Enhancing Network Lifetime and Data Integrity in WSNs via Optimized Mobile Robot Trajectories

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***Abstract*—Recent research has shown that utilizing mobile robot data collection from sensor nodes is one of the most critical schemes to prolong the network lifetime in wireless sensor networks (WSNs). By overcoming some limitations of traditional methods where sensing data is sent to a static data collection node through multiple routing paths, the mobile data collection robot-based approaches can completely avoid "hotspot" problem, energy-holes issues thereby balancing node energy consumption in the network. Consequently, many ideas and publications on improving network lifetime in WSNs by utilizing mobile data collection robot(s) have been proposed. However, there is little research that has studied the impact of mobile robot trajectory types on network lifetime improvement. Therefore, it becomes very interesting to investigate data collection process of mobile robots in wireless sensor network. In this paper, we proposed a geometric solution to find optimal trajectories of utilized mobile robots (MRs). Our proposed solution consists of four main stages. In the first stage, the number of cluster head nodes is estimated based on the network size and the density of sensor nodes in the WSN. The second stage involves estimating the spatial region that each mobile robot must cover to collect sensed data from all assigned sensor nodes. In the third stage, an optimal trajectory for each mobile robot is determined. In the fourth and final stage, the Network Control Center (NCC) proceeds to assign optimized trajectories to the remaining mobile robots until all cluster head nodes in the network have been visited. The proposed optimal trajectory for the mobile robot is designed not only to ensure timely collection of all sensed data in the field, but also to minimize the energy consumption of sensor nodes, thereby improving the overall network lifetime. A large number of numerical tests were carried out to evaluate the performance of our proposed algorithm. The simulation results demonstrate that our proposed algorithm achieves a 5.4% improvement in network lifetime compared to other traditional algorithms. Nevertheless, the network lifetime improvement remains dependent on several assumptions made in this study. To address this limitation, the discussion section of the paper outlines potential directions for future work aimed at enhancing the practical applicability of the proposed solution.**

Keywords*—*WSNs; Energy-Efficient Trajectory Optimization for Mobile Robots in WSNs; Geometric Solution; Network Lifetime; Data Integrity in WSNs

I. INTRODUCTION

It is known that the network lifetime is one of the most important factors in wireless sensor network (WSNs) studies [1]–[6]. To improve the network lifetime through mobility models, which not only avoid the hotspot problem [7]–[12] in the network but also guarantee the balanced energy consumption among nodes in WSNs [1], [13]–[16], is one of the main concerns in WSNs [17], [18]. To enhance data acquisition efficiency, in [17], a mobile sink is employed to navigate through the sensing area and collect data from distributed sensor nodes. During the data gathering time, the residual energy information of sensor nodes is collected for scheduling the next stopping position of the mobile sink [19]–[21]. By this way, the mobile sink tends to move toward the high residual energy nodes. As a result, the imbalanced energy consumption among nodes in the network persists and which becomes a major factor contributing to reduce the network lifetime.To address this limitation, various solutions have been proposed, including clustering algorithms, multi-hop routing protocols, and mobile sink deployment strategies. Among these, the use of mobile sinks has shown great promise in balancing energy consumption and extending network lifetime by dynamically collecting data from different locations in the network. In [22]–[24], the authors focused on improving the network lifetime by proposing a new routing scheme, which selects the number of utilized mobile sinks and their corresponding parking positions. In [1], two approaches named OMS1 and OMS2, which utilize mobile sinks for data collection, are proposed. These approaches have demonstrated that employing mobile sinks with adaptive mobility schemes significantly enhances network lifetime and improves the network reliability compared to stationary or fixed-trajectory sink models. Similar conclusions are presented in [25]. The authors in [25] have investigated the use of a mobile robot for data collection and data transmission. In this study, the locations of the WSNs nodes are assumed to be known in advance by a mobile robot and this location information is utilized to solve the Traveling Salesman Subset-tour Problem (TSSP) in order to determine an optimal trajectory of a mobile robot. The experimental and simulation results demonstrate the effectiveness in enhancing the network reliability of the WSNs. In a recent study, Bilal R. Al-Kaseem et al., in [26] have proposed an optimized energy-efficient path planning approach, which mitigated the limitation of energy challenges in WSNs when integrated into the Internet of Things (IoT). The authors have developed three optimization techniques, based on the multi-objective evolutionary algorithms, to evaluate the trajectory of deployed mobile sinks. The simulation results show that by the proposed approach, the network lifetime of the WSNs can be prolonged up to 66% compared to the existing approaches. As a result, several studies in the literature have integrated the mobile robot platform for environmental monitoring schemes [27]–[35]. In [27], the combination between robotics and internet of things (IoT) [36]–[45] is used for monitoring agriculture fields. The mobile robots are developed for data gathering from agricultural fields or greenhouses [46]–[48]. The gathered data is then posted to the web application for monitoring purposes via IoT devices. By this way, the proposed design scheme showed the advantage of applying mobile robot platforms in agricultural environments [49], [50]. In another study, Ashish Gupta et al., (2018) proposed a prototype for a real-time monitoring agriculture sensor network [51], [52]. In this system, a single mobile sink, which is attached to a tractor moving along a predetermined path, is utilized for data collection. The sensing data from each sensor node is transmitted to the mobile sink via Wi-Fi. The proposed prototype results show that the velocity of the mobile sink and the sampling rate of the sensor nodes affect the quality of the monitoring data. Unfortunately, there is insufficient evidence to demonstrate that the aforementioned solutions are effective in extending the lifetime of wireless sensor networks while simultaneously ensuring data integrity i.e., guaranteeing that all sensor measurements are transmitted completely and in a timely manner to the control center.

Therefore, this paper addresses the problem: *how to collect the sensing data in the sensing fields in time with the smallest energy consumption?* The main objective is to find the smart trajectories of mobile robots [53]–[59] that enable efficient data collection with minimal energy expenditure. To address this problem, we extend the approaches introduced in [3], [60] and obtain an optimal trajectory of the mobile robot. The research contribution is a novel multi-parameter optimization algorithm for trajectory planning of mobile robots in wireless sensor networks. Unlike previous approaches that focus solely on minimizing travel distance or energy usage, this method integrates network geometry, residual energy of sensor nodes, and communication latency with cluster heads. This holistic design enables energy-aware and communication-efficient paths, ensuring timely data collection while reducing sensor node workload. As a result, the approach enhances network lifetime, improves load balancing, and demonstrates strong performance across various deployment scenarios.

The remainder of the paper is organized as follows:

- In Section 2, we present the model of system and the basic assumptions.
- In Section 3, we describe the proposed approach.
- The performance of the our algorithm is analyzed and compared to the other algorithms in Section 4.
- Finally, in Section 5, we conclude this paper and give some suggestions for future works.

II. System Model and Assumption

A. Basic Assumptions

To begin with, we would like to specify more precisely the general assumptions about the wireless sensor network (WSN) model adopted in this study.

- Sensor nodes (N) in the network are distributed uniformly with limited initial energy E_0 and are stationary after deployment.
- The MR can move freely in the monitoring area with unconstrained energy and storage capacity. The MR does not receive any data packets while in motion. The MR only receives sensed data from a CH when it falls inside that CHs transmission range. We assume that the network lifetime is not affected by MRs operation and movement because they can periodically return to the support center for recharging themselves.
- In every operation round, after cluster head election, all the geographic position information of the CHs will be sent to the Network Control Center (NCC), where this information is carefully analyzed to optimize the trajectory of the MR. The NCC is also known as the depot in the Vehicle Routing Problem (VRP), where the MRs start and end their data collecting tour.
- In this paper, the network lifetime is defined as the number of operation rounds until 85 percentage of the network nodes run out of energy.
- Within reporting time ξ, all buffered data of the CH must be transmitted to the MR in order to avoid overflow.
- In this research, (T_r) is a cycle time in which sensing data from all (N) sensor nodes in the network can be collected at the NCC successfully.
- In every operation round, each sensor node has a data sample of γ-bit data packet which must be transmitted to its corresponding CH.

In the following section, we present the network and energy models employed in our proposed scheme.

B. Network Model

Fig. 1 illustrated the structure of WSN with $N = 30$ sensor nodes are randomly deployed on the monitoring area A. This area (A) will be divided into $M = 6$ equal parts $\{A_1, A_2, ..., A_M\}$. The value of subareas (M) is the function of sensing field acreage (H) and the node density (ρ), $M = f(H, \rho)$, which guarantees that one CH only need one MR to collect data.

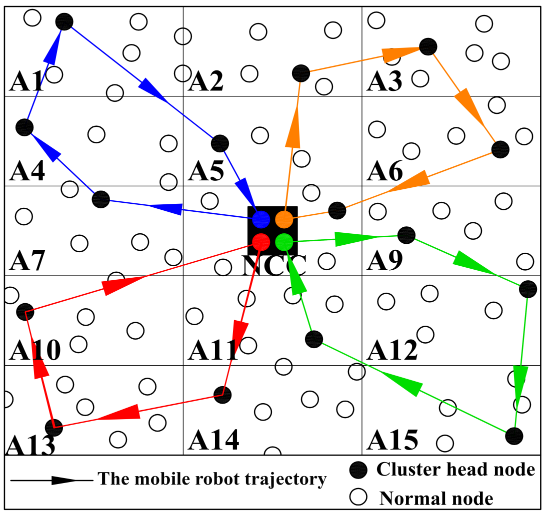


Fig. 1. Wireless sensor networks structure

In each operational round, the cluster head election will be repeated, resulting in changes to the positions of the CHs. Therefore, our objective is to find the optimal movement strategy for the MR that can collect all sensing data within a desired time deadline while minimizing energy consumption thereby improving the overall network lifetime.

C. Energy model

The source node has to spend an amount of energy E_{TX} if it transmits m-bit data packet to the destination node over a distance d. It can be calculated by (1) [61].

$$E_{TX} = \gamma E_{elec} + E_{amp}(\gamma, d) \quad (1)$$

or

$$E_{TX} = \gamma E_{elec} + \gamma \varepsilon d^{\chi} \quad (2)$$

where $\begin{cases} \varepsilon = \varepsilon_{fs}; \chi = 2 \text{ if } d < d_0 \\ \varepsilon = \varepsilon_{mp}; \chi = 4 \text{ otherwise,} \end{cases}$

E_{elec} is the electronic energy, $E_{amp}(\gamma, d)$ is the energy needed by the radio amplifier circuit to send γ bits to the receiver node over d meters. To receive γ-bit data packet, the received node also has to consume E_{RX} amount of energy power, and it is calculated as

$$E_{RX} = \gamma E_{elec}. \quad (3)$$

The load $L_k(t)$ of node k during round tth is the total power that node consumes to receive and transmit data on that round:

$$\mathrm{L}_k(t) = \mathrm{E}_{TX}(t) + \mathrm{E}_{RX}(t). \quad (4)$$

The lifetime of a sensor node (LF_k) refers to the time when its residual energy is less than a threshold (θ). Therefore, we have:

$$E_0 - \sum_{t=1}^{LF_k} L_k(t) = \theta, \{k = 1, ..., N\} \quad (5)$$

It is clear that the higher the load $L_k(t)$ on node k, the shorter its lifetime. Therefore, to maximize the overall network lifetime, it is essential to minimize the network load and enhance load balancing among the nodes in WSN.

III. The Proposed Approach

A. Estimating the Number of Cluster M for Energy Efficient Deployment Scheme in WSNs

In this subsection, we develop an approach to estimate the optimal number of clusters within the sensing field, which ensures full coverage of the WSN, and timely collection of all sensed data.

Without loss of generality, we consider a wireless sensor network with rectangle field as can be seen in Fig. 2. l_1, and l_2 are length and width of rectangle sensing field. In the initial network deployment, every sensor node has the same transmission area with transmission radius l_0. The location of the NCC is center of the sensing field. In order to optimize the number of clusters in sensing field, we state the following theorem.

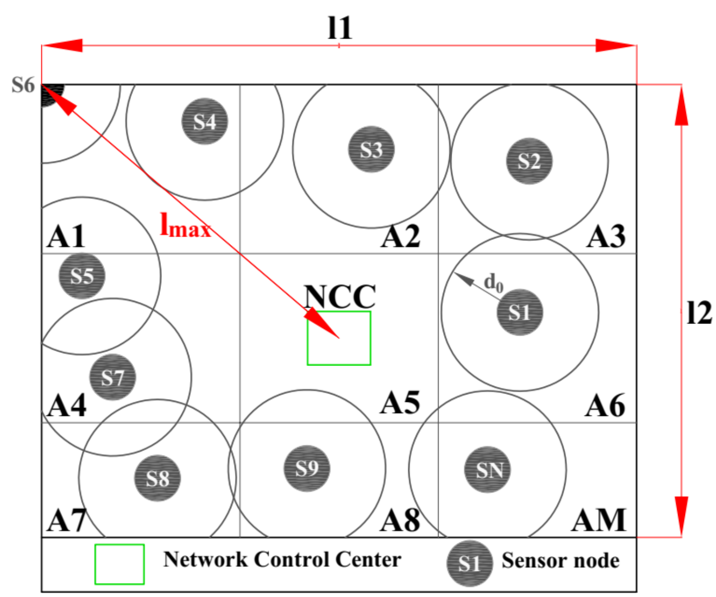


Fig. 2. Estimating the number of clusters (M) in the sensing field

Theorem 1
Let l_{max} denote the maximum distance between the NCC and one sensor node in sensing field, R is transmission rate between a CH and the MR, v indicates the speed of the MR. It will be an optimal scheme to divide sensing field into M equal parts if it satisfies (6).

$$M = \frac{\gamma l_1 l_2 v}{\pi {l_0}^2 R \left(\xi_0 v - 2l_{\max}\right)} \tag{6}$$

Proof
In order to achieve a fully coverage in WSN, the transmission area of all N sensor nodes has to cover all targets in sensing field [62]. It means that:

$$N\pi {l_0}^2 = l_1 l_2 \tag{7}$$

We have:

$$N = \frac{l_1 l_2}{\pi {l_0}^2} \tag{8}$$

Let $N_m, m \in [1, M]$ denote the number nodes in cluster A_m, therefore, we have:

$$N_m M = N = \frac{l_1 l_2}{\pi {l_0}^2} \tag{9}$$

or

$$N_m = \frac{l_1 l_2}{M\pi {l_0}^2} \tag{10}$$

In order all sensing nodes can be collected in time, and it is no need to spend more than one MR to visit one cluster head for data collection, the total spending time of the MR for traveling (t_{tr0}) and collecting data (t_{col0}) from one furthest CH is less than a threshold of reporting time (ξ_0).

$$t_{tr0} + t_{col0} \leq \xi_0 \tag{11}$$

The longest duration required for the robot's movement is defined as the time taken to travel from the NCC to the farthest sensor node (at a distance l_{max}), and subsequently return to the NCC. This duration is quantified by Equation (12).

$$\mathrm{t}_{tr0} = \frac{2l_{\max}}{v} \tag{12}$$

The spending time of the mobile robot to collect all sensed data from N_m nodes is computed by Equation (13).

$$\mathrm{t}_{col0} = \frac{\gamma N_m}{R} \tag{13}$$

From Equations (12), (13), we can rewrite the equation (11) as follows.

$$\frac{2l_{\max}}{v} + \frac{\gamma N_m}{R} \leq \xi_0 \tag{14}$$

where R indicates the transmission rate from transmitter to receiver. γ indicates total data packets that is generated by each sensor node in each round. We have

$$N_m \leq \frac{R}{\gamma}\left(\xi_0 - \frac{2l_{\max}}{v}\right) \tag{15}$$

By inserting 10 into 15, we have

$$M \geq \frac{\gamma l_1 l_2 v}{\pi {l_0}^2 R \left(\xi_0 v - 2l_{\max}\right)}.$$

B. Optimizing the Trajectory of the Mobile Robot for Data Collection

According to the M cluster heads locations [63]–[65], several MRs will be sent from the NCC to its assignment area to collect data. The question here is how to find the optimal trajectories of MRs, which can collect all data from N nodes in the network with the smallest energy consumption, within a predefined running time ξ_0, and minimizing the number of utilized mobile robots (F)?

The basic idea of our proposed algorithm is based on the geometric solutions to optimize the Trajectory of the MR (OTMR), which helps total spending time of the MR_f for traveling and collecting data in its assignment area is within the reporting time. We assume that there are N_f nodes inside the assignment area of the MR_f. To facilitate the OTMR algorithm, we firstly introduce following theorem that helps to construct the infrastructure of our algorithm.

Theorem 2
Let $\Re_f(t)$ denote the total length of the MR_f trajectory in its assignment area at the current round tth. In order to collect all sensed data from N_f sensor nodes within a threshold of reporting time ξ_0, the MR_f has to move with speed $v(t)$ after collecting data at each CH position with the transmission rate R. One is called as an efficient algorithm for data gathering without loss of sensed data if only if:

$$\left(\frac{\Re_f(t)}{v(t)} + \frac{\gamma N_f}{R}\right) \leq \xi_0 \tag{16}$$

Proof
In order to collect data from all sensor nodes inside the assignment area of the MR_f without loss of data, the reporting time at every cycle time ($\xi(t)$) has to be lower or equal to the threshold of reporting time ξ_0.

$$\xi(t) = t_{travelling}(t) + t_{collecting}(t) \leq \xi_0 \tag{17}$$

The total traveling time of the MR_f at the current round tth is calculated in Equation (18)

$$t_{travelling}(t) = \frac{\Re_f(t)}{v(t)} \tag{18}$$

And the total time, which the MR_f spends for collecting data from N_f sensor nodes, is given in (19).

$$t_{collecting}(t) = \frac{\gamma N_f}{R} \tag{19}$$

By inserting (18), (19) into (17), the reporting time can be given as in (20).

$$\xi(t) = \frac{\gamma N_f}{R} + \frac{\Re_f(t)}{v(t)}. \tag{20}$$

Therefore, total spending time of the MR_f in each operation round is given as

$$\left(\frac{\Re_f(t)}{v(t)} + \frac{\gamma N_f}{R}\right) \leq \xi_0 \ .$$

The question here is how to determine the optimal trajectory of the MR within its assigned area, where each MR can travel with reasonable speed ($v(t)$) along the shortest possible path to collect data, as defined in (16)? To answer this question, we propose a heuristic solution to find the optimal trajectory of the mobile robot by solving the vehicle routing problem. The proposed solution is designed to satisfy the following requirements:

- Minimizing the total length of the mobile robot's trip.
- Each cluster head node has to be visited by a mobile robot within a threshold of reporting time ξ_0, which means that no CH can be overflowed.
- Mobile robots are supposed to complete their individual trajectories within a threshold of reporting time ξ_0.
- In order to minimize the system cost, the trajectory of each mobile robot is designed to be non-overlapping.
- There is also no overlap between two or more trajectories of different mobile robots.

We consider that, all cluster head nodes, to be visited by a mobile robot, are distributed over a region of circular sector. The sector vertex will be on the NCC, which serves as both the starting and ending point of the mobile robots trajectory. It can be seen in Fig. 4, in order to find the trajectory of the MR, the circular sector is divided into three parts including two right triangles ($\Delta C_1C_2C_3$, $\Delta C_1C_3C_4$) and a circular segment $\Delta C_4C_5C_2$. As indicated in [66], when connecting all visiting points (CHs' positions) in each part, we will get three open paths. Fig. 4b illustrates the open path of each path. The trajectory of the MR will be found when we join these paths together. The trajectory of the MR is shown in Fig. 4c.

The total path length of the MRs depends not only on the sector angle $\varphi_f, f \in (1, ..., F)$, number of CHs need to visit, total number of sensor nodes within the assignment area of the MR_f, but also on the geographic positions of the CHs. Therefore, according to the threshold ξ_0, the sector angle φ_f will be adjusted in order each cluster head node in the circular sector will be visited within the reporting time.

Choosing the sector angle for each MR

As can be seen in Fig. 4a, if the average radius of circular sector is $l_f = 0.5\,(l_{f1} + l_{f2})$, the acreage of the circular sector is

$$H_f = \frac{\varphi_f l_f^2}{2} \tag{21}$$

The number of nodes inside the assignment area of the MR_f is:

$$N_f = \rho H_f \tag{22}$$

Inserting (21), (22) into (16), we have:

$$\varphi_f \leq \frac{2R}{\gamma\rho l_f^2}\left(\xi_0 - \frac{\Re_f(t)}{v(t)}\right) \tag{23}$$

Considering the Assignment Area of The MR_f, we have

$$\min\{\Re_f(t)\} \geq 2l_f \tag{24}$$

Therefore, the equation (23) can be rewritten as

$$\varphi_f \leq \frac{2R}{\gamma\rho_f^2}\left(\xi_0 - \frac{2l_f}{v(t)}\right) \tag{25}$$

By (25), we can choose the suitable sector angle (φ_f) of the MR_f assignment area, which guarantees that all sensing data can be transmitted in time to the BS.

Optimizing the Trajectory of the MR_f Inside Its Assignment Area

Let $G = (V, E)$ be a connected digraph including a set of $M+1$ visiting points (M CHs and one NCC), each of which can be visited only within a threshold visiting time ξ_0, and E is the set of edges.

Parameters:

- $x_{ijf} \in \{0, 1\}$, 0 if there is no arc from node i to node j, and 1 otherwise $i \neq j; i, j \in \{0, 1, ..., N\}; f \in \{0, 1, ..., F\}$;
- N total number of nodes;
- M total number of clusters;
- F total number of utilized mobile robots;
- ξ_{ij} denotes a cost (execution time for data propagation and the MRs traveling from node i to node j).

Objective:

$$\min\left\{\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{i\neq j, f=1}^{F}\xi_{ij}x_{ijf}\right\} \tag{26}$$

Subject to:

$$\sum_{f=1}^{F}\sum_{j=0}^{N}x_{ij} \leq F, \quad \text{for } i = 0 \tag{27}$$

$$\sum_{i=1}^{N}x_{ijk} = 1 \quad \text{for } j = 0 \quad \text{and } f \in \{1, ..., F\} \tag{28}$$

$$\sum_{j=1}^{N}x_{ijk} = 1 \quad \text{for } i = 0 \quad \text{and } f \in \{1, ..., F\} \tag{29}$$

$$\sum_{f=1}^{F}\sum_{j=0, j\neq i}^{N}x_{ijk} = 1 \quad \text{for } i \in \{1, ..., N\} \tag{30}$$

$$\sum_{f=1}^{F}\sum_{i=0, i\neq j}^{N}x_{ijk} = 1 \quad \text{for } j \in \{1, ..., N\} \tag{31}$$

$$\sum_{i=0}^{N} \sum_{j=0, i \neq j}^{N} \xi_{ij} x_{ijk} \leq \xi_0 \quad \text{for } f \in \{1, ..., F\} \tag{32}$$

Constraint (27) enforces the number of utilized mobile robots is always less or equal to F, whose trajectories start and end from the NCC $(i, j = 0)$. Constraint (28) implies that each MR has only one outgoing arc from the NCC. Constraint (29) ensures that there is only one entering arc into the NCC. Constraints (30) and (31) guarantee that one CH is only visited by a MR. Finally, constraint (31) guarantees that total time of a MR for traveling and collecting data is always smaller than the threshold reporting time. The optimal trajectory of the MR is shown in Fig. 5.

The process of optimizing the trajectory of the mobile robot is given in algorithm 1 and Fig. 3.

Algorithm 1 The OTMR algorithm

1: **Input:** Parameters of model: Number of sensor nodes N, Network size l_1xl_2; The velocity of the mobile robot (v); Initial energy E_0; Threshold of reporting time ξ_0; γ-bit data packet; Node density (ρ); Transmission range R;

2: **Output:**
- ⋆ The number of optimal subareas M;
- ⋆ The number of utilized mobile robots F;
- ⋆ Assignment area to collect data for each MR φ_f;
- ⋆ The optimal trajectory of each MR at each operation round $\Re_f(t)$.

3: Estimate the number of cluster (M) for energy efficient deployment scheme in WSNs based on equation (6);

4: Estimate the assignment area (25) for each MR and then calculating the number of MRs need to be utilized for data collection. Steps 3 and 4 will be done by the NCC. After these steps, the NCC will flood this information to all sensor nodes in the sensing field. By this way, every sensor node know its cluster and the MR's assignment area, where it belongs to. Then every sensor node in each cluster will elect their cluster head node. The locations of these cluster head nodes will be sent back to the NCC to find the optimal trajectories of F mobile robots.

5: Finding the optimal trajectory of each MR in its assigned area can now be considered as a vehicle routing problem (VRP). It notices that, the NCC knows all the CH locations in each MR assignment area.

6: Begin the trajectory of the MR_f starting from the NCC (the depot) $\Re_f^{i=0}$.

7: Among all unvisited CHs inside the assignment area of MR_f, select the farthest CH from the NCC and add into the current trajectory of the MR_f: $\Re_f^{i=1}$.

8: If all CHs are visited, then goto step 11. else: Go to step 10 if the reporting time $\xi(t)$ of the MR_f involved in the current trajectory $\Re_f^i$ is exceeded. Find the best candidate node among unvisited CHs, which the MR_f is expected to visit with the smallest spending time.

9: Pick the CH with the smallest spending time and add it into the current trajectory $\Re_f^{i=i+1}$. Update the reporting time $\xi(t)$ of the MR_f. Go to step 8

10: Start new trajectory of the new mobile robot $f = f + 1$; goto step 7.

11: The algorithm will be terminated with F optimal trajectories of the mobile robots.

IV. Performance Evaluation and Discussion

In this section, the simulation results of our algorithm is performed in MATLAB environment.

A. Simulation Environment

In our simulations, the setting parameters are given in Table I. One sensor node can neither transmit, nor sense data, is called dead node if its residual energy is lower than $\theta = 0.0001$(J).

TABLE I. The Settings of Simulation Parameters

Parameter	Value
Node deployment & Random	Uniform
initial energy (E_0)	0.1 (J)
Energy for data aggregation (E_{DA})	5 (nJ/bit)
E_{elec}	50 (nJ/bit)
ε_{fs}	10 $(pJ/bit/m^2)$
ε_{mp}	0.0013 $(pJ/bit/m^4)$
Maximum speed (v_{max})	25 (m/s)
Packet length (m)	4000 $(bits)$
Transmission range (r)	30 (m)
Data transmission rate (R)	250 (Kb/s)
Reporting time (ξ_0)	60 (s)

B. Numerical results and discussion

a) Performance Analysis of the Mobile Robot Trajectory: In this section, a series of numerical experiments were carried out in order to measure the execution time $(\xi_f, f \in \{1, ..., F\})$, and the length $\Re_f(t), f \in \{1, ..., F\}$ of each utilized mobile robot trajectory. Figure 5 shows the optimal trajectory of the MR with the smallest spending time. Table II summaries the results from two scenario experiments with different network size (200x200, 150x150) and the number of node deployment (N= 250, 200). The simulation results show that all the case experimental results, each mobile robot travels in the shortest path to collect all sensed data in its assignment area within the the reporting time. In the first scenario, 250 sensor nodes are deployed uniformly over 200m x 200 m area.

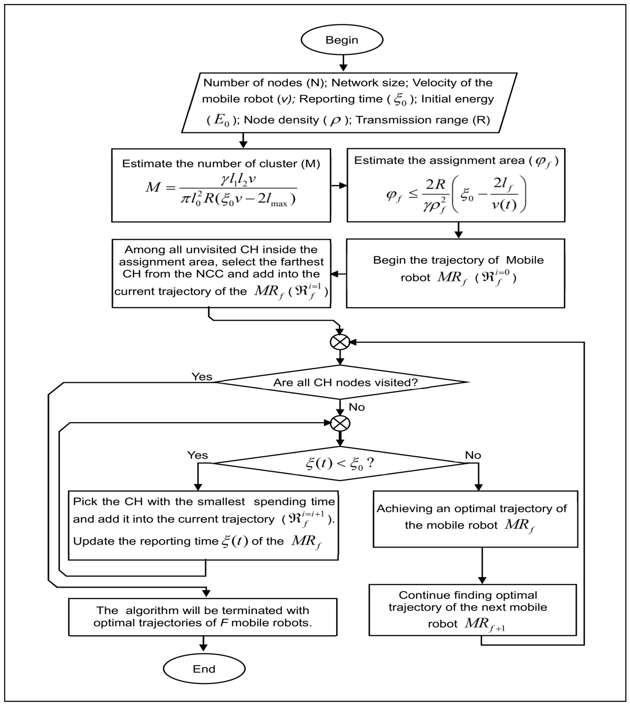
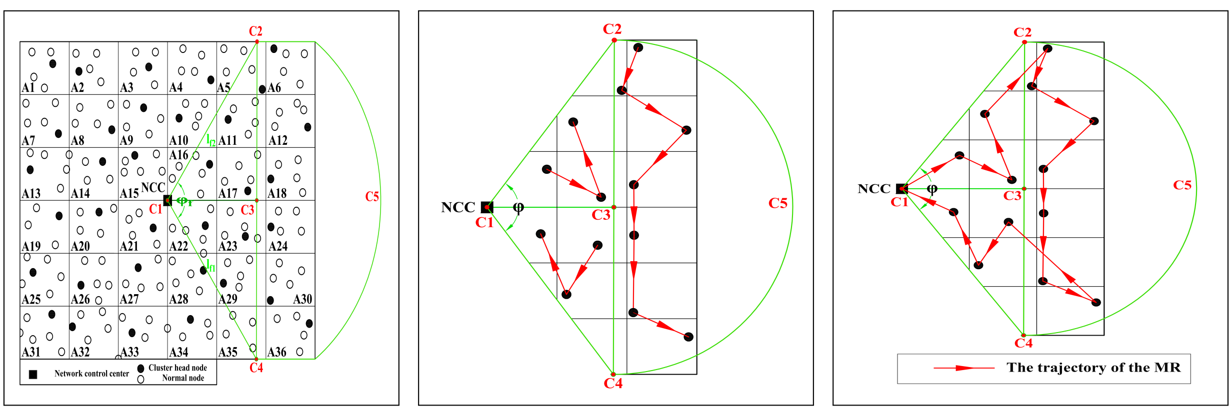


Fig. 3. The Flowchart of the Proposed Algorithm



(a) The division of the circular sector (b) The open path of each part (c) The trajectory of the MR

Fig. 4. The MR Trajectory by Solving the Geometric Traveling Salesman Problem

It is observed that four mobile robots are required to simultaneously collect data from the nodes in sensing field. Each robot moves at a speed of 8 m/s within the individual travel time ranging from 54.2 seconds to 59.5 seconds. In the second scenario, 200 sensor nodes are deployed within a 150 Œ 150 m sensing area. It shows that the network density is significantly lower compared to the first case. As shown in the Table II, to ensure complete data collection from all nodes, three mobile robots are required, each traveling at a speed of 7 m/s. These results suggest an effective distribution of the data collection workload and indicate that the proposed approach is able to adjust automatically the number of deployed mobile robots in a flexible manner, while consistently ensuring that all sensed data are collected completely, reliably, and within the allowable time constraints.

We further conducted experiments by varying the network density to evaluate its impact on network lifetime and to determine the number of utilized mobile robots to ensure all the sensed data is collection within a specified time. The simulation results presented in Table III indicate that increasing the transmission radius of each sensor node leads to a significant reduction in the overall network lifetime.

TABLE II. ESTIMATES THE LENGTH TRAJECTORY AND THE EXECUTION TIME OF THE MR

No.	Network size		N	ξ_0	F	v (m/s)	Length of MR trajectory (m)				Execution time ξ (s)			
	l_1 (m)	l_2 (m)					$\Re_1(t)$	$\Re_2(t)$	$\Re_3(t)$	$\Re_4(t)$	$\xi_1(t)$	$\xi_2(t)$	$\xi_3(t)$	$\xi_4(t)$
1	200.0	200.0	250.0	60.0	4.0	8.0	397.5	391.8	395.1	399.3	58.1	54.2	56.4	59.3
2	200.0	200.0	250.0	60.0	4.0	8.0	395.4	399.3	396.3	397.5	56.6	59.3	57.3	58.1
3	200.0	200.0	250.0	60.0	4.0	8.0	391.5	394.5	399.0	398.1	54.0	56.0	59.1	58.5
4	200.0	200.0	250.0	60.0	4.0	8.0	389.4	395.1	391.2	394.5	52.6	56.4	53.8	56.0
5	200.0	200.0	250.0	60.0	4.0	8.0	399.3	391.5	399.6	396.0	59.3	54.0	59.5	57.1
6	200.0	200.0	250.0	60.0	4.0	8.0	399.6	399.3	398.1	399.6	59.5	59.3	58.5	59.5
7	200.0	200.0	250.0	60.0	4.0	8.0	391.8	397.2	396.9	394.8	54.2	57.9	57.7	56.2
8	200.0	200.0	250.0	60.0	4.0	8.0	395.1	399.0	394.2	395.1	56.4	59.1	55.8	56.4
9	200.0	200.0	250.0	60.0	4.0	8.0	396.6	392.4	397.5	397.8	57.5	54.6	58.1	58.3
10	200.0	200.0	250.0	60.0	4.0	8.0	394.8	393.6	395.4	398.7	56.2	55.4	56.6	58.9
11	150.0	150.0	200.0	60.0	3.0	7.0	348.1	349.3	349.2	0.0	49.5	50.8	50.7	0.0
12	150.0	150.0	200.0	60.0	3.0	7.0	349.6	348.4	347.6	0.0	51.1	49.8	49.0	0.0
13	150.0	150.0	200.0	60.0	3.0	7.0	350.0	348.2	348.8	0.0	51.5	49.6	50.2	0.0
14	150.0	150.0	200.0	60.0	3.0	7.0	347.9	349.7	349.7	0.0	49.3	51.2	51.2	0.0
15	150.0	150.0	200.0	60.0	3.0	7.0	348.6	347.9	347.2	0.0	50.0	49.3	48.6	0.0
16	150.0	150.0	200.0	60.0	3.0	7.0	348.2	348.8	348.7	0.0	49.6	50.2	50.1	0.0
17	150.0	150.0	200.0	60.0	3.0	7.0	349.3	349.1	348.1	0.0	50.8	50.6	49.5	0.0
18	150.0	150.0	200.0	60.0	3.0	7.0	348.6	347.6	349.3	0.0	50.0	49.0	50.8	0.0
19	150.0	150.0	200.0	60.0	3.0	7.0	348.3	348.9	349.6	0.0	49.7	50.3	51.1	0.0
20	150.0	150.0	200.0	60.0	3.0	7.0	349.7	349.9	348.4	0.0	51.2	51.4	49.8	0.0

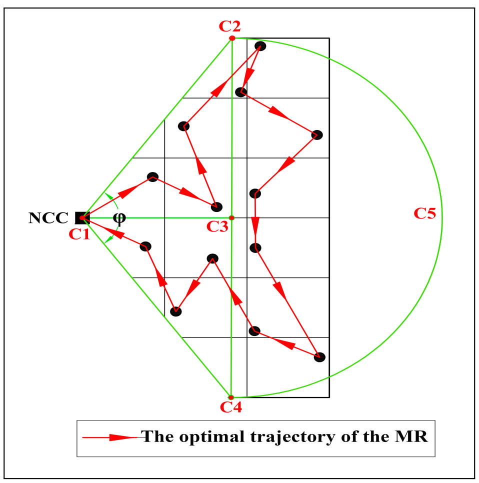


Fig. 5. The Optimal Trajectory of the Mr by Solving the Geometric Traveling Salesman Problem

This phenomenon is clearly supported by Equation (2), which demonstrates that the energy consumption for wireless communication increases exponentially with transmission range. Conversely, when the transmission range is reduced, more mobile robots are required to ensure complete data collection, thereby increasing operational costs. This also introduces additional complexity in robot coordination and data aggregation from multiple sources. These findings highlight a fundamental trade-off between communication energy consumption and mobility-related costs. Larger transmission ranges reduce the need for robot mobility but accelerate energy depletion at the sensor nodes, thereby shortening network lifetime. In contrast, minimizing node-level communication energy by using shorter transmission ranges requires a greater number of mobile robots, thereby increasing system-level costs and control complexity. Therefore, an optimal configuration must balance transmission power and robot deployment to ensure both energy efficiency and scalability in practical WSN applications.

TABLE III. NETWORK LIFETIME UNDER VARYING THE NETWORK SIZES AND THE NETWORK DENSITIES

No.	Network size		N	r (m)	F	Network lifetime
	l1(m)	l2(m)				
1				10.0	6.0	3417.0
2				15.0	5.0	3364.0
3				20.0	5.0	3311.0
4				25.0	4.0	3258.0
5	200	200	250	30.0	4.0	3125.0
6				35.0	4.0	3056.0
7				40.0	3.0	2542.0
8				45.0	3.0	2318.0
9				50.0	2.0	1872.0
10				55.0	2.0	1561.0
11				10.0	4.0	3381.0
12				15.0	4.0	3325.0
13				20.0	4.0	3247.0
14				25.0	3.0	3115.0
15	150	150	200	30.0	3.0	3057.0
16				35.0	3.0	2465.0
17				40.0	2.0	2084.0
18				45.0	2.0	1912.0
19				50.0	2.0	1815.0
20				55.0	2.0	1673.0

b) Performance Analysis of the Network Lifetime: Prolonging the network lifetime of WSNs is an important issue in many studies [1], [67]–[79]. It is also proved that employing mobile robots is among the most effective strategies for enhancing network longevity to improve the network lifetime [1]. In this subsection, the performance of our proposed OTMR algorithm is evaluated and compared with three similar methods. The first traditional method is utilizing mobile sinks nodes which moving along the network boundary for data collection

[22], [80].

The second algorithm is OMS1 [1], a single mobile sink moving on the shortest path for data collection. The final algorithm is OMS2 [1], which sends a number of mobile sinks to their network field for data collection. The simulation esults of network lifetime with varying numbers of sensor nodes from 10 to 250 are presented in Fig. 6. From Fig. 6, one can infer that our proposed OTMR algorithm outperforms the other two algorithms in [22] and OMS1 algorithm in [1]. In [22], the mobile sinks move along the network boundary to gather monitored data in different location areas. In this case, some sensor nodes were located in the center of the field, which were far from the parking positions of mobile sinks, may consume more energy than other sensor nodes. In OMS1 algorithm [1], the cluster head nodes have to change their transmission range, which may increase the energy consumption exponentially. These factors lead to an imbalanced energy consumption among nodes in the network.

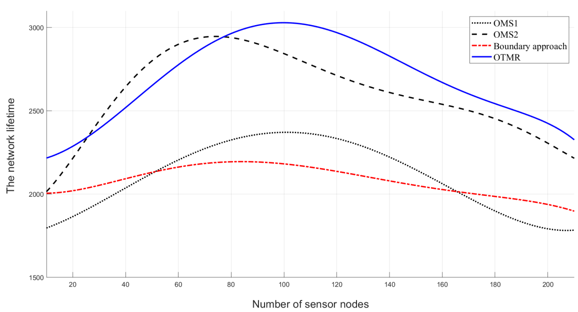


Fig. 6. The comparison of the network lifetime

Therefore, achieving balanced energy consumption among sensor nodes [81]–[83] in the network after each operational round is a critical factor, which affects the network lifetime. Given higher balance energy consumption among sensor nodes in the network, our proposed OTMR algorithm and OMS2 algorithm in [2] achieve higher network lifetime than OMS1 algorithm and the algorithm proposed in [22]. Based on the results obtained from 350 experimental trials, the maximum network lifetime achieved using the OMS2 algorithm was 2,964 rounds. In contrast, our proposed algorithm consistently outperformed OMS2 under identical experimental conditions, achieving a higher average maximum network lifetime of 3,125 rounds. This represents an improvement of approximately 5.4%. To assess the statistical significance of this difference, we performed a two-sample t-test, which confirmed that the observed improvement is statistically significant at the 95% confidence level ($p < 0.05$). These findings suggest that our algorithm not only extends network longevity but also maintains consistent performance, underscoring its practical advantage in real-world sensor network deployments. It means that our proposed algorithm can improve the network lifetime by up to 5.4% compared to the OMS2 algorithm. Based on these numerical results, our proposed method outperforms the traditional methods and can be applied in any application that requires the timely transmission and reception of monitored data at the lowest cost.

Our proposed approach for sensed data collection in the sensing field involves interdependent steps, including estimating the number of clusters (M), assigning a great number of mobile robots to their assigned subregions, and solving the Vehicle Routing Problem (VRP) to determine optimal trajectories. The clustering phase is based on geometric partitioning, which has linear complexity $\mathrm{O}(N)$ with respect to the number of sensor nodes N. Unfortunately, the optimal trajectory-finding process is based on the VRP, which is NP-hard. To address this, we use a heuristic approach that reduces the per-robot complexity to approximately $\mathrm{O}(K)$, where (K) is the number of cluster heads in the sensing field. This ensures practical feasibility for medium-scale networks, while further optimization may be needed for large-scale or dynamic scenarios.

However, our achieve results in this study are based on several assumptions regarding the structure of WSN, as given in Section II. First, it is assumed that N sensor nodes in the network are uniformly distributed in the sensing field. However, the density of the WSNs may vary depending on the criticality of the sensed data in each monitoring area. Second, the utilized mobile robots are assumed can move freely in the sensing field without energy constraints. Specifically, this study assumes that the residual energy of each mobile robot is continuously monitored. If its residual energy is lower than a predefined threshold (the remaining energy is insufficient to complete its next assigned task), these mobile robots automatically return to the NCC for recharging themselves. Nevertheless in practice the energy consumption of mobile robots is highly dynamic and cannot always be accurately predicted. Furthermore, the energy storage capacity of the mobile robots is limited and they may not be able to harvest sufficient renewable energy in a timely manner to sustain its continuous operation. These practical constraints should be carefully considered in the real field conditions.

V. Conclusions

This paper presented a geometric solution to find optimal trajectories of the mobile robots, enabling them to collect all sensed data in sensing filed within a desired deadline with the smallest energy consumption. The main advantage of the proposed approach is that the trajectory of each mobile robot is optimized based on solving the traveling salesman problem. Another advantage of our proposed approach is that it can estimate both the number of required mobile robots and their respective trajectories which help to find an efficient data gathering without loss of sensed data. Compared to traditional multi-hop or cluster-based routing approaches, the use of mobile robots for data collection significantly enhances energy efficiency by reducing long-range transmissions. Additionally, mobile robots improve the network coverage, particularly in agricultural applications. By reducing the collisions of data packet through short-range communication, the utilized mobile robot for data collection approach is also proven in improving the data fidelity. The simulation results have clearly proven the superiority of our proposed approach, which prolong the network lifetime up to 5.4% than other traditional approaches. We conclude from the proposed approach results that the balancing node energy consumption of the mobile data collection approaches play an important role on the network lifetime improvement.

This work, however, dose not consider the irregular topologies of the network or the security issues associated with data transmission in WSNs based on mobility model. Additionally, limited storage capacity at each sensor node and the computational complexity of path planning poses additional challenges for our proposed approach. Therefore, one of our possible work will focus on enhancing the security of data transmission in WSNs by integrating secure data aggregation techniques into the system architecture. Moreover, secure data collection will be considered to prevent spoofing and replay attacks during data collection. To overcome the limited storage capacity of sensor nodes, some data collection techniques in WSNs, such as data compression and filtering to eliminate redundant data, will be implemented and reported in future publications.

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