data before a given deadline. We also defined a cost function based on two parameters namely the age of data and the distance separating the sensor node and the drone.

To evaluate the performance of our two approaches, we implemented both DDG and TDG on the OMNeT++ simulator. We compared our results to other existing approaches. The obtained results show that DDG allows the drone to follow a collection path that maximizes the amount of data collected regardless of their deadline. On the other hand, the TDG strategy maximizes the amount of data collected while respecting their deadlines.

In our future work, we plan to extend this study by considering the information in each node’s vicinity in order to improve the performance of our approaches. The use of multiple UAV is also worth to explore.

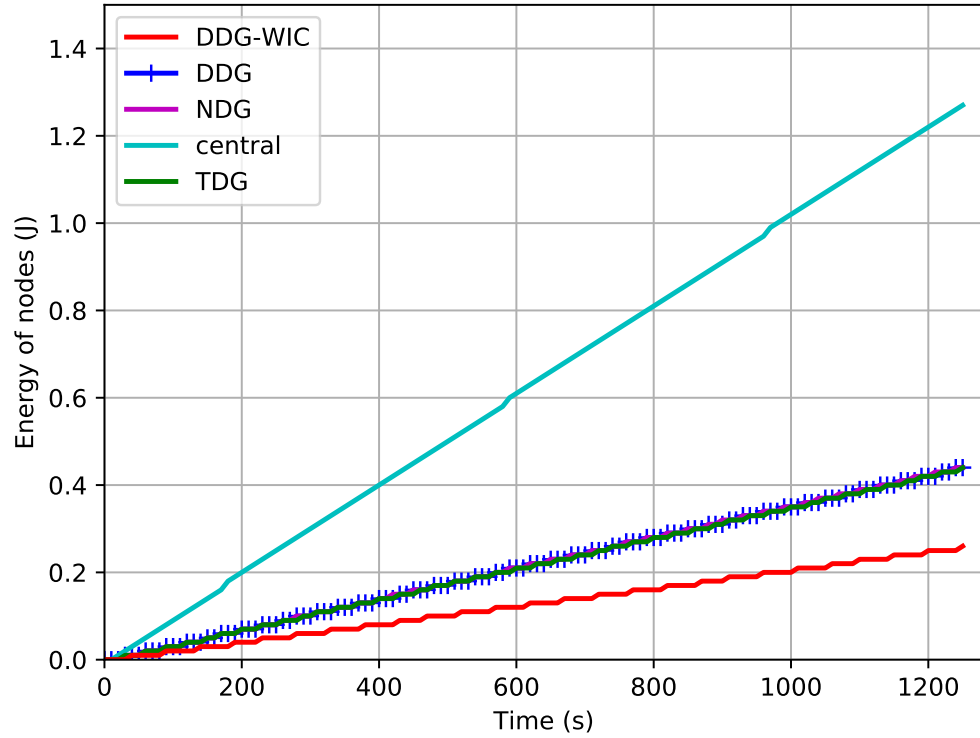


Figure 11: sensor nodes energy consumption

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