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## Power-saving system designs for hexagonal cell based wireless sensor networks with directional transmission

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## ABSTRACT

This paper examines the lifetimes of alternative system configurations for a wireless sensor network (WSN) in a circular region. The coverage region is divided into hexagonal cells, and the information from each cell is combined and transmitted to the sink or to other cells. Sensors are equipped with directional antennas that improve transmit/receive power efficiency and potentially reduce interference. Simultaneous transmission to multiple cells is permitted, and the power level of different transmissions can be controlled to different levels. Under the assumptions of uniform information density and uniform sensor distribution, we show that for larger systems (with 800 cells or more) lifetime can be prolonged by more than 10 times by introducing a limited number of transmission lines or line sinks to facilitate information transfer to the main sink. Alternatively, introducing up to six secondary sinks can increase the system lifetime by a factor of about 4.5 for the same size region. Our results imply that incorporating line or secondary sinks may provide simple, low-cost solutions for extending system lifetime for larger WSN's.

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## 1. Introduction

Wireless Sensor Networks (WSN) are widely used to remotely sense data from physical environments for digital systems. Initially, WSNs were designed for military purposes. Nowadays, with massive connectivity enabled by 5G, various applications of WSN interconnect to create a comprehensive Internet of Things (IoT) ecosystem, where any object in our environment can be connected and tracked through the Internet. Furthermore, the sensor-based systems that comprise IoT enable communication between devices without human intervention (Hashem et al., 2016; Alaba et al., 2017). Consequently, besides traditional applications including disaster monitoring, pollution monitoring, climate change, IoT

has extend the scope of WSN applications to smart homes, smart cities, smart grids, smart agriculture, and so on (Nels and Singh, 2021; Gunduz and Das, 2020; Dileep, 2020).

The task of data collection in WSNs requires comprehensive and efficient data fusion algorithms in order to meet system constraints. A major constraint is the limited energy capacity of the sensor nodes. Nodes expend energy to receive data from other nodes, then merge and retransmit so that the data eventually reaches the base station (sink node). Data aggregation refers to strategies used to decrease the amount of data transfer in WSN so as to retain only useful information in the network (Nels and Singh, 2021; Zhou et al., 2019; Djedouboum et al., 2020; Pundir and Sandhu, 2021). Optimization of the data aggregation process is known to be NP-hard (Chen et al., 2005; Titouna et al., 2018; Gbadouissa et al., 2020). To address this issue, various architectures and approaches have been developed (Khedo et al., 2010; Coudert et al., 2015; Xie and Chen, 2017; Priya and Enoch, 2018; Maivizhi and Yogesh, 2020; Ullah and Youn, 2020; Ullah et al., 2021; Jan et al., 2021). These approaches rely on the fact that data from sensor nodes includes redundant information which may be reduced by data preprocessing, thus reducing transmission and consequently network energy consumption. In most cases, spatial

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data correlation is exploited for this purpose, i.e. data from nearby sensors is aggregated before transmission. This aggregation may be repeated at multiple levels, leading to a hierarchical aggregation model (Dhand and Tyagi, 2016; Xu et al., 2015).

Since data aggregation in WSNs produce large quantities of data, many recent studies in this field use approaches from machine learning and data sciences to perform data prediction so as to decrease network energy consumption, data duplication, bandwidth usage, packet delay as well as data loss due to node failure. Methods used include Least-Mean-Square and Root Mean Squared Error analysis, ARIMA model for time series forecasting, Kalman filtering, k-nearest neighbors algorithm and deep learning algorithms (Nels and Singh, 2021; Ullah and Youn, 2020; Avinash et al., 2015; Fu et al., 2016; Cheng et al., 2019; Zhang et al., 2019; Aboubakar et al., 2020; Mohanty et al., 2020).

As previously indicated, data aggregation helps to eliminate similar data and not valuable data in order to properly and efficiently use network resources. Therefore, some studies direct their reflections on the development of mechanisms for an efficient use of the bandwidth and a reduction of latency, packet loss and packet delivery time. As one might naturally expect, the proposed schemes include data compression techniques, data clustering algorithm and data priority policy (Jan et al., 2021; Mantri et al., 2013; Mohanty and Kabat, 2016; Devi et al., 2020; Babu et al., 2021). The combination of these techniques allows efficient monitoring of data flows in the network and consequently better use of network bandwidth and energy.

Another technique for reducing sensor power consumption is to employ directional antennas (Wang et al., 2017; Dunlop and Cortes, 2007) which produce more focused signals, thus both reducing interference and increasing effective transmitted power. The usefulness of directional antennas in increasing system capacity is attested by their widespread use in wireless cellular communications systems (Liberti and Rappaport, 1994).

In this paper, we investigate a hierarchical spatial aggregation scheme based on congruent hexagonal cells, such as are often used in wireless cellular communications (Baltzis, 2011). The same geometry was studied for WSNs in Debessu et al. (2011) and Debessu et al. (2010); however, we consider alternative designs that utilize directional transmission, and involve introducing either repeaters that function essentially as secondary sinks, or power lines that enable powered information transfer for sensors lying along the power line. These innovations greatly reduce power consumption, thus prolonging system lifetime.

The remainder of this paper is organized as follows. Section 2 is devoted to the related work on data aggregation. The challenges and related solutions are clearly identified and exposed. Section 3 focuses on the designing of an efficient data aggregation model based on hexagonal cells. Section 4, we describes numerical simulations and discuss our experimental results. Section 5 furnishes a conclusion and proposes future research directions.

## 2. Related work

As pointed out in Pundir and Sandhu (2021), energy efficiency is the most important performance criterion for data aggregation since it determines network lifetime. Different researchers have taken different approaches to improve energy efficiency including network topology, data predication, data compression, data redundancy elimination, security effects, routing, mobility impacts, bandwidth management, latency and pack delivery ratio have been carried out for efficient data fusion in WSN (Pundir and Sandhu, 2021; Jan et al., 2021; Devi et al., 2020; Wang et al., 2019; Gupta and Sharma, 2019; Ahmed et al., 2019; Yadav and Mahapatra, 2021). These approaches are described briefly below.

Network topology refers to the manner in which sensor nodes are organized to capture and forward data in the network. The cluster topology based on low energy adaptive clustering hierarchy routing protocol (LEACH) (Heinzelman et al., 2000; Heinzelman, 2000) is the most well-known and widely-used architecture designed for traffic control to minimize energy consumption by selecting the cluster heads (CHs) among nodes which are responsible to transfer data to the base station or the next cluster head (Pundir and Sandhu, 2021; Ahmed et al., 2019). To achieve this, several studies seek to propose cluster head selection schemes that avoid redundant data, more work load on CHs, and oversize clusters which can lead to rapid CH discharge. For example the hybrid energy efficient distributed (HEED) clustering algorithm takes both residual energy and the node proximity into account to avoid unbalanced clustering (Younis and Fahmy, 2004). Similarly, a genetic algorithm clustering method is proposed in Yuan et al. (2017) using the node density, the residual energy and the expected node energy consumption. Observing that HEED leads to cluster CHs variation during clusters election, the set of fuzzy rules and the bacterial foraging method are used to develop various clustering schemes in Gupta and Sharma (2019) in order to limit hot spot formation that cause more work load on clusters. The CH election must also consider network scalability. For this purpose, based on K-means++, a novel Multi-Scale Parallel clustering (MSPK++) algorithm was proposed in Mydhili et al. (2020). The network energy consumption is reduced by exploiting distributed behavior of WSNs on both virtual and real cluster machines to balance the routing load. As highlighted in Pundir and Sandhu (2021), the implementation of MSPK++ in real-world applications is complex. In addition to the network topology, efficient data collection requires building a comprehensive, efficient pattern of field coverage. To achieve this, a very common strategy involves structuring the coverage region into hexagonal cells (Carr et al., 1992). A distributed algorithm that divides the network into hexagonal cells were proposed in Li et al. (2014) to reduce aggregation latency under WSNs physical interference. A cellular network configuration helps to handle simultaneous transmissions which can cause interference, without needing an overall view of the information moving through the network. In the same way, an analysis of network lifetime extension for data reporting using hexagonal clustering was presented by Debessu et al. in Debessu et al. (2011). The network lifetime was investigated through various data reporting configurations including direct transmission to the base station, transmission via random CHs position and data transfer using CHs situated at the centers of hexagons. Similarly, Kumar et al. Kumar et al. (2018) showed that a data aggregation scheme for WSN's based on hexagonal and Voronoi cells clusters led to reduced energy consumption. Hexagonal patterns were also used by Ramkumara et al. Ramkumara et al. (2021) for efficient relay nodes selection during data routing in order to save nodes' energy consumption.

The clustering methods presented above do not consider in general the nodes mobility. However, it is well know that the mobility factor can save energy consumption in WSN. Following this logic, the network lifetime is improved in heterogeneous nodes environment by using a mobile sink, which helps to reduce the communication cost between CHs and sink in Mantri et al. (2016). The proposed cluster-based data aggregation algorithm (MHCDCA) organizes the network in two layers. The static layer, which is composed of source nodes and CHs, and the mobile layer, which is bring out by the sink mobility through the network. In this architecture, each CH exploits data correlation from its member sources node to limit packets transmission. Subsequently, a mobile sink moves through the network for data gathering from the CHs. In the same vein, a cluster-chain mobile agent routing (CCMAR) protocol was proposed in Sasirekha and Swamynathan (2017). To perform data aggregation, the proposed protocol first combines the cluster-chain routing algorithm presented in Du et al. (2003) and

the (LEACH) for CHs formation. Afterwards, a mobile agent is deployed for data collection and data forwarding to further reduce energy consumption during data transmission to the sink node. In static WSNs, the nodes closer to the sink generally die faster because of unbalance traffic among nodes. To cope with this issue, an Enhanced Power Efficient Gathering in Sensor Information Systems (EPEGASIS) clustering, which include mobile sink and chain-based routing was proposed in Wang et al. (2018). Data aggregation involves also the selection of optimal paths to transmit data. For this purpose, a mobile sink and a greedy scheme for intercluster communication are used in Wang et al. (2019) to choose low energy consumption paths when transferring data.

Data compression and data redundancy elimination are the classical mechanisms used in data aggregation to reduce communication overhead that has a direct impact in nodes depletion, latency, packet delivery and network congestion (Maivizhi and Yogesh, 2020; Jan et al., 2021; Ahmed et al., 2019; Mantri et al., 2016; Sasirekha and Swamynathan, 2017). To address the data redundancy issue, the authors of Jan et al. (2021) proposed a lightweight twofold data aggregation. At the source node level, similarity analysis is realized by decreasing or increasing the weight of the captured data. When a given node senses a data, the value of the current captured data is compared to that of the previous sensing data based on a modified version of Euclidean distance function. If the two data values are equal, the current captured data is discarded by increasing its weight with 1. However, if the value is less the defined threshold, the value of the previous captured data is set to the average of the current data and that of the previous data. In the case where the data values are different, the weight of the current data is set to 0 to say that there is no similarity between data. The effectiveness of the proposed scheme is established through data loss ratios, node integrity and energy consumption levels. A multilevel redundant data elimination and energy efficient algorithm, Data Redundancy-controlled Energy Efficient Multi-hop (DREEM) was proposed in Ahmed et al. (2019). DREEM is a protocol combining cluster and statistical tests with an appropriate threshold. To remove similar data, DREEM divides the network in small and big clusters. The small cluster head (SCH) aggregates data from source nodes and forwards to the big cluster head (BCH). Then after, the surface sink collects data from BCHs. In addition to the improvement of the network lifetime, DREEM helps to enhance the throughput of the network.

Likewise, to further reduce the communication cost in a dense WSN where massive data are generated, a data compression technique is employed. In Azar et al. (2019), an adaptive version of error-bounded lossy compression scheme based on Squeeze (SZ) algorithm was proposed to reduce the amount of forwarding data with no effect in data quality. SZ uses bounded errors to control the information loss and to appreciate the compression ratio. The performance studies show that when data are compressed before transmission, the battery level of IoT nodes decreases slowly. In the same way, SZ is combined with compressed sensing, discrete wavelet transform and deep learning model to build time series compression for efficient bandwidth usage and network lifetime extension (Azar et al., 2020). Compression allows the reconstruction of signal from a fewer number of measurements whereas discrete wavelet transform uses filters to split the signal for time–frequency representation. The deep learning method helps to classify original data from approximation data.

### 3. System model

#### 3.1. Model assumptions and notation

In this paper, we consider a sensor network with a single sink node, and with sensors densely distributed in a circular region sur-

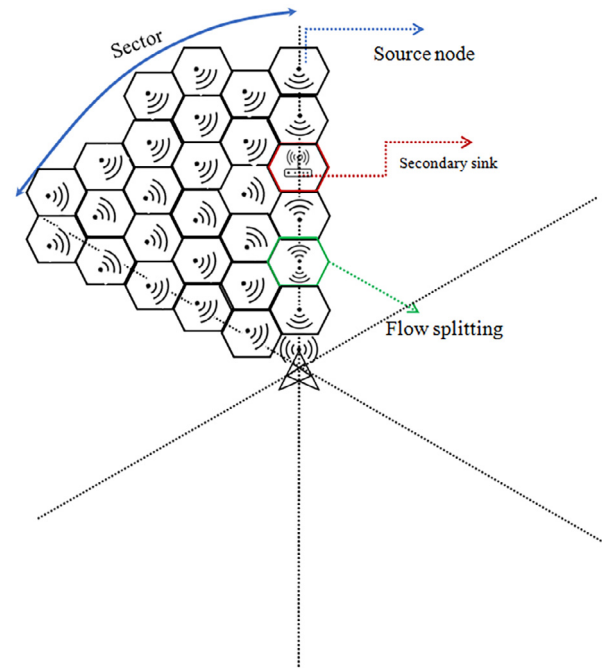


Fig. 1. Network system.

rounding the sink node (see Fig. 1). For the purposes of this paper, we assume uniform density of sensors throughout the region (the model can easily be modified to accommodate nonuniform density). We also assume that sensors are grouped into congruent hexagonal cells, and the sensors from each cell send their information to a single node at the center of the cell where the information is aggregated before being passed to the sink. Cell nodes may pass their information directly to the sink node, or indirectly via other cell nodes. A cell node's information can also be split into multiple channels, which can then be reassembled at the sink node. Cell nodes can also multiplex together information from several other cell nodes, with negligible information loss or overhead.

Our notation is defined as follows. In all definitions, the index  $j$  ranges from 1 to  $N$ , and the index  $i$  ranges from 0 to  $N$ .

- $a_j \geq 0$  is the information per time associated with cell node  $j$  that is to be transmitted the sink;
- $c_j \geq 0$  is the current energy capacity left in cell node  $j$ ;
- $t_{ij} > 0$  is the power cost to cell node  $j$  of transmitting a unit of information to cell node  $i$  (which may also include processing power cost). In general,  $t_{ij}$  is a convex function of the distance between nodes  $i$  and  $j$ ;
- $x_{ij} \geq 0$  is the information per unit time that flows from node  $j$  to node  $i$ .

We suppose that the values  $a_j$  and  $t_{ij}$  remain approximately constant over the time interval of interest.

#### 3.2. Model constraints

The total information processed by cell node  $j$  per time is equal to the information originating from  $j$  (i.e.  $a_j$ ) plus the information per time that flows into node  $j$  from other nodes. This information is subsequently transmitted to other nodes. This balance between inflowing and outflowing information for each node gives an equality constraint for each node  $j, j = 1, \dots, N$  as follows:



$$\sum_{i=0}^N x_{ij} = \left( a_j + \sum_{i=1}^N x_{ji} \right), j = 1, \dots, N \quad (1)$$

The sum of the  $N$  Eqs. (1) gives:

$$\begin{aligned} \sum_{j=1}^N \sum_{i=0}^N x_{ij} &= \sum_{j=1}^N a_j + \sum_{j=1}^N \sum_{i=1}^N x_{ji} \\ \Rightarrow \sum_{j=1}^N x_{0j} &= \sum_{j=1}^N a_j. \end{aligned} \quad (2)$$

Eq. (2) guarantees that all information eventually flows to the sink node at 0.

We also impose a nonnegativity constraint on the information flows  $x_{ij}$ , and prohibit flows from nodes to themselves:

$$x_{ij} \geq 0; \quad x_{ii} = 0, \quad 0 \leq i, j \leq N. \quad (3)$$

### 3.3. Maximization of network lifetime

In the case where nodes' energy capacities are limited, the network can no longer fully function when any node's energy reserve is depleted. The remaining lifetime of any node at current energy usage is given by the node's remaining energy capacity divided by its rate of consumption (i.e. power). Due to linearity, it is not necessary to look for time-dependent solutions, since a time-averaged strategy will have the same system lifetime.

Using the terminology defined above, the energy consumption of node  $j$  is given by  $\sum_{i=0}^N t_{ij} x_{ij}$ , so the remaining lifetime of node  $j$  is  $\left( \sum_{i=0}^N \frac{t_{ij} x_{ij}}{c_j} \right)^{-1}$ . Thus system lifetime may be maximized by solving the following minimization problem: Minimize  $\Phi$ , subject to constraints (1), (3) and

$$\Phi \geq \sum_{i=0}^N \frac{t_{ij} x_{ij}}{c_j}, j = 1, \dots, N. \quad (4)$$

We will refer to  $\Phi$  in (4) as the system's depletion rate, since the system lifetime is  $\Phi^{-1}$ . The solution to (4) may be readily found using linear programming.

### 3.4. Sectorization of uniform model

The geometry of the model has 12-fold symmetry, in the sense that one 30° slice of the hexagon can be mapped to 11 other similar slices through rotations and reflections. Because of linearity, any non-symmetric solution can be symmetrized to obtain a solution that will be at least as good as the original solution. It suffices therefore to look for solutions with 12-fold symmetry. Thus we may solve the equations for a single 30° slice, then map the solution to all other slices.

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**Algorithm 1** Optimization algorithm pseudocode for a single sector for a uniform hexagon model

---

**Input:**  $nMax$ : Maximum distance from hexagon to sink

**Output:** Location  $xVec$  and  $yVec$  of hexagons; information matrix  $infoMx$ ; and power matrix  $powerMx$

1: Compute the upper bound of number of hexagons in a sector:  $kMax \leftarrow nMax * (nMax + 1) / 2$

2: Generate  $(xVec, yVec)$  coordinates of hexagons in the sector (some of these will be too far away and are removed)

3: Compute the matrix of inter-hexagon distances  $dhsqMx$

4: Remove hexagons with distance  $> nMax$  from the sink from  $xVec, yVec, dhsqMx$ . Let  $nHex$  = number of remaining hexagons.

5: Create  $nHex \times nHex$  0–1 matrix  $maskMx$  to indicate possible information flows between hexagons.  $nz = \text{sum}(maskMx)$ .

6: Initialize to zero: objective vector  $objVec$  ( $1 \times nz$ ); inequality constraints vector  $bVec$  ( $nHex \times 1$ ); inequality constraint matrix  $Aineq$  ( $nHex \times nz + 1$ ); equality constraint vector  $cVec$  ( $nHex \times 1$ ); equality constraint matrix  $Aeq$  ( $nHex - 1 \times nz + 1$ ).

7: **for**  $ih \leftarrow 1$  **to**  $nHex$  **do**

8:   add a new row constraint to  $Aineq$

9:   **if** hexagon is on edge of sector **then**

10:     Only  $\frac{1}{2}$  of hexagon is included in sector

11:   **end if**

12: **end for**

13: **for**  $ih \leftarrow 1$  **to**  $nHex$  **do**

14:   add a new row constraint to  $Aeq$

15:   **if** hexagon is on edge of sector **then**

16:     Only  $\frac{1}{2}$  of hexagon is included in sector

17:   **end if**

18: **end for**

19:  $infoVec$  = solution of linear program with parameters  $objVec, Aineq, bVec, Aeq$  and  $cVec$

20: Reshape  $infoVec$  vector to  $nHex \times nHex$  matrix

21: Double the information for hexagons on boundary

22: Compute  $powerMx \leftarrow infoMx \times dhsqMx$  (elementwise)

---

The complete solution for all sectors may be obtained from the solution for one sector by successive duplication via reflection, as follows. To duplicate the first sector, we employ the polar coordinate representation of hexagon positions. Let  $\phi_{max}$  be the maximum polar angle for hexagons in the sector. Then the hexagons in the second sector are obtained by reflecting the hexagons in the first sector around the  $\phi = \phi_{max}$  line. Mathematically, this corresponds to the polar coordinate transformation:

$$(r, \phi) \rightarrow (r, 2\phi_{max} - \phi) \quad (5)$$

Following this, the second sector is similarly duplicated to obtain the third sector, and so on until all 12 sectors are generated.

## 4. Results

### 4.1. Simulation parameter values

In this study we consider a uniform model where all nodes have the same information density:

$$a_j a_{and} = c_j = c \quad \forall 1 \leq j \leq N. \quad (6)$$

It is sufficient to consider the case  $a = c = 1$ : if  $x_{ij}, \Phi$  correspond to the solution with  $a = c = 1$ , then the solutions for different values of  $a, c$  are given by  $a x_{ij}, \frac{a\Phi}{c}$ . We also assume a quadratic power law for transmission power:

$$t_{ij} \propto \text{dist}(i, j)^2, \quad (7)$$

where  $\text{dist}(i, j)$  is the distance from cell node  $i$  to cell node  $j$ . This assumption corresponds to a free space path loss propagation model with uniform background noise (Richards, 2008), which is most suitable for a sensor field with uniformly-distributed sensors. Because of the low data rates involved (as well as directional transmission), we may ignore the effect of possible interference between signals from different nodes. In the simulations, distances are normalized so that the distance between any cell node and its closest neighbors is 1.

The regions used in this study are circular with radii ranging from 9 to 12. However, we have also verified that larger regions display similar behavior.

4.2. Information and power flow for single-sink system configuration

As mentioned previously, WSN systems commonly have a single sink node at the center of the covered region to serve the entire area. To prolong system lifetime, we may introduce powered secondary sink nodes, which can transmit information to the central sink without depleting their capacities. Alternatively, we may run several transmission and/or power lines radially from the source that connect hexagons to the central sink, effectively reducing the transmission power for these hexagons to zero. The secondary sinks and lines used can have different geometries. In the following, we demonstrate the lifetimes of various system geometries.

Fig. 2 displays the patterns of information flow for a system with a single central sink. A region with a radius of 9 hexagons is shown, but regions of all sizes show similar patterns. The color of the dot in each hexagon indicates the combined total information flow from the given hexagon to all sink nodes. The colored arrows from each hexagon indicate the direction and size of all information flows to neighboring nodes.

The information flow in Fig. 2 follows a very regular pattern. The flow from any given node is divided between flows directly to the sink node (represented by the colored dots in each hexagon) and flows to neighboring nodes (represented by arrows to adjacent hexagons). The same is true for all other system configurations examined in this study, and it appears to be true in general. It may be seen that outer hexagons' adjacent flows all move directly towards six symmetrically-arranged rays along which the stepwise information flow is also large. But within an inner hexagon with radius roughly half of the region radius, the adjacent flows no longer move towards these rays but rather parallel to them.

Fig. 2 shows that with a single central sink, the information flows from nodes adjacent to the sink are almost 18 times as large as the information associated with a single hexagon.

Fig. 3 shows the power flows associated with the information flows in Fig. 2. In this case, the colored dot in each hexagon indicates the base 10 logarithm of the power flow from the given hexagon directly to the sink (according to the color scale in the figure). The arrows between hexagons give the base 10 logarithms of power flows between adjacent hexagons. The figure shows that many nodes expend most of their power for direct transmission

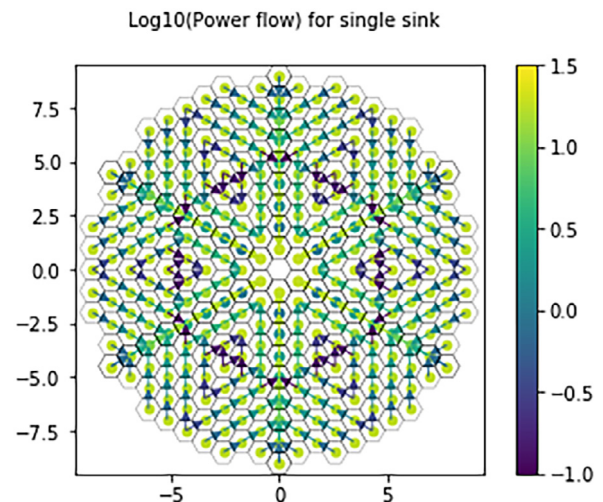


Fig. 3. Power flow for single sink.

to source—this is to avoid overloading the nodes along the six rays referred to in the previous paragraph, which pass information down to the central sink. Indeed, the direct-to-source power expenditure is nearly equal for most hexagons, except for those along the six rays mentioned above where more power is spent for adjacent transmission, because the information concentration is highest along these rays.

4.3. Information and power flow for system configurations based on 6-fold symmetry

The information and power flows shown in Figs. 2 and 3 respectively suggest that a system configuration that focuses on reducing the energy of transmission along the six symmetrical rays would reduce the need for direct transmission from other nodes, thus prolonging system lifetime. One possible way of doing this would be to introduce effective line sinks (in the form of transmission lines or power lines) into the system along the six ray directions, so that information can be transmitted along these directions at negligible cost. Fig. 4 shows the information flow for a system design with six line sinks. In the figure, hexagons that lie along line sinks are indicated with black crosses. The information diffuses towards the line

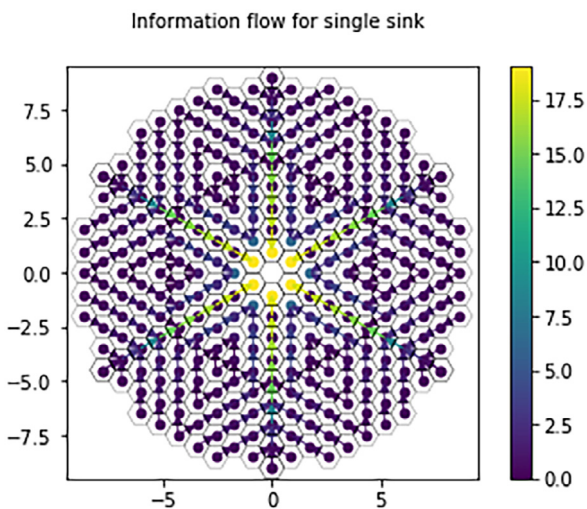


Fig. 2. Information flow for single sink.

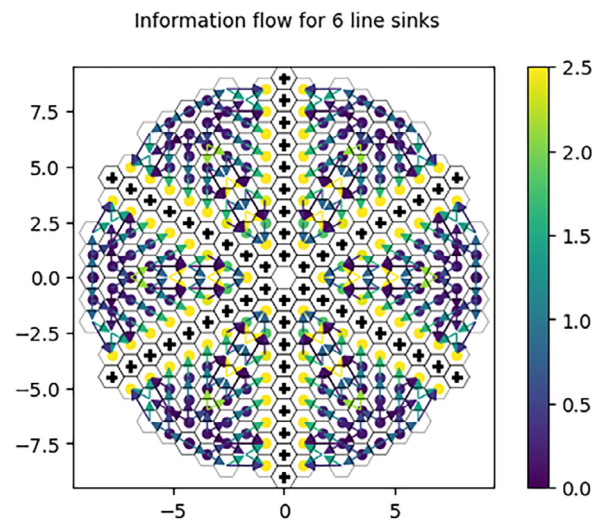


Fig. 4. Information flow for 6 line sinks.



sinks, from whence it is passed directly to the main sink. The maximum information flow from nodes adjacent to sink nodes is about 2.5, which is greatly reduced compared to the information flow of 18 for nodes adjacent to the main sink in Fig. 2. The corresponding power flow is shown in Fig. 5, where the power scale is the same as in Fig. 3. Clearly, the direct-to-sink power flow from hexagons in the region has been greatly reduced. Indeed, some hexagons have no direct power flow, and all flow is to adjacent hexagons.

A different way to reduce the large information and flows in Figs. 2,3 would be to introduce secondary sources (such as repeaters) at locations along the six rays. Figs. 6,7 show the information and power flows respectively for such a system. It is clear from comparison with Fig. 3 that this system configuration is also effective in reducing power consumption compared to the original single-sink system. The information and power flows are more complex, because there are now seven different nodes that attract power flow. Some of the power flows away from the central node and towards secondary nodes.

#### 4.4. Information and power flow for system configurations based on 3-fold symmetry

An intermediate approach between the single-sink and six-sink configurations would be to introduce effective line or point sinks along three symmetrical directions. Figs. 8–11 show information and power flows for a three secondary line and point sinks, respectively. The observed flows have similar characteristics to the 6-line flows in Figs. 4 and 9.

#### 4.5. Direct comparison of alternative system configurations

Figs. 12 and 13 directly compare the system lifetimes for the five alternative system configurations described above, for two different region sizes. In the graphs, system lifetimes are scaled so that the y axis shows the relative system lifetime compared to the base configuration with no secondary nodes or lines. The curves for the solutions with secondary nodes show scaled system lifetime as a function of secondary sink position, measured in hexagons from the center of the region. Lines for other solutions are flat because these systems have no secondary sinks.

The graphs show that a system with six line sinks consistently has the longest lifetime. Furthermore, the relative advantage of line sinks compared to basic and secondary node solutions increases with increasing region size. This tendency is clarified in Fig. 14,

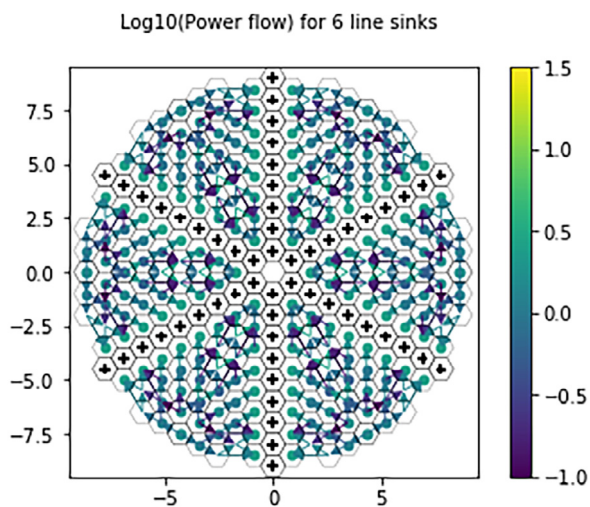


Fig. 5. Power flow for 6 line sinks.

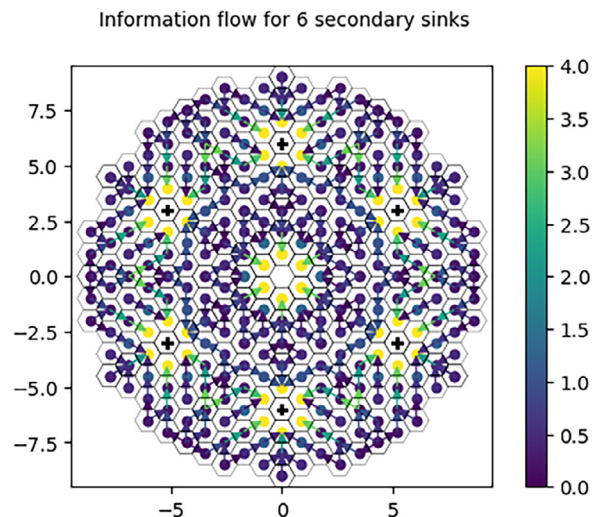


Fig. 6. Information flow for 6 secondary sinks.

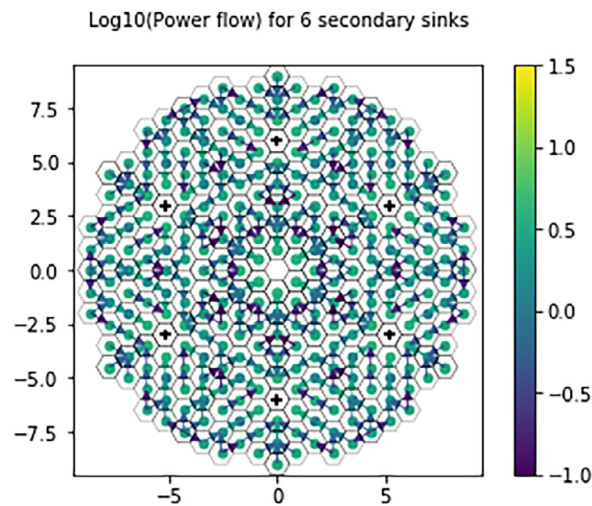


Fig. 7. Power flow for 6 secondary sinks.

which shows that the relative advantage of line solutions compared to the basic solution increases about 3 times when the region size is increased from 4 to 20 hexagons.

In contrast to line solutions, the relative advantage of solutions with secondary nodes compared to the basic solution increases only slightly as the region size increases, as shown in Fig. 14. Both Fig. 12 and Fig. 13 show that the best position for secondary sinks is roughly 2/3 of the distance to the edge of the region. This makes sense because this placement minimizes the maximum distance to the nearest sensor for points in the region.

### 5. Discussion and conclusion

This paper presents a detailed investigation of the lifetimes of alternative system configurations for a WSN in a circular region. The region is divided into hexagonal cells, and the information from each cell is combined and directionally transmitted to the sink or to other cells. Simultaneous transmission to multiple cells is permitted, and the power level of different transmissions can

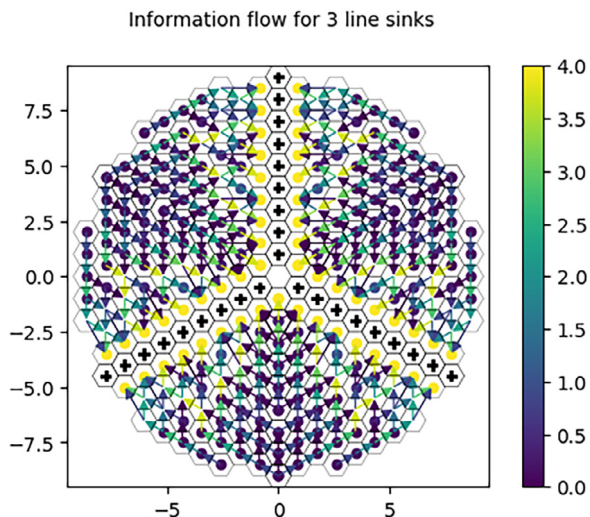


Fig. 8. Information flow for 3 line sinks.

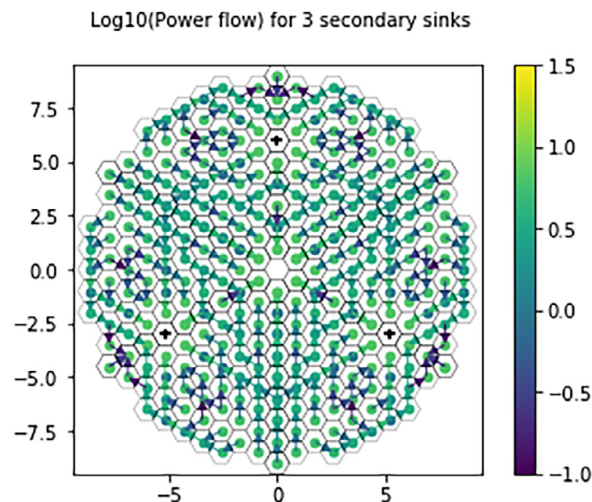


Fig. 11. Power flow for 3 secondary sinks.

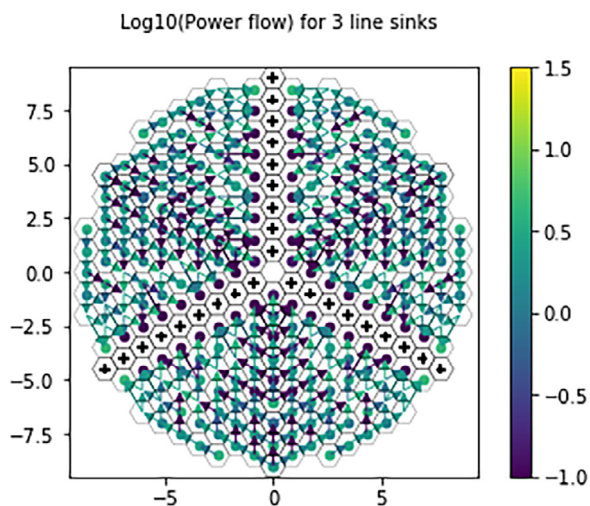


Fig. 9. Power flow for 3 line sinks.

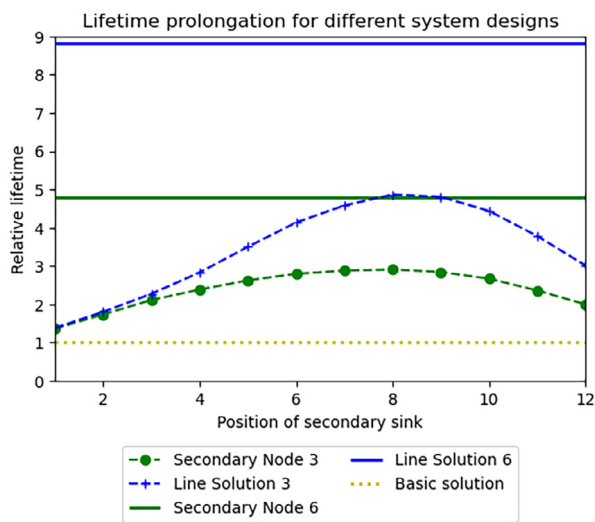


Fig. 12. System lifetime enhancement for various system configurations, for a region with a radius of 12 hexagons.

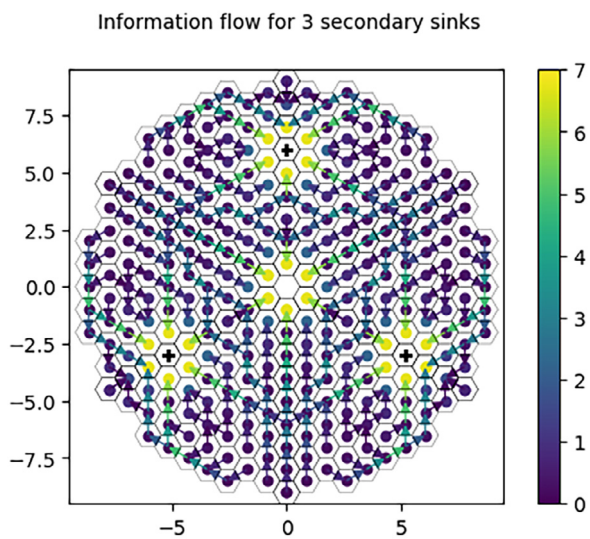


Fig. 10. Information flow for 3 secondary sinks.

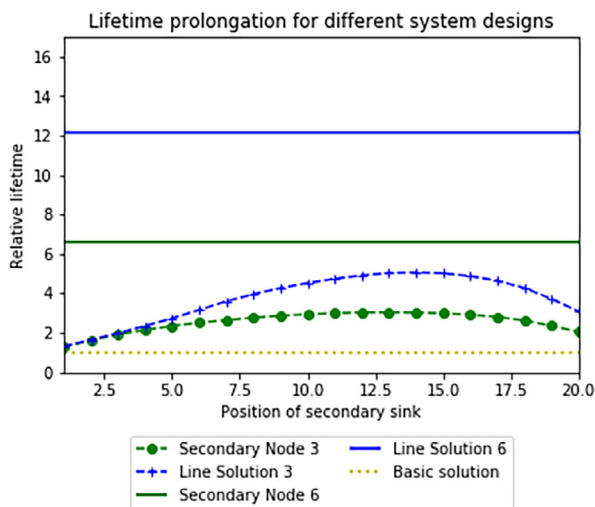


Fig. 13. System lifetime enhancement for various system configurations, for a region with a radius of 20 hexagons.



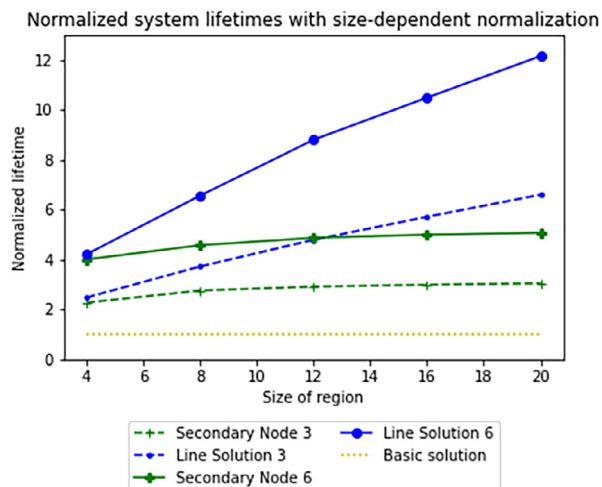


Fig. 14. Relative lifetime for different solutions as a function of region size. All lifetime values for each region size are normalized by dividing by the lifetime for the basic solution for the same region size.

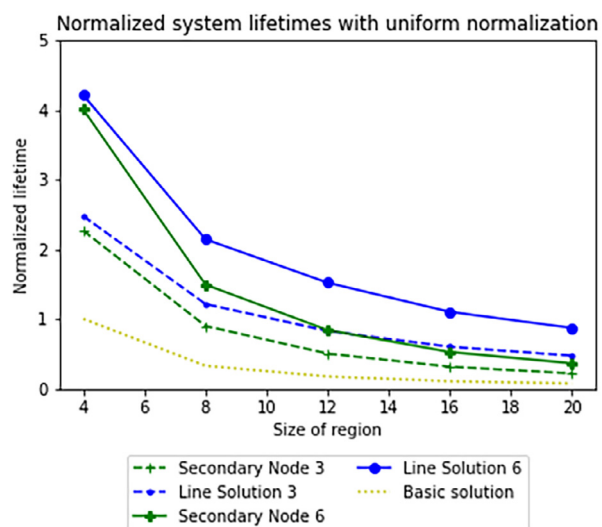


Fig. 15. Normalized lifetime for different solutions as a function of region size. All lifetime values are normalized by dividing by the lifetime for the basic solution for a region with a radius of 4 hexagons.

be controlled to different levels. Under the assumptions of uniform information density and uniform sensor distribution, system lifetime can be greatly prolonged by introducing a limited number of transmission lines or repeaters to facilitate information transfer. Line sinks are more effective than secondary point sinks, and their relative effectiveness increases as the size of the coverage region increases. Fig. 14 shows that using six line sinks for a region with a radius of 20 hexagons increases the system lifetime by a factor of 12. Indeed, Fig. 15 shows that a system with radius 20 hexagons that uses line sinks has about the same lifetime as a basic (single-sink) system with 1/5 the radius, while providing coverage for an area 25 times larger.

Our results indicate that symmetric line sinks hold promise as a practical alternative for a WSN with extended lifetime. Naturally, the introduction of line sinks brings additional cost, so cost-benefit tradeoffs may vary from situation to situation. By quantifying the improvements in performance, our results provide essential information for a cost-benefit analysis.

Future work may investigate non-uniform systems, or systems with irregular shape having multiple sinks. Eqs. (1)–(4) are still valid in more general systems. Further investigation with latency is also left for future work.

### 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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