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Impact of drone route geometry on information collection in wireless sensor networks☆

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ABSTRACT

The recent technological evolution of drones along with the constantly growing maturity of its commercialization, has led to the emergence of novel drone-based applications within the field of wireless sensor networks for information collection purposes. In such settings, especially when deployed in outdoor environments with limited external control, energy consumption and robustness are challenging problems for the system's operation. In the present paper, a drone-assisted wireless sensor network is studied, the aim being to coordinate the routing of information (among the ground nodes and its propagation to the drone), investigating several drone trajectories or route shapes and examining their impact on information collection (the aim being to minimize transmissions and consequently, energy consumption). The main contribution lies on the proposed algorithms that coordinate the communication between (terrestrial) sensor nodes and the drone that may follow different route shapes. It is shown through simulations using soft random geometric graphs that the number of transmitted messages for each drone route shape depends on the *rotational symmetry* around the center of each shape. An interesting result is that the higher the order of symmetry, the lower the number of transmitted messages for data collection. Contrary, for those cases that the order of symmetry is the same, even for different route shapes, similar number of messages is transmitted. In addition to the simulation results, an experimental demonstration, using spatial data from grit bin locations, further validates the proposed solution under real-world conditions, demonstrating the applicability of the proposed approach.

1. Introduction

Modern network systems are characterized by large volumes of data that call for novel and more efficient methods to gather, process, disseminate, etc. the acquired information. This need becomes a necessity when it comes to instances like disaster and post-disaster management, area monitoring and surveillance, smart agriculture, and military applications, where networking and communication infrastructures are a vital aspect, especially for Wireless Sensor Networks (WSN) [1,2]. In such network environments, information collection and dissemination are crucial mechanisms and they are closely related to the energy consumption and network lifetime [3].

The growth of the technologies related to unmanned aerial vehicles, most commonly known as *drones*, has led to their consideration as potential assets in the direction of enhancing the dynamics of Internet of Things (IoT) and WSNs [4], especially due to their broad availability and continuously decreased cost. This is, also, valid for 5G mobile infrastructures [5], where it is expected that reliable communication with efficient and effective connectivity for a massive number of devices, could benefit from the use of drone-based systems. Due to their functionality and the degrees of free movement, drones can enable line-of-sight links and improve communication for many demanding applications. Therefore, drones are increasingly and widely deployed as means of collecting (or disseminating) information [6,7].

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The launch of (relatively) cheap and easy to deploy drones is expected to increase the dimensional space (by adding an extra degree of freedom) of a network, covering scenarios where aerial assistance may be vital. This is evident in WSN environments, where metrics like the number of exchanged messages, distance, etc., are crucial for the system's efficiency (e.g., reduced energy consumption and lifetime elongation). The majority of recent works discuss hybrid architectures and solutions that combine drones with terrestrially deployed WSN nodes [4,7–9]. Drone-based systems are used for a variety of purposes, ranging from data collection [10–14], disaster recovery [15–17], agriculture and environment monitoring [18–20], disaster monitoring and response [21–24], patrolling and military tasks [25], multimedia, etc. [15,26].

A challenging problem in drone-based WSN systems is related to the discovery of appropriate drone routes, since drones are characterized (due to current manufacturing procedures) by battery constraints, which limit their viability and efficiency regarding real-world applications. Features like their shape size and geometry, flight time, and the number of turns are often connected with energy consumption [27,28], thus, also considered challenging issues. In fact, some of them, like the geometry of predefined drone routes, still have not been thoroughly explored in the considered WSN environment. Studying the geometry of the route shapes that correspond to the trajectory of a drone is one of the motivations for this work. In particular, a WSN along with a drone as information collector is considered here and given the geometry of the various route shapes, various metrics like the number of exchanged messages, the average hops, drone flight time, etc., are explored.

Initially, an algorithm is proposed that groups nodes under a simple, cost-effective approach. Next, different drone route shapes (simple geometrical shapes of equal length) are examined along with their impact on the network's performance in terms of transmitted messages. It is shown that the number of transmitted messages for each drone's route shape depends on the *rotational symmetry* around the center of each shape. However, when the order of rotational symmetry is the same, this leads to equal number of messages being transmitted, even for different route shapes. This holds also true for average distances among arbitrary and covered nodes. It is derived that the circular route shape is the best among the tested geometries, whereas the square is, also, good and close to the circular in terms of transmitted messages. This research conjecture appears to be an interesting one, since it allows the study of drone trajectories to be seen under a different light that should be further investigated beyond the scope of current paper. Indicative simulations, both based on synthetic and real data from the city of Edinburgh [29], validate the proposed algorithm's operation.

The paper's contribution is summarised as follows: (i) proposal of a simple, cost-effective algorithm to organize ground nodes in a drone-assisted WSN; (ii) study of the impact of drone route shapes on the network's performance (number of messages); (iii) identification of a relation between the number of transmitted messages and the rotational symmetry of each shape (i.e., the higher the order of rotational symmetry, the lower the number of transmitted messages); (iv) a key result that the circular route shape performs best for the considered scenarios (the performance for square case is close to that of the circle); and (v) validation of the algorithm's performance through simulations on synthetic and real-world data.

The paper is structured as follows: the main motivation is described in Section 1, whereas the related literature lies in Section 2. Section 3 includes all the needed definitions and model descriptions regarding the underlying network, whereas the detailed algorithm's description is found in Section 4. Simulation results are presented in Section 5, whilst Section 6 presents experimental results based on real data. Finally, Section 7 concludes the paper and draws guidelines regarding future potential work in the field.

2. Past related work

Drones, known as unmanned aerial vehicles, and their application capabilities, either as passive nodes or base stations, have attracted an increasing research interest, giving rise to the so-called flying ad hoc networks [30]. Bor-Yaliniz et al. [7] consider drones as base stations, that undertake duties related to data gathering and dissemination among the ground nodes, ultimately having in mind the reduction of energy cost. The use of drones as base stations in WSNs is also investigated by Hua et al. [31], where appropriate drone trajectories and their speed parameter are examined in order to minimize the overall energy consumption of the underlying scheme.

A recent survey paper by Mozaffari et al. [32] presents a useful overview of drone usage in wireless networking. In particular, current specifications and capabilities of different types of drones are discussed, highlighting the applicability for each one of them in a variety of network environments, along with some state-of-the-art approaches from literature to tackle known problems, such as coordination and route planning. An interesting overview of drone-based implementations in WSNs can be found in [33] by Jawhar et al., where a structured categorization of drone routing algorithms is provided. Moreover, Jawhar et al. [14] present an elegant categorization of the node types that participate in integrated drone and WSN systems, along with the various roles these nodes undertake (for example a drone as a base-station or as a sink node, and so on).

Several works consider problems related to communication and routing among drones [27,34–36]. These works deal with networks mainly consisting of drones, like the recent work by Yanmaz et al. [37], where the monitoring of a real site using a drone network is described, using multiple drones simultaneously. In the work described in this paper, the underlying scenario involves ground-to-drone communication [4,6,9], rather than inter-drone communication.

The recent work of Liu et al. [24] is one of the most related to the one presented here, at least as far as the underlying networking environment is concerned. Their emphasis is on a post-disaster scenario where the established telecommunication infrastructures have supposedly collapsed. They propose a device-to-device networking scheme facilitated by the use of drones, exploiting the fact that these machines are ideal alternatives in such scenarios (e.g., flooded areas, building ruins, other obstacles, etc). Similar to the multihop mode of this paper, each device communicates and sends messages in a multihop manner. Note that the multihop device-to-device network of Liu et al. [24] assists in the area coverage provided by the drone aiming to minimize the number of hops, whereas the WSN nodes in their work have been assigned the same role as in the present work.

Sallouha et al. try to solve a similar problem (i.e., node localization) in multi-drone-assisted networks, by exploiting the impact of drones' altitude on localization error levels [38]. Particularly, they exploit the power of the received signal from ground nodes, including height-dependent path loss exponent and shadowing. The outcome of this solution is the optimum drones' flight altitude in terms of minimal localization error in urban settings, which outperforms other approaches that use ground-based anchors.

The advantage of using drones as base stations is also investigated in a recent work by Karaman et al. [39]. Similarly to [38], the aim of Karaman et al. is to localize nodes by exploiting a particle filter method, producing some promising results to tackle nodes' localization and tracking. It shares some similarities with the work proposed here in terms of studying different drone trajectories. The reported results show that under the same conditions, the circular route is better (as is the case for most of the results in the present paper that follow). Unlike the present work, though, the focus was not entirely on the route planning, thus some route shapes (like square, rhombus etc.) were not examined.

Although this work is one of the first that discusses a hybrid model of employing a drone to collect/disseminate information in a multihop terrestrial WSN, there are numerous works that concentrate on route planning and route geometries. The proposed algorithm in this paper shares a lot of similarities with the carrot chasing algorithm described in [40]. The carrot chasing algorithm dictates that a desired route is followed by introducing a virtual target point (VTP) to act as the “carrot”. The drone is then ordered to chase the VTP, which in sequence can be used to model straight or circular lines, as it is the case for the drone’s planned route shapes described later in this work. It should, also, be mentioned that weather conditions and other phenomena may affect and disturb a drone’s flight [41–43]. However, studying these parameters is beyond the aim of this paper.

A similar work with the one presented here is the one of Yang et al. [9]. In particular, a drone-based data collection system is described, their aim being reducing energy consumption, by designing proper routes for the drone (studying circular and straight line routes). Yang et al. approach the drone-based model using the two aforementioned drone trajectories (that require simple and easy implementation), whereas in this paper, additional route shapes are studied. This differentiation is meaningful, since new results are derived and alternative solutions might be proposed (for example, the square route performing as good as the circular one). Moreover, Yang et al. aim at balancing two energy consumption factors of a UAV (for communication and propulsion), whereas here, the second parameter is assumed to be fixed (in the sense that each drone route has strictly the same length).

In the same manner, Wang et al. [6] address the problem of data collection using drones, aiming to plan efficient routes for the drone, in order to minimize its flight distance. Similarly to the work presented here, the data collection model of Wang et al. consists of a large-scale WSN where a terrestrial transportation is a difficult task. Contrary to the aforementioned paper, the problem of path planning is not addressed here. Rather, the performance and effectiveness of a set of simple predefined routes are investigated, thus the complexity cost of dynamically calculating routes is avoided, by balancing the node coverage of the underlying nodes (thus, part of the communication has to be done in a multihop manner).

Kothari et al. [44] offer an iterative, sub-optimal approach based on Rapidly-exploring Random Trees to guide a drone in real time, taking into consideration the inherited constraints of the drone. Again, Kothari et al.’s attention is on dynamically calculating proper trajectories for the drone, taking into account various environmental characteristics and natural obstacles that affect a drones performance. Some natural assumptions regarding the drone’s capabilities and constraints, such as constant velocity and limited transmission range are also followed in their work (as in the present one). On the other hand, collision avoidance is an important characteristic for Kothari et al.’s approach, considering also the as smooth as possible drone trajectory.

Besides implementing straight lines, the use of curved routes is, also, found in the literature [45]. Straight lines and simple line-based trajectories like zigzag (known also as Bountrophedon path [46,47]) are usually preferred due to their simple implementation and low complexity. Nevertheless, many studies promote the use of curved lines as guide routes for drones, in order to increase coverage [45]. Artamenko et al. [45] examine the advantage of using curve-like versions of known trajectory routes by smoothing the turns using the Bézier curve theory. The main advantage of using line-based methods, like zigzag, is that fewer and simpler turns are required for the drone, meaning that less energy is expected to be consumed [28]. The deployment of multiple drones for area covering purposes is proposed by Avellar et al. [48], using zigzag-like trajectories as a strategy for each drone. Unlike the work presented here, the number of drones varies and depends on some of the algorithm’s parameters. Alcarria et al. [49] summarize different types of drones and the respected scenarios where they can be applied, depending on the drone’s capabilities and the phenomenon that has to be monitored.

Unlike the proposed solution here that considers predefined trajectories for the drone, da Silva and Nascimento [50] calculate appropriate sets of nodes that act as trajectory guide points for the drone, with emphasis on reducing the overall distance of the calculated route. On the other hand, their work has a hybrid approach to the data collection of the network, meaning that the terrestrial nodes operate in a multi-hop manner, similarly to the proposed method here. Other works focus on the use of multiple (instead of a single one) drones and the drawing of their associated routes under particular constraints [16,17,48,51–55] or even their efficient placement as base-stations [56]. For example, Zhong et al. propose an optimization heuristic (by using integer linear programming) to obtain efficient drone routes in terms of flight time [16]. Malandrino et al., also, propose a heuristic based on integer linear programming, stretching the fact that their drone-based system can be applied to post-disaster scenarios [17].

Optimization techniques, like those based on Travelling Salesman Problem (TSP) variants, are also considered when it comes to solving the route planning problem for data collection through means such as drones and mobile sinks [13,16,53,55,57–60]. Energy efficiency in drone-based networks is achieved also by appropriate allocation of resources, as discussed by Xiao et al. [13]. Chiaraviglio et al. study drones that realize small cell connectivity (called UAV-SC) and they propose an optimization model to plan drone routes in order to maximize energy gains, whereas they, also, investigate the throughput in cases with or without UAV-SCs [59]. Similarly, Hua et al. study energy efficiency and throughput of a drone-assisted cellular network by applying the block coordinate descent method [60].

In this direction, Wu et al. examine a multi-drone network where drones are employed to assist ground nodes [55]. They, also, use the block coordinate descent and unlike other similar approaches (as the one presented here), they examine aspects beyond the drones trajectories, like user scheduling and association and transmit power. In a recent work, a drone-based application regarding urban video monitoring is proposed by Trotta et al. [61]. Their rationale is based on an interesting and novel concept, namely they develop a mathematical framework to select the drones that will follow periodic recharging cycles by landing on public transportation buses. For this purpose, they model the drone scheduler as a multi-commodity flow problem, which is then solved using mixed integer linear programming. Note that, unlike the work presented here, their approach takes into account that the ground nodes that serve as recharging stations, are mobile.

Calculating the appropriate set of nodes to minimize the communication overhead has attracted a lot of interest. Techniques that are based on the construction of dominating sets to enable data collection in an efficient manner [62–64] have, also, been proposed. Here, where the extended work of [65] takes place, a dominating set is not practically useful, since the drones routes are already defined, but the algorithm’s sketch stretches the calculation of the proper network’s nodes subset to facilitate the efficient communication between ground nodes and the drone. Lastly, the proposed algorithm is evaluated in a real-world dataset regarding the placement of grit bins in the city of Edinburgh. Garbage collection and bin monitoring constitute problems with increasing importance as the global levels of urbanization tend to grow, especially in the frame of smart-cities and IoT applications [37,66–73].

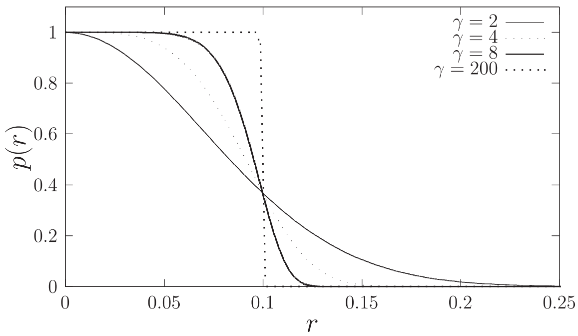


Fig. 1. Probability of connection for the SRGG model with $r_c = 0.100$. On the *x*-axis the distance between two nodes and on the *y*-axis the probability for these two nodes to be connected. It is observed that as the value of γ increases, the connection probability approximates that of RGG.

3. Network and problem definitions

Due to their functionality and degrees of free movement, drones are able to follow varying trajectories, even in 3-dimensional spaces. For simplicity reasons, most works investigate such issues in 2-dimensional spaces using the projected trace of the drone's passing, as it is the case in this work.

Regarding the underlying network, nodes are assumed to be uniformly distributed on a plain area sized $[0, \ldots, 1] \times [0, \ldots, 1]$ (that is, a unit square). Let r be the *euclidean distance* between a certain pair of nodes in the considered network area, r_c be the *connectivity radius* and δ_1 the *1-hop neighbors* of a node. The SRGG model [74] is chosen as topology exemplar, which considers a *connectivity probability* $p(r)$ for any pair of nodes at euclidean distance r, given by

$$p(r) = e^{-(r/r_c)^{\gamma}}, \tag{1}$$

where γ is a constant related to the particular environment. Thus, any pair of nodes at distance r (given a connectivity radius r_c) is connected with probability $p(r)$. It is worth mentioning that for large values of γ, e.g., $\gamma \to +\infty$, then if $r \leq r_c$, then $p(r) = 1$ and if $r > r_c$, then $p(r) = 0$, thus, SRGG reduces to the well known deterministic random geometric graph (RGG) model [75]. For instance, for an open area, it has been shown that the best suited value is $\gamma = 2$ [74]. Fig. 1 depicts $p(r)$ for the case where $r_c = 0.100$ and the values for the parameter γ is 2, 4, 8 and 200.

A sole drone is used for the proposed scenario, which is responsible for collecting data from the deployed WSN. The drone moves above the ground nodes in a fixed altitude and its connectivity radius (in order for a link between the drone and a terrestrial sensor node to exist) is, also, fixed (nodes' elevation is zero and there are no obstacles preventing communication). Furthermore, it is assumed that the drone follows a predefined trajectory or route in order to collect the information sensed by the WSN nodes. Since the drone routes form a polygon in the general case (see also Fig. 3), only the coordinates of its peak points are necessary for the sensor nodes to derive the drones' route. Thus, nodes can deterministically calculate if they lie within the range of the drone's route. Limitations imposed by the drone's construction (e.g., battery capacity, etc.) affect the drone's behavior (e.g., how long it remains operational). This observation is an important factor to consider shorter routes over longer ones, when possible.

The problem that this work tries to tackle is to find the appropriate single-drone routes for information collection from a terrestrially deployed WSN. By *appropriate routes*, one declares the routes of the smallest length and at the same time covering as many terrestrial nodes as possible. The data input for each node is the drone's trajectory path coordinates. The output is each node's information for the appropriate neighbor to which it will forward the collected information until they reach the drone-sink.

3.1. The data collection model

The task of the deployed drone-based WSN is for the drone to ultimately gather data from each node, thus the drone acts as a mobile sink node. Each node is equipped with the necessary modules, depending on the actual application (e.g., temperature and humidity sensors for agriculture monitoring, etc.). The aim is to forward and ultimately collect these sensed data in one or more sink nodes.

Regarding the formal description of the system model, the network consists of the following tuple $\langle N, Col, S, RM \rangle$:

- $N = \{n_1, n_2, \ldots, n_{|N|}\}$ denotes the set of n terrestrial nodes that communicate in a distributed, multihop manner.
- $Col = \{$grey,red,black$\}$ is the set of colors that label each node according to the algorithm execution (as dictated by a coloring function $C(n_i)$).
- $S = \{$arbitrary line, line crossing center, square, rhombus, eq. triangle, circle$\}$ represents the set of route shapes that a drone can follow (see, also, Fig. 2). This set could be expanded to include more variants, but for the purposes of this study, this number is kept to 6. For each shape, a set of corresponding coordinates is assumed.
- $RM = \{rm_1, rm_2, \ldots, rm_{|N|}\}$ denotes the set of min distances for each node n_i from the drone's route.

A *covered area* denotes the part of an open planar space that coincides with the transmission range of a particular reference node. In the case of a mobile node (like a drone), covered area refers to the accumulative open planar space that is covered throughout the complete trajectory of the mobile node. The nodes inside the covered area are called *covered nodes* (to be referred later as black nodes as per the algorithm description). Covered nodes are able to establish a direct communication with the reference node, thus they can send their sensed data to the sink (that acts as a reference node) without the intervention of any intermediate nodes. Not covered nodes should instead follow a multi-hop procedure for this task.

3.2. Symmetries

If a geometric shape can be divided into two or more identical pieces through a transformation, it is characterized as symmetric. There are different types of geometric symmetry, depending on the type of transformation, the two most frequent being the reflection symmetry and the rotational symmetry [76]. Reflection symmetry (or line symmetry) is the particular type of symmetry associated with the reflection transformation, i.e., the shape remains the same when reflected across a line (for 2-dimensional shapes). Rotational symmetry, on the other hand, refers to the property of a shape, when being rotated a certain number of degrees around a point, to look exactly the same as before the rotational transformation.

The order of symmetry for a shape is expressed by using the number of distinct ways the shape can be reflected (for the reflection symmetry) or rotated (for the rotational symmetry). For the latter, a rotational symmetry of order n means that a rotation of the shape by an angle $2\pi/n$ does not change the appearance of the shape. In Fig. 2, the symmetries for six different shapes are depicted (the reflection symmetry lines are drawn with dashed lines and the rotational pivot is shown at the center of each case). All shapes have the same reference point as rotation point (at the center).

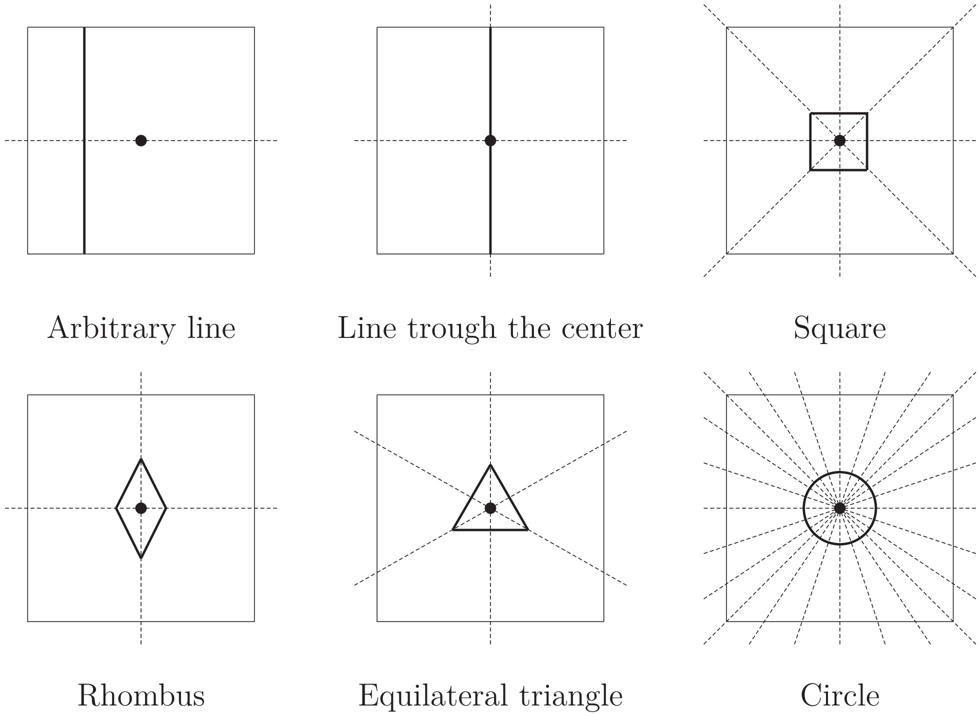


Fig. 2. Symmetries for six different shapes. The reflection symmetry lines are depicted with dashed lines and the rotational pivot for each shape is shown in the centre of each case (the same for all shapes).

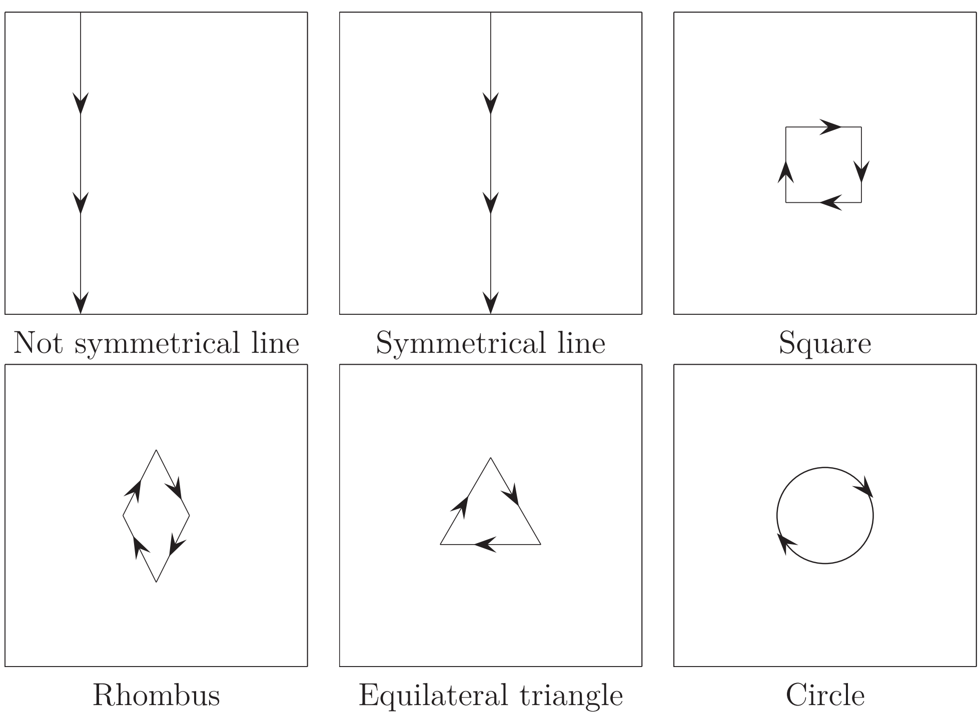


Fig. 3. Drone's considered route shapes. It is assumed that drone's initial and final transfer to the base-station do not affect the network's functionality (e.g., by not operating until they reach a starting point of each shape).

4. The proposed algorithm

A novel algorithm is proposed here that forwards the sensed (or collected hereafter) data in a set of sensor nodes that are within range (i.e., the communication radius) of the drone, that follows a predefined route. It is a distributed algorithm, inspired by the construction of minimum connected dominating sets [64].

All nodes in the network have a *color* variable initially "White", however, by the time the proposed algorithm terminates, the network nodes are painted either "Grey", "Red", or "Black". Each node calculates the best fitted of its δ_1 neighbors to forward the collected data and save it as its own “Red” node. At the end, each “Grey” node will forward the collected data to its own “Red” node, whereas each “Red” node collects data from all the *dominated* nodes and forwards them to its own “Red” node that may have color “Red” or “Black”. At the end of the procedure, all the collected information has been gathered on the “Black” nodes and, consequently, when the drone flies over, these nodes transmit the information to the drone.

A more mathematically rigorous description of the node's coloring procedure is as follows. Let $N = \{n_1, n_2, \ldots, n_{|N|}\}$ the set of network's nodes, rm_i the node's n_i minimum distance from the drone's route, rnm_i the minimum rm_j: $\forall n_j \in \delta_1(n_i)$, and $C(n_i)$ the color of n_i:

$$C(n_i) = \begin{cases} \text{'Black'} & \text{if } rm_i \le r_c \\ \text{'Red'} & \text{if } rm_i > r_c \text{ and } \exists n_j : rnm_j = n_i \\ \text{'Grey'} & \text{in all other cases} \end{cases} \quad (2)$$

The above coloring scheme is the mechanism that helps to identify the role of each node after the proposed method is concluded.

In the beginning, all nodes are aware of the coordinates of a number of points that are the start and the end points of the line segments of the drone's route and all of them are on **State 0**. According to Algorithm 1, each node on **State 0** calculates the distance from the specific line segments of the drone's route and stores the minimum of them in r_m. Then, it sends r_m to all $\delta_1(u)$. If r_m is within the drone's communication range in relation to the drone's route, it can transmit the collected data directly to the drone when it passes over. In that case it changes the variable *color* to “Black”, sends the ‘*OK*’ message to $\delta_1(u)$ (which means that its part of the algorithm execution is terminated) and changes its **State** to **2**. Contrary, if r_m is not within the drone's communication range, the node changes its **State** to **1**.

Algorithm 1 Nodes are on **State 0** and advertise their distance from the drone's route.

```
Data: Start and End points of the line segments of the drone's route.
State 0: The state that all nodes begin with.
color: the particular color of a node          ▷ Initially white
red: the nearest δ1(u) to the drone route      ▷ Initially None
r_m : The minimum distance from the drone route.  ▷ “The node computes the minimum distance from the drone's route.”
r_m → δ1(u)      ▷ “The node sends the minimum distance to all δ1(u)”.
if r_m < r_c then      ▷ “If r_m is in communication range with the drone's route”
    color = Black
    'OK' → δ1(u)     ▷ “Sends OK message to δ1(u) that means it finished”
    Change State to 2
else
    Change State to 1
```

According to Algorithm 2, each node on **State 1** waits until it receives the r_m message from all $\delta_1(u)$. Then, it calculates the minimum of them and stores it as variable rn_m. If its own distance from drone's route r_m is smaller than rn_m, then there is no other neighbor node to forward the collected data, so in order to avoid a dead end, it changes its r_m to infinity and transmits the new value of r_m to all $\delta_1(u)$. Otherwise, it stores the node with the minimum distance rn_m to variable *red* and sends ‘*OK*’ message to $\delta_1(u)$. Eventually, it is no more at **State 1** and has changed to **State 2**.

According to Algorithm 3, each node on **State 1** waits until it receives an ‘*OK*’ message from all $\delta_1(u)$. Then, it transmits a ‘*RED*’ message to the node in variable *red*. If its *color* is “White”, it changes it to “Grey”. Finally, it changes its **State** to **2**.

Algorithm 2 Nodes are on **State 1** and calculate the proximity to the drone's route.

```
State 1: The node does not have the nearest neighbor to drone route.
while Not received r_m from all δ1(u) do
    Wait
rn_m = The minimum r_m of all δ1(u)
if r_m < rn_m then     ▷ “This node has no direct route to a black node”
    r_m = ∞
    r_m → δ1(u)
else
    red = The nearest neighbor to drone route
    'OK' → δ1(u)    ▷ “Sends OK message to δ1(u) that means it finished with commands in State 1.”
    Change State to 2.
```

Algorithm 3 Nodes discover their nearest neighbor to the drone's route.

```
State 2: The node knows the nearest neighbor to drone route.
while Not received “OK” message from all δ1(u) do
    Wait
'RED' → red▷ “Inform the nearest neighbor to drone route that is the red node for him”
if color = White then
    color = Grey
The receiver of a “RED” message :
if color ≠ Black then
    color = Red
    Append sender to Dominated list.
Change State to 2
State 2: The node finished with the algorithm.
```

The exact time a node receives a ‘*RED*’ message, it immediately appends the sender in a *dominated* list and if its *color* is other than “Black”, it changes to “Red” (Algorithm 3).

In summary, the proposed distributed algorithm uses the drone's route as input, while after its application, each and every node is assigned a 1-hop neighbor node to forward the sensed data, along with the received data from other nodes in case it dominates other neighbor nodes. By the time the drone is about to begin its flight course, all sensed data are collected to the “Black” nodes that lie within the drone's transmission range across its route.

The proposed method implemented using Algorithms 1–3 has a simple implementation. As a distributed procedure, it does not require global information, thus each node is aware of only its 1-hop neighbors. Nodes are assumed to have acquired the drone route coordinates, which is an easy task using a common broadcast protocol. Also, from the drone's point of view, it only requires as an input the choice of the predefined route it will follow, thus no knowledge on the actual WSN ground topology is needed at any stage of the algorithms.

Regarding the complexity of exchanged messages imposed by the algorithms in order to organize the terrestrial nodes, each node sends at least $\delta_1(u)$ messages (not black nodes send their r_m value and black nodes send their ‘*OK*’ messages), thus $\mathcal{O}(n\delta_1(u))$ messages are initially needed. Since each node expects to receive ‘*OK*’ messages from all $\delta_1(u)$, then on average another $\mathcal{O}(n\delta_1(u))$ messages are needed, along with $\mathcal{O}(n)$ ‘*RED*’ messages. Overall, $\mathcal{O}(n(2\delta_1(u)+1))$ messages are expected to be transmitted. From this analysis, it is concluded that the algorithm's performance for the nodes coordination is actually immune to the choice of the drone route, but rather it depends on the size of the network (n) and the average number of 1-hop neighbors ($\delta_1(u)$).

5. Simulation results

For the purposes of the simulation scenarios presented in this section, it is assumed that the area in which the networks are deployed is normalized to a square with sides equal to 1 (i.e., a unit square). The number of network nodes is in all cases 1000 and the model used for the construction is SRGG (presented in Section 3) with varying values for parameter $\gamma = 2, 4, 8, 200$ that successfully capture various environments (like urban, interior of buildings, open areas etc.) [74,77]. The case of $\gamma = 200$ corresponds to the construction of networks similar to those under the RGG model [75]. A program was developed in Python 3.7.3, using the SciPy and NumPy libraries [78]. Randomness is generated by the random number generator of Scipy (i.e., the Mersenne Twister pseudo-random number generator) using different seeds for each run. Various scenarios are presented in each simulation that correspond to networks with $r_c = 0.070, 0.090, 0.100, 0.120, 0.140$. As r_c increases, the denser the network becomes. When $r_c = 0.070$, the average number of $\delta_1 = 14.476$, while for $r_c = 0.140$, the average number of $\delta_1 = 52.386$. Since the proposed algorithm is based on the exchanged messages between 1-hop neighbors, it is obvious that the denser the network is, the more messages are transmitted.

It is important to calculate the appropriate trajectory shape of the drone's route in order for the proposed algorithm to collect the sensor nodes' data optimally, reducing the number of transmitted messages. The number of transmitted messages is closely related to energy consumption and eventually to the network's lifetime. Since drones have strict limits of flying capabilities the route's length in all the following simulation scenarios is equal to one (the size of the normalized field's side that is used), thus, the total length of the drone's flight distance is the same for all considered scenarios.

Fig. 3 depicts the drone's route shapes considered in the simulation scenarios of this work. The first depicted route shape is a straight line vertical to two sides of the field, that does not cross the center point of the field. The second is, also, a straight line, vertical to the same sides of the field, which passes from the center of the WSN field. A rhombus, a equilateral triangle, a square and a circle, all with perimeter equal to one, are also tested. For these shapes, their center lies on the center of the WSN field.

Ten networks are constructed according to the SRGG model for each pair of values for r_c and γ, thus 200 networks in total. For each network, the proposed distributed algorithm runs on each node, in order to determine their nearest neighbor within the drone's route. The area covered directly by the drone (meaning that no external node is required) is a projected strip with the drone's route in the middle of it and $2r_c$ wide. This is derived considering the fact that a drone's range is a r_c-radius disk, thus, it creates a cylindrical projection of diameter $2r_c$ and length one. As such, since in all scenarios presented here the drone's route length is equal to one, the area directly covered by the drone is $\approx 2r_c$ (approximately due to the strip's bends) and, consequently, the number of directly covered nodes (black nodes on the presented algorithm) is $\approx 2Nr_c$.

Fig. 4 depicts the mean values of the nodes that are directly covered from the drone for connectivity radius $r_c = 0.090, \ldots, 0.140$ for all the considered route shapes. The previously mentioned values for $\approx 2Nr_c$ are also depicted. Note that the particular values that stem from the analysis, i.e., the vertical line routes and the circle routes, are almost equal. On the other hand the routes of square shape cover directly approximately 5% less nodes, whereas routes with rhombus and equilateral triangle cover approximately 10% less nodes. The discrepancy of the square, rhombus and equilateral triangle is expected due to the bends of the covering strips of the drone's routes. These differences have no real effect on the performance of the presented algorithm, as will be shown later.

The mean values of the transmitted messages under the proposed algorithm are depicted in Fig. 5. These messages are necessary to organize the drone-assisted terrestrial network and their transmission is an unavoidable task in every distributed method. The number of the transmitted messages varies from 36.5 messages per node for sparse networks, to 145 for the denser ones. This is expected, since during the execution of the proposed algorithm, each node sends ≈ 2 messages to all its δ_1 neighbors.

Another interesting observation from Fig. 5 is that in all cases the form of the curves is almost identical. More specifically, the number of transmitted messages is almost the same for all route shapes, in all cases, and varies $\approx 10\%$ for different values of parameter γ. The first observation confirms that the drone's route shape has no real effect on the algorithm's performance, as mentioned earlier. The second demonstrates the fact that the best performance of the presented algorithm is for $\gamma = 4$ in all cases. This is due to the effect of Eq. 1 on the construction of the network under the SRGG model. This is attributed to the fact that for $\gamma = 4$, the particular type of topology that is created, shares the advantages of RGGs along with the existence of a few "longer" edges between some nodes, which ultimately decreases the average distance from black nodes.

Parameter's value $\gamma = 2$, as can be observed in Fig. 1, causes nodes that are located in distance $r < r_c$ (i.e., closer than the actual transmission range) to have relatively high probability not to be connected and for nodes that are located in distance $r > r_c$ (i.e., further than the actual transmission range) the probability for the connection is not negligible, while for $\gamma = 8$ this probability is much lower and for $\gamma = 200$ is almost zero. Parameter's value $\gamma = 4$ is in the middle and that enables nodes to be able to find shorter routes (with less hops) for their data to reach black nodes (i.e., that are directly covered by the drone).

Fig. 6 depicts the number of transmitted messages required to send the sensed data to the black nodes (that will eventually transmit them to the drone). This figure demonstrates the effectiveness of the proposed algorithm, since the number of transmitted messages for the collection of the sensed data is significantly low. In particular, it ranges from 5 messages per node on the extreme case of marginally connected networks (when $r_c = 0.070$, SRGG model's parameter $\gamma = 200$ and a not symmetric line –"Vertical not sym" on the figure – as the drone's route shape), to 0.9 messages per node on denser networks ($r_c = 0.140$, SRGG model's parameter $\gamma = 2$ and a circle as the drone's route shape). It is worth mentioning that the value of 0.9 messages per node is due to the fact that a significant part of the network topology is directly covered by the drone ($\approx 28\%$ black nodes) and most of the rest nodes ($\approx 53\%$) are only 1-hop away from these black nodes, meaning that the majority of nodes are zero or one hop from the drone's covering area.

Another interesting observation is that these networks, created according to the SRGG model, require a lower number of messages for the collection of the sensed data, as γ decreases. This holds true for every scenario and it is expected, since, as mentioned before, it is obvious from Fig. 1 that each node can have neighbors in distance $r > r_c$ with higher probability when SRGG model's γ parameter has a lower value, and, thus, can reach the black nodes with fewer hops.

Finally, it is easily observed from Fig. 6 that in all cases the drone route shape of straight line not passing through the center of the WSN field ("Vertical not sym" on the figure), requires the largest number of transmitted messages for the collection of the sensed data. Next come, in terms of transmitted messages, the

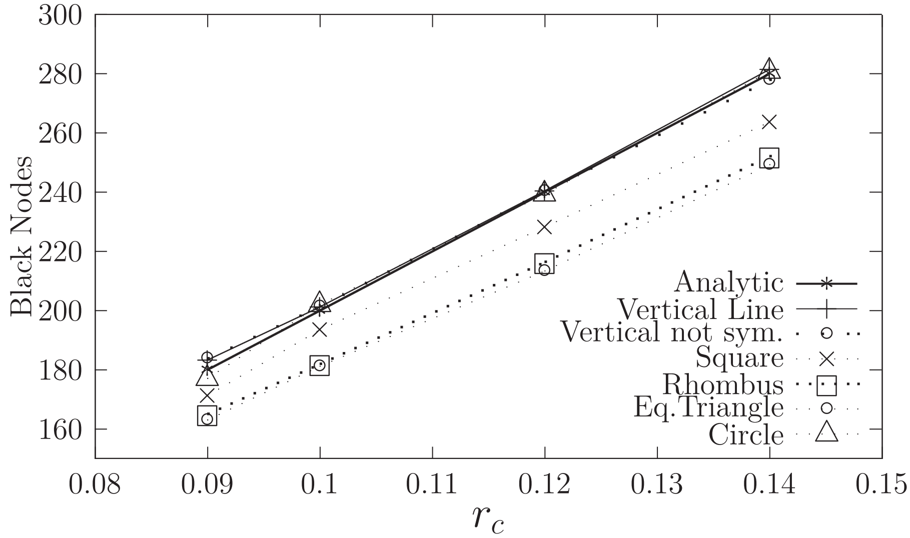


Fig. 4. Mean value of black nodes for various drone route shapes with length one, along with the analytic prediction.

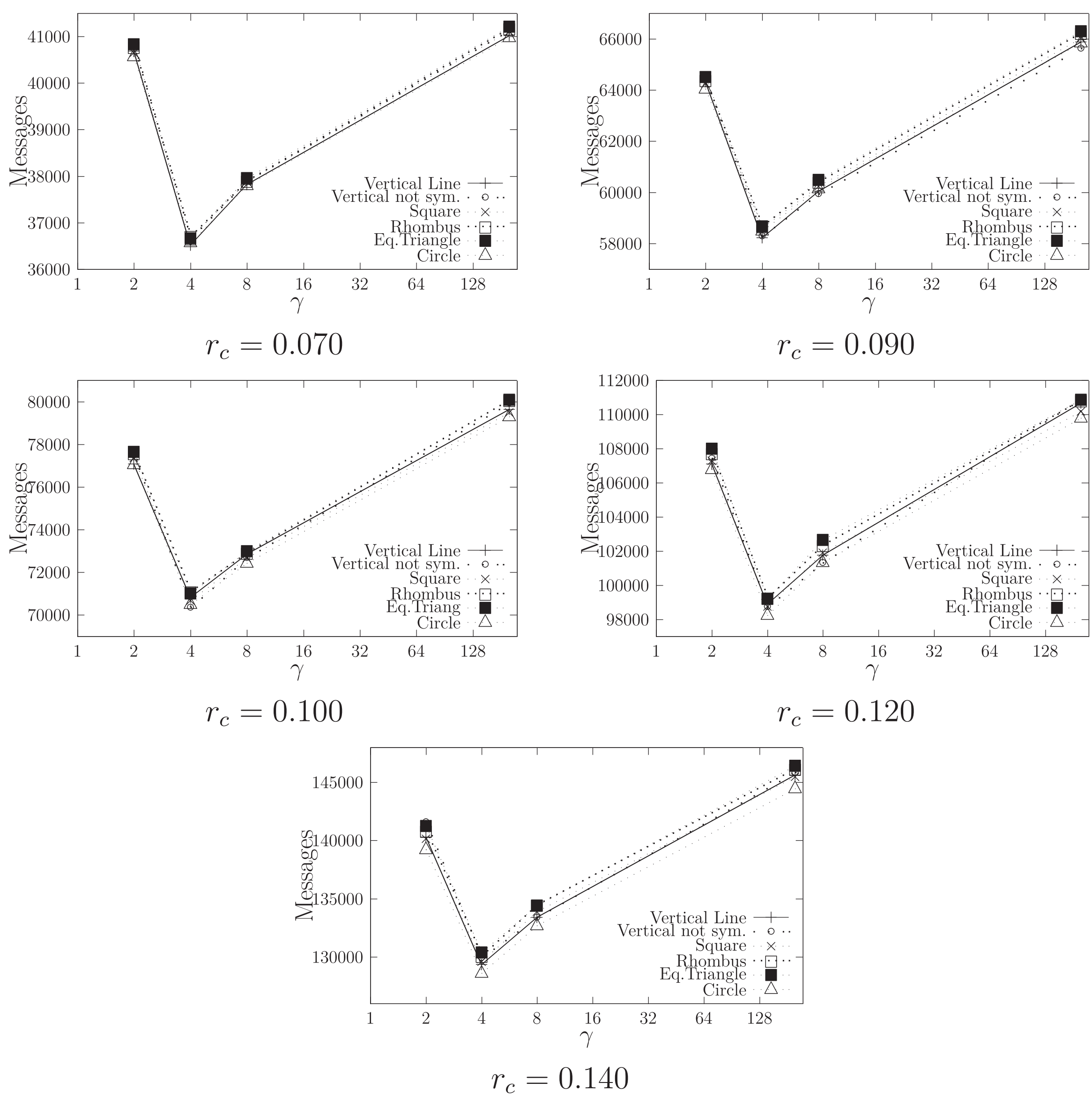


Fig. 5. Number of messages for networks with 1000 nodes constructed using the SRGG model and $r_c = 0.070, 0.090, 0.100, 0.120, 0.140$. The x-axis corresponds to parameter γ and the y-axis to the number of transmitted messages of the proposed algorithm that are necessary to distributely organize the drone-assisted terrestrial network.

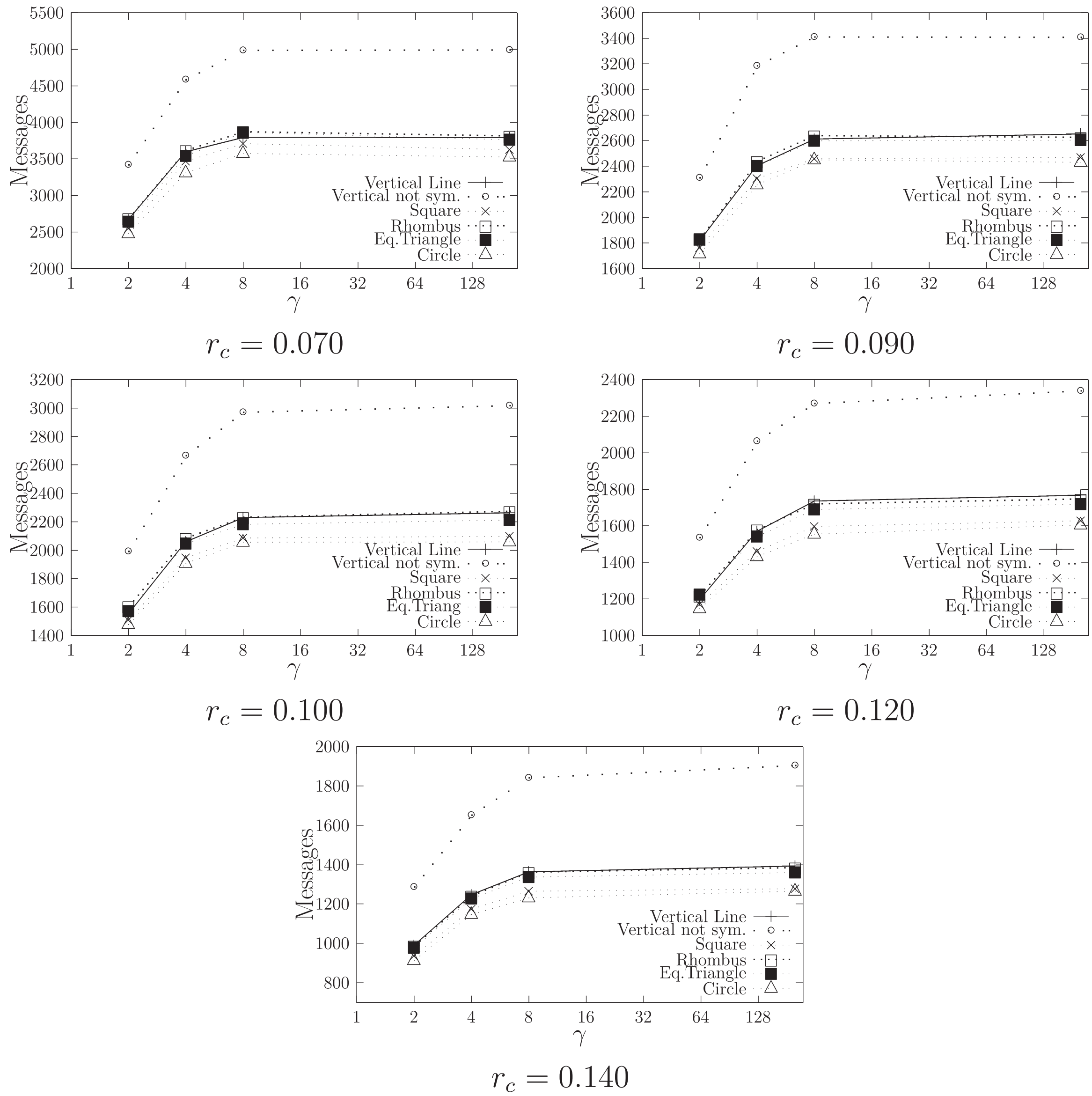


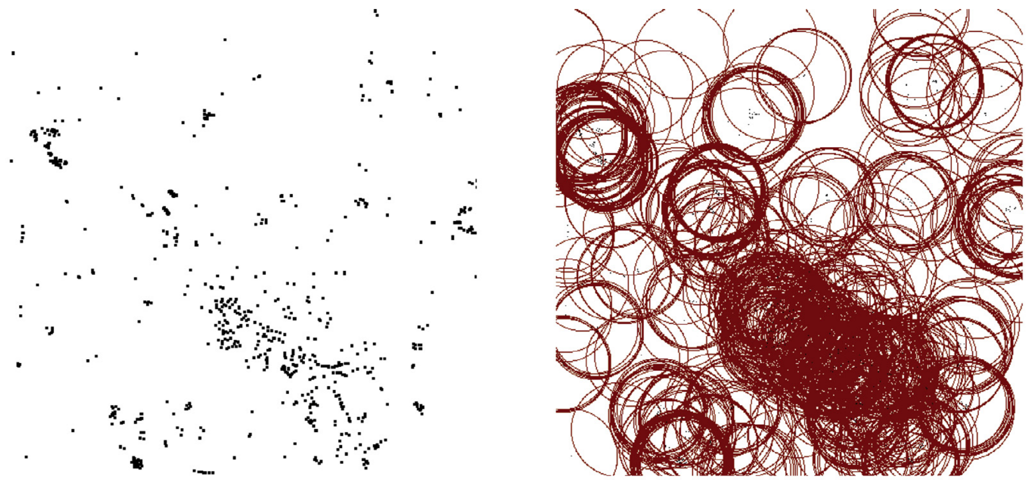
Fig. 6. Number of transmitted messages required to send the sensed data to the black nodes for networks with 1000 nodes constructed using the SRGG model and $r_c = 0.070, 0.090, 0.100, 0.120, 0.140$. The x-axis corresponds the model's parameter γ and the y-axis to the number of transmitted messages of the proposed algorithm for each case.

case of the vertical line shape (that crosses the center of the WSN field), and the cases of the rhombus and the equilateral triangle (that are located on the center of the WSN field), with all three of them requiring almost the same number of transmitted messages. These are followed by the shapes of square and circle that yield the fewest number of needed messages. This is a key observation given the paper's aim, i.e., to derive the drone route shapes that require the minimum number of transmitted messages, as discussed next.

5.1. Correlation of route shapes' symmetries and messages

The gap in the number of transmitted messages for different shapes of the drone's trajectories is obvious. An explanation for this observation, consistent with all obtained data, is that the number of transmitted messages for each drone's route shape depends on the *rotational symmetry* around the center of the WSN field for each shape. The fact that all the studied shapes have the same rotational point (i.e., the center of the WSN field), is the reason to consider rotational over reflection symmetry for this conjecture.

As already mentioned, the distance covered by the drone is the same for all scenarios. The higher the order of the rotational symmetry around the center of the WSN field for a given shape, the lower the number of transmitted messages required for the collection of the sensed data. Therefore, the not symmetrical vertical line has rotational symmetry of order one and it is the particular shape that yields the highest number of transmitted messages during the data collection process. Subsequently, the symmetric vertical line and the rhombus that both have rotational symmetry of order two, follow in terms of transmitted messages (which is the same in all scenarios). The equilateral triangle, with rotational symmetry order three (in the first two cases of sparse networks with $r_c = 0.070$ and 0.090 the results coincide with that of rotational symmetry of order two) is next, followed clearly by the square with rotational symmetry of order four and the circle with rotational symmetry of order the infinity.



(a) Visualization of the bins' location in Edinburgh.

(b) Bins' locations with an arbitrary connectivity radius $r_c = 0.1$.

Fig. 7. Location of 1000 grit bins in Edinburgh, Scotland, retrieved from [29] (depicted in a normalized square $[0, \ldots, 1] \times [0, \ldots, 1]$).

Table 1
Mean distances from black nodes in terms of hops for networks constructed under the SRGG model (with $r_c = 0.140$ and $\gamma = 2$), for six different shapes of drone routes.

Shape	Rotational Symmetry Order	Mean Distance
Vertical not sym.	1	1.29
Vertical	2	0.99
Rhombus	2	0.99
Eq. Triangle	3	0.97
Square	4	0.93
Circle	∞	0.91

This symmetrical relation is, also, present when considering average distances. In particular, Table 1 contains the mean distances of every node from the black ones in number of hops (black nodes are covered directly by the drone, thus their distance is 0 hops) for networks with $r_c = 0.140$ and $\gamma = 2$, separately for every tested drone's route shape. It is proposed, when it is possible, that the drone route shape of a circle, located on the center of the WSN field, is the one to be preferred, since fewer messages are required for data collection purposes. This result is closely tied to energy efficiency, since a fewer number of transmissions leads to lower energy consumption. It is clear that the circle route outperforms the other drone routes shapes. Still, this interesting research conjecture, that came upon as a side effect of the proposed algorithm, should be further investigated beyond the scope of present work.

This observation can be summarized in the below formal conjecture.

Conjecture 1 (Route shapes' symmetries)**.** *It is assumed that a drone's route follows a predefined geometrical shape, e.g., circle, lines, square, and rhombus, which constitutes the drone's route shape. It is conjectured that the order of symmetry of the route shape is related to the number of transmitted messages. Specifically, the higher the order of symmetry, the lower the number of transmitted messages.*

6. The case study of edinburgh grit bins

So far, the proposed algorithm was evaluated through exhaustive simulation using artificial data points. In this section, a real-world case study is used to further demonstrate the algorithm's functionality and performance. Particularly, the following scenario has been designed to test the proposed method for information dissemination on wireless sensor networks using a drone. A city's grit bins are assumed to be equipped with wireless sensors that could be harnessed for various applications. Such applications gain more and more attention lately, especially in the area of smart cities and IoT systems [37,66–72]. A drone is employed to collect periodically the available information.

The implementation presented here is based on data about the location of 1000 grit bins in Edinburgh, Scotland, retrieved from The City of Edinburgh Council [29]. These data contain spatial information regarding the locations of these bins. On each point/bin it is assumed that a wireless sensor is located. The nodes located at far remote locations were excluded, leading to a total number of 880 bins. These 880 bins correspond to the nodes of a wireless network. The field is normalized to a square $[0, \ldots, 1] \times [0, \ldots, 1]$. The topology used is SRGG with parameter $\gamma = 6$ and connectivity radius $r_c = 0.140 \ldots 0.170$. The connection radii are carefully chosen, since smaller radii result in not connected networks, while larger result in dense networks.

It should be noted that a significant difference between these networks and the ones created in simulations, is that the spatial distribution of the nodes in the former is not uniformed. This is a natural consequence and derives from the fact that the morphology of the city roads and the overall density of the city center affect the placement of the bins. It, also, emphasizes the need of using real-world datasets.

Note that the bins (or nodes) are not uniformly distributed due to the fact that the underlying topology is based on a real urban road network. Consequently, they are denser in the center of the city and sparser in the outskirts, and also the center of the city premises does coincide with the center of the field (it is located towards the bottom-right region of the field, see Fig. 7).

The drone's planned route shapes are the same as in Section 5, i.e., a vertical line that does not pass from the center of the underlying WSN field, a vertical line passing from the center of the WSN field, a rhombus, a square and a circle. All drone routes have length of one (that is the size of the city of Edinburgh in the normalized setting).

Fig. 8 depicts the number of nodes directly covered by the drone (i.e., the black nodes in the proposed algorithm) for connectivity radius $r_c = 0.140 \ldots 0.170$, for every drone's planned route shape. Because of the concentration of the majority of nodes around the center of the underlying WSN field, the vertical line not passing from the center of the WSN field has in all cases a

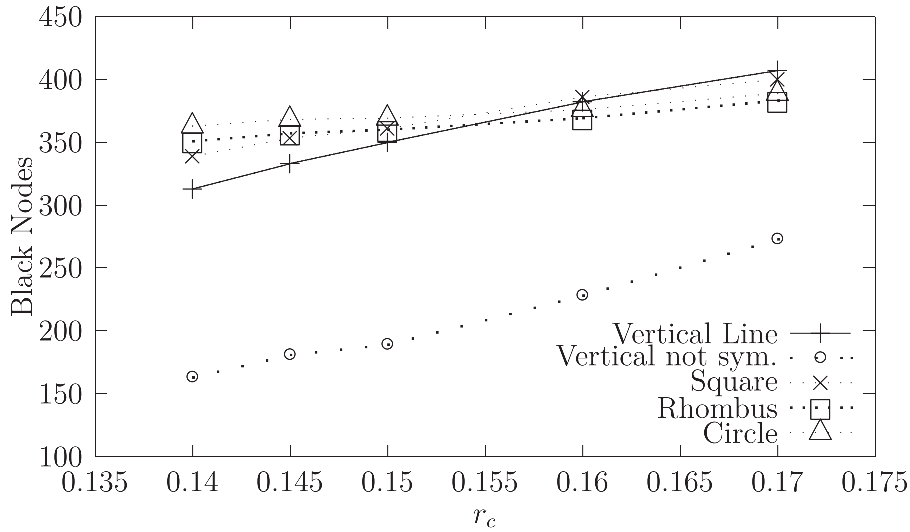


Fig. 8. Number of nodes covered directly by a drone (black nodes of the proposed algorithm) as a function of the connectivity radius r_c for the various drone route shapes. The underlying network corresponds to the locations of 880 grit bins in Edinburgh, Scotland.

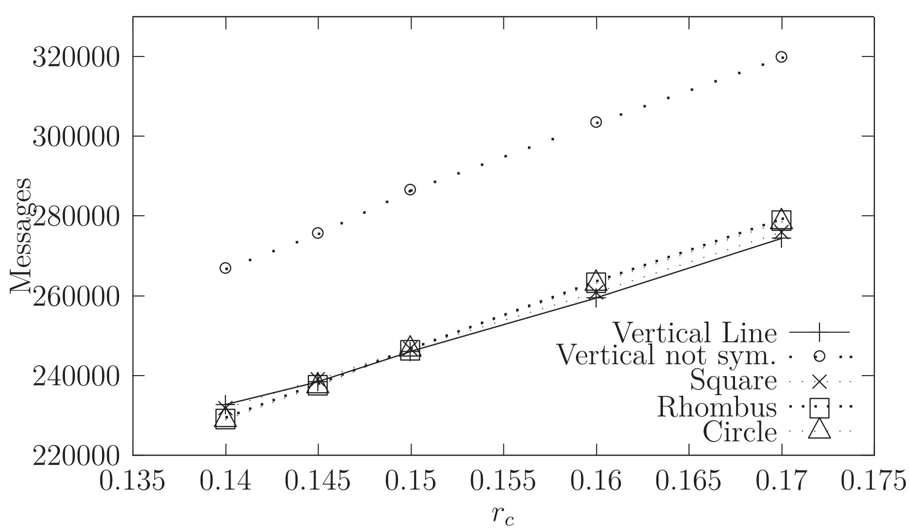


Fig. 9. Number of messages under the proposed algorithm as a function of the connectivity radius r_c for various drone's route shapes. The underlying network corresponds to the locations of 880 grit bins in Edinburgh, Scotland.

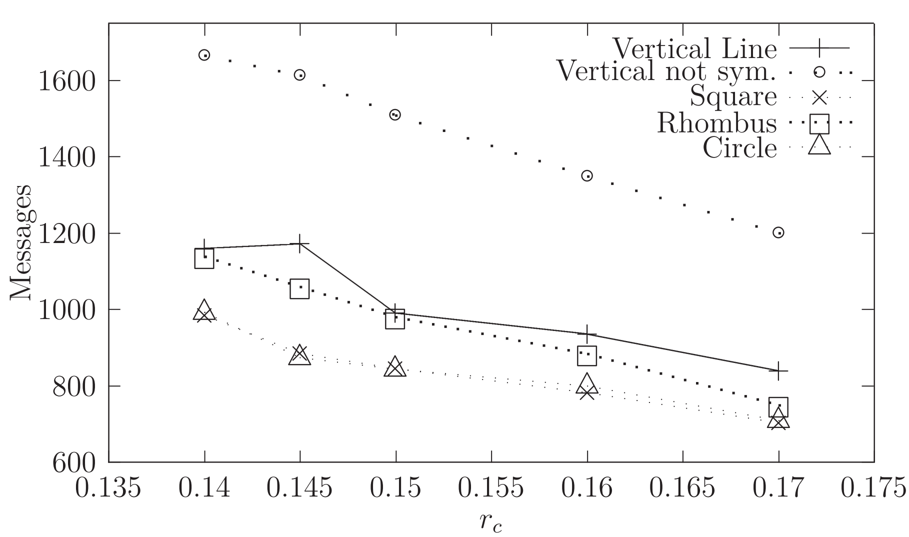


Fig. 10. Number of messages for data collection using a drone as a function of the connectivity radius r_c for various drone's route shapes. The underlying network corresponds to the locations of 880 grit bins in Edinburgh, Scotland.

significantly lower number of directly covered nodes compared to those of the other considered shapes. This concentration of nodes around the central region of the area is, also, the reason for the reported low difference among all the other route shapes.

Fig. 9 depicts the number of transmitted messages for the execution of the proposed algorithm. The number of transmitted messages is much higher (almost double) than the ones reported during the simulations in the previous section. This is, again, attributed to the fact that the network around the center of the city is much denser than a simulated network with the same r_c and uniform distribution of the nodes in the field. It is worth mentioning that the proposed algorithm takes place once and the information gathered can be used as long as the drone's route remains the same.

Fig. 10 depicts the number of the transmitted messages needed for the collection of the sensed data on the nodes that are able to transmit them directly to the drone (i.e., the black nodes of the proposed algorithm). For the aforementioned reason the vertical line not passing from the center of the WSN field demands a much higher number of transmitted messages in order to forward the sensed data to the black nodes. For all the other drone route shapes, the number of transmitted messages varies from 0.9 to 1.5 messages per node. Finally, similarly to Fig. 6, it is obvious that in all cases the number of transmitted messages follows the same order regarding the route's shape, although this time, the x-axis corresponds to the connectivity radius r_c, instead of the SRGG's parameter γ. This observation enlightens further the aforementioned conclusion that symmetry order of the drone's route shape is closely associated with the number of the transmitted messages required for data collection from the deployed sensor nodes. As before, the circular and square route shapes provide the best performance.

7. Conclusions and future work

The broad availability and the decreasing cost of drones have made them ideal candidates to be used as leveraging factors in a variety of networking environments. As such, drone-based wireless sensor networks have already been proposed. A novel drone-assisted, distributed algorithm for data collection in a wireless sensor network is proposed in this paper. A set of nodes that are within the radius of a drone's route is efficiently calculated using small number of messages. The proposed algorithm is simple to implement and it is shown to consume minimal network resources in terms of messages. Various route shapes are examined for the drone trajectory, which are then evaluated through simulation. Multiple scenarios are considered, along with experimentation with real data from the grit bins' placement in the city of Edinburgh [29]. Since a cost function was not discussed in this paper, an optimization-based approach with a mathematically enhanced framework may reveal some interesting additional outcomes, withe the hope that this work could act as an inspiration and motivation to other researchers from different fields. Such approaches could illuminate aspects other than the ones discussed in this paper, e.g., solution convergence, constrained-based modeling, etc [79].

The results showed a variation on the number of generated messages in relation with the drone's route shape. The main outcome of the study is that the circular trajectory yields the lowest number of messages, with the square route being close. Since every route has the same distance, it is conjectured that the order of symmetry for each shape is responsible for the discrepancy among each case. Future efforts will shed more light upon this symmetry hypothesis, especially in the prism of alternative networking environments, such as IoT and smart cities' systems, environments with extreme conditions (e.g., for outdoor monitoring), nodes' mobility, etc.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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