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A New Nonuniform Random Deployment Method to Minimize Cost for Large-Scale Wireless Sensor Networks

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ABSTRACT Network deployment is one of the key research issues of Wireless Sensor Networks(WSNs), and it has an essential impact on the performance of the network. Due to the geographical environment limitation, random deployment has become a critical deployment method. There are many random deployment methods, and they focus on different network performance (network coverage, connectivity, energy efficiency, lifetime, and so on). This paper proposes a nonuniform random deployment method to minimize the network cost for homogeneous WSNs. Firstly, we define the problem to be solved and give an optimization model. A new cost concept is defined that combines several measurements, such as covered area, lifetime, and cost. Secondly, based on the theoretical analysis of energy consumption, node density, and network cost, a new deployment method and corresponding routing strategy are proposed. To ensure energy efficiency and minimize cost, a multi-sink and corona structure is adopted. Finally, simulation experiments verify the effectiveness of the method by comparing it with the other four random deployment methods. Compared with the other four methods at the two densities, the cost is reduced by at least 40% (density is 0.04) and 24.1% (density is 0.025), respectively.

INDEX TERMS Wireless sensor networks, random deployment, minimize cost, energy consumption.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) is composed of a large number of wireless sensors equipped with sensing, computation, storage, and communication capabilities to monitor a region. They can collect surrounding information and then transmit data to the sink or base station. WSNs are utilized to gather information about environmental and habitual monitoring, disaster managing, production control, traffic management, and so on. As the sensors have limited energy, transmission and sensing range, there exist many open research challenges.

The sensors' location can affect the fulfillment of the applications' requirements and multiple network performance metrics, such as connectivity, coverage, lifetime, and cost. Network deployment is a fundamental design issue in WSNs. The two major types of deployments are deterministic and non-deterministic placement. In the former, the position of sensors is pre-computed prior. The non-deterministic deployment is also called random deployment that sensors are randomly scattered in an interesting region. The selection of a suitable approach depends on many factors, such as the application needs and nature of the monitor region. The deterministic deployment is impractical sometimes due to the large-scale of networks, or the inaccessibility of the terrain(battlefield, disaster region). In this case, random deployment becomes the only option. Whatever type of deployment, the sensors in the networks can be homogeneous or heterogeneous. The first uses the same sensors, and the second contains the sensors with different features (e.g., sensing range, energy). Much research has been done in the field that focuses on different network performance, such as connectivity, coverage, energy efficiency, network cost, and so on.

A sensor can collect information within its sensing range and transmit to another sensor(or the sink node) within its communication range. The energy of sensors has been

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consumed while sensing, sending, and receiving data. The battery energy of sensors is limited and not be replenished once it gets exhausted. Reducing energy consumption and increasing energy efficiency can extend network lifetime. In large-scale networks, the multi-hop model is adopted. The sensors near the sink have a higher load than the remote sensors form the sink in a uniformly deployed WSNs. It causes the 'Energy Hole Problem' that there are still significant amounts of residual energy in the sensors while the network becomes invalid. That energy is wasted to make the network cost increase significantly. Researchers have proposed various schemes for deployment to avoid the problem [1], such as nonuniform node distribution schemes, multi-sink deployment, mobile sink deployment, cluster-based deployment, and so on.

In this work, we focus on homogeneous WSNs, and non-uniformly deploy sensors in large-scale filed to minimize the network cost under satisfying various performance requirements. To sum up, the main contributions are presented as follows.

1) We introduce an optimization model that minimizes cost per area and time, and give the relevant theorems through the analysis of node density and energy consumption.
2) We propose a nonuniform random deployment method, corresponding network topology, and data routing strategy.
3) We simulate the proposed deployment algorithm and compared it with four other random deployment methods to verify its effectiveness.

In the remainder of the paper, we review the literature on the deployment of WSNs in Section II. The related knowledge and concepts are introduced in Section III. We give the problem formulation and a programming model in Section IV. A nonuniform random deployment strategy has been presented in Section V. Some numerical analysis and simulation results are in Section VI. The paper will be summarized in Section VII. Finally, Section VIII gives the acknowledgment.

II. RELATED WORK

The deployment of WSNs affects almost all its performance metrics. The coverage, connectivity, energy efficiency, lifetime, and cost are the several most essential metrics. In the large-scale field or the inaccessibility/harshness field, random deployment becomes only one option, and the sensors can be deployed from a plane or other aerial vehicle. In this section, we review the literature related to random deployment and energy efficiency.

Random deployment is the most practical way of placing sensors. The position of sensors is defined by a probability density function. There are two classes random deployment strategies, simple strategies and compound strategies [2]. The simple strategies contain Simple diffusion [3], Continuous diffusion [4] and Discontinues diffusion [5]. In [3], this deployment process was modeled by a linear diffusion equation; the sensor's position follows a two-dimensional normal distribution. The paper [4] presented continuous diffusion that the sensors are thrown off an aircraft that flies over the middle of the field. The x and y of the sensor's position follow the uniform distribution and normal distribution, respectively. Discontinuous diffusion proposed in [5] was defined as follows: sensors are thrown discontinuously in a single flying-over. Some sensors can be dropped in each throw and multiple throws were carried out. A compound random strategy is realizable by repeated simple diffusions. The constant diffusion [6], [7] means that the sensors' density is constant in the field. The R-random diffusion was proposed in [3], where the nodes are uniformly scattered with respect to the radial and angular directions from the sink. It simulates the effect of an exploded shell that the density of sensors is higher near the sink. In the exponential law model [8], the probability density of sensor-positions follows an exponential law. The Power law strategy in [9] means the degree of the sensors follows a power law. Its features are similar to those of the R-random. In [10], a partition-based random node placement algorithm was proposed. A rectangular area is classified into small cells and up to one sensor in one cell. In [11], the hybrid diffusion mode are proposed. Some nodes follow the simple diffusion strategy and others follow the constant diffusion.

The theoretical analysis of random deployment strategies is complicated. In paper [12], [13], the WSNs were typically modeled as random graphs based on its characteristics of topology. To detect the distance between sensors, the Random Geometric Graphs(RGG) [14] are used to depict WSNs. The paper [6], [15] gave the relation between the transmission range of sensors and the connectivity of RGG. The paper [16] gave an analytical expression for estimating the average minimum number of nodes for getting full connection of networks, and study several graph metric properties of the networks such as mean shortest path, mean clustering coefficient, etc.

The percolation theory is used to analyze coverage and/or connectivity. The [17] proposed a probabilistic approach to compute the covered area fraction at critical percolation for both of the SCPT and NCPT problems. In [18], a novel framework was proposed for solving optimal deployment problems for randomly deployed and clustered WSNs. The percolation theory is adopted to analyze the degree of connectivity when the targeted degree of partial coverage is achieved.

Many researcher focus on the relocation of Mobile sensors after random deployment. In these schemes, sensors were initially deployed by dropping from the flying machine (helicopter, airplane, etc.) over the interesting region. In order to optimize the deployment, sensors mounted on a mobile device can change their position during the relocation phase. Virtual Force Method was used to change the position of sensor [19]–[21]. Each sensor exerts a force on other sensors. The force can be attractive or repulsive, depending on the distance of the sensors. The sensors move to a new position with the resultant force, come close to uniformly spread in the candidate region, and increase the coverage. In [22], a distributed scheme for the homogeneous deployment of MSNs was presented for complete coverage. The entire scheme is divided into four basic activities, namely, Snap, Push, Pull, and Tiling merge. It does not require prior knowledge of the working scenario nor any manual tuning of key parameters. The sensors make movement decisions based on locally available information. Authors of [23] proposed a distributed deployment scheme for homogeneous distribution of randomly deployed mobile sensor nodes in WSNs. The deployment area is divided into a number of concentric regions centered at Base Station. These regions are separated by half of the communication range, and further deployment area is divided into numbers of regular hexagons. The mobile sensors will set themselves at the center of the hexagon on the instruction provided by the BS to achieve maximum coverage and better connectivity.

In order to balance the node's energy consumption and extend the lifetime under energy-constrained WSNs, the energy efficient clustering schemes have been used. The authors of [18] proposed a novel framework to solve optimal deployment problems for randomly deployed and clustered WSNs. They introduced cluster size formulations. The cluster size concept serves as a useful tool to estimate partial coverage, and this estimated value is the primary constraint in Optimal Deployment(OD) problems. The framework provides a designer with the opportunity to introduce any combination of various constraints to OD problems in addition to partial connected coverage and to solve these optimization problems accordingly. In order to solve such defects as uneven distribution of cluster heads and fast energy consumption. The paper [24] put forward an energy-efficient cluster routing protocol that the energy of each node and its distance to the sending node are fully considered for cluster head selection and cluster formation. Each cluster head determines its set of relay nodes according to the minimum hop-count algorithm and the residual energy of each node. In paper [25],A clustering Algorithm for Energy-Efficient Adaptive(EEA) was proposed for reducing the data communication distance in WSNs. The routing protocols can be implemented for homogeneous and heterogeneous networks. The results show that the proposed scheme is more efficient than other protocols. In paper [26], an enhanced low-energy adaptive clustering hierarchy (LEACH) protocol was proposed to prolong the network lifetime and reduce the packet loss for mobile sensor networks. The fuzzy inference systems were adopted to the cluster head selection. The paper [27] gave a survey about clustering and cluster-based multi-hop routing protocols. Some parameters are given to evaluate the properties of the different methods. The studied methods are classified into four categories: classical approaches, fuzzy-based approaches, metaheuristic-based approaches and hybrid metaheuristic- and fuzzy-based approaches. In each category of the classification, criteria and parameters are presented according to the type of methodology.

When the WSNs are composed of a large number of sensors, their monitoring ranges overlap. Therefore, not all the sensors have to be active all the time. In order to maximize network lifetime, sensors activity schemes that guarantee satisfying coverage and connectivity have been developed in much research. The author of [28] proposed a mixed integer programming formulation, i.e., SPSRC, that combines all design issues in a single model. The SPSRC finds the sensors' and sinks' optimal locations, active/standby periods of the sensors, and the data transmission routes from each active sensor to its assigned sink. In [29], centralized activity strategies have been given. The set of sensors is divided into subsets, which can be disjoint or non-disjoint so that every subset completely covers the sensing field. Each subset is activated successively one at a time for different periods. In paper [30], a subtraction deployment strategy (SDS) combined with the unequal node duty cycle in the network was presented. This strategy improves the duty cycle of nodes in non-hotspots area when reduces the number, thereby minimizing the deployment cost under the premise of meeting the detecting quality requirements. In [31], the optimization problem of the network energy efficiency without loss of its communication reliability was transformed into Integer Linear Programming. A solution, called Sense-Sleep Tree, is a group of sensors that are connected to each other. For maximizing WSNs lifetime, authors of [32] presented three heuristic algorithms for sensors activity scheduling: a random and fine-tuning approach, an approach inspired by cellular automata, and a hypergraph model approach. Then a local search strategy has been employed to improve the solutions obtained. In paper [33], an enhanced clustering hierarchy approach(ECH) has been proposed for WSNs. The ECH uses sleeping-waking mechanism for the neighboring and overlapping nodes to minimize data redundancy. The main objective of our approach is to maximize lifetime by minimizing data redundancy in WSNs. In paper [34], a packet routing scheme was proposed to reduce channel competition conflicts and energy consumption, increase network throughput, and then reduce end-to-end delay in data transmission for WuR-enabled WSNs. The scheme combines the selection of the relay node with the consecutive packet routing scheme, which greatly improves the performance of the network.

For balancing energy consumption of sensors, the mixed/hybrid transmission schemes appeared in many paper [35]. Each sensor can adjust its transmission power level and alternates between direct transmission mode (sending data directly to sink without using any relay node) and hop-by-hop transmission mode (forwarding data to next-hop neighbors). Efthymiou *et al.* [36] proposed a solution in which the probability of next-hop transmission depends on the distance of a node from the sink and the number of ring sectors in the network. Zhang *et al.* in [37] computed the probability of next-hop transmission based on the distance and the number of sensors in a slice. They assume a uniform deployment of the nodes in the network area.

Boukerche *et al.* in [38], Boukerche and Efstathiou [39] considered heterogeneous/non-uniform networks and use a mixed-hop transmission scheme to balance energy consumption. The relative densities of the nodes in the neighborhood are considered while making the decision. In addition to hop-by-hop transmission and direct transmission, by-pass transmissions are used. Erdun *et al.* in [40] proposed a solution for calculating the probability values depending on the distance of the nodes from the sink and the number of sensors in adjacent slices for clustered wireless sensor networks. Wang and Tan in [41] presented a Distributed Adaptive Probabilistic Routing algorithm (DAPR). The sensors can self adjust their routing probability values locally to their next hop forwarder based on their neighborhood information and converge to an optimal value.

In this article, we propose a nonuniform random deployment strategy to minimize the cost of large scale homogeneous WSNs. The approach comprehensively considers vital metrics such as regional coverage, network connection, and network lifetime, and designs a corresponding data routing strategy.

III. PRELIMINARIES

This section gives the related concepts and models.

A. RANDOM NODE DEPLOYMENT

In random node deployment, sensor positions are defined by a Probability Density Function (PDF). Depending on the deployment strategy, the coordinates of the sensor positions may follow a particular distribution [11]. A sample way is that the node's density is constant and the node distribution is uniform in the area. The PDF of the sensor positions is given by the following equation:$f(x) = \frac{1}{|A|}, x \in R^2$, where $|A|$ is the area of the Region of Interest(RoI). The number of sensors n in area follows the Poisson distribution with parameter (mean)$\lambda > 0$. The probability $Pr(n = k) = \frac{e^{-\lambda}\lambda^k}{k!}$. When λ is not a constant, we have an inhomogeneous Poisson point process [42]. The mean number of sensors in area $n(A) = \int_A \lambda(u)du$.

B. ENERGY MODEL

The sensor has a fixed sensing range, transmission radius, and energy. During the network work, a sensor's energy consumed can be divided into two categories: the consumption related to the amount of data and other consumption. The former includes the energy consumption of generating data, transmitting data, and receiving data. The latter includes the energy consumption of other network operations, e.g., the establishment of routing, time synchronization, and idle listening. The first type of energy is our concern. The energy consumed per unit time by a sensor $e = e_s \times x + e_r \times y + e_t \times z + e_0$, where e_g, e_r, e_t, e_0 stand for the energy consumption of generating unit data, receiving unit data, transmitting unit data, and no relation to the amount of data respectively. The e_t is related to transmission distance. $e_t = e_1 + e_2 d^k$, there d is transmission distance, k is path loss exponent$(2 \leq n \leq 4)$.

In the uniformly deployed and multi-hop WSNs, the sensors near the sink need to relay more packets from other sensors to the next node, and their energy depletion is faster than other sensors. The uneven energy depletion triggers the ''Energy Hole Problem'' and reduces energy efficiency. A considerable amount of energy is wasted so as to make the network cost increase significantly.

C. NETWORK LIFETIME

The Network Lifetime(NL) is the total amount of time during which the network can maintain the operational or desired performance. The NL is one of the most critical design factors in WSNs. The NL's definition depends on the network application and the network structure. So there are various NL definitions. They can be classified into four categories: the node-lifetime based NL, coverage and connectivity based NL, transmission based NL, and parameterized NL [43]. The node-lifetime based NL definitions depend on the lifetime of nodes, for example, the earliest time instant at which any of the sensor nodes in the network fully depletes its battery [44]. The coverage and connectivity based NL definitions are based on the quality of network coverage or/and network connection. In [45], it was defined as the time duration up to the moment when the coverage is lost. The transmission based NL definitions rely on data delivery, for instance, on data reception failure at the sink, on event detection ratio. In paper [46], the parameterized NL was defined to incorporate different aspects for different application scenarios. The definition comprises metrics that have been used in the definitions mentioned above, such as node availability, sensor coverage, and connectivity.

D. COST OF WSNs

Generally, network cost refers to the cost of hardware needed to deploy the network, mainly the cost of sensors and sinks. We call it an absolute cost. In the network design stage, the cost (budget) of the network is closely related to the network lifetime and the size of the detection area. The network costs for different areas and different design lifetime are not comparable. So in this paper, we define the relative network cost(Cost Per Area and Time) associated with the area of RoI and network lifetime. Let c be the cost of a sensor and c^* be the cost of a sink. The Cost Per Area and Time(CPAT) is defined as

$$CPAT = \frac{cn + c^* m}{AT} \tag{1}$$

where n and m are the number of sensors and sinks, respectively, A denotes the area of sensing region, and T denotes the network design lifetime(or the ideal value of actual network lifetime).

E. COVERAGE AND CONNECTIVITY OF WSNs

The sensing range and data transmission distance of each sensor are limited. It has caused some problems about coverage and connectivity of the network. As the measure of the

Quality of Service(QoS) of sensing function for a sensor network, network coverage is one of the most key research issues in WSNs. The goal of coverage is to have each location in RoI within the sensing range of at least one sensor. Depended on the coverage objectives and applications, they can be roughly classified into three categories: area coverage, point coverage, and path coverage. The area coverage means that every single point in the region is monitored by at least one sensor. The main aim of point coverage is to cover a set of points with the known location that needs to be monitored. It can be a particular case of area coverage. Barrier coverage refers to the detection of movement across a barrier of sensors. The network coverage determines the network's ability to access information within the RoI.

A sensor can send signals to any other node within its transmission range. The two sensors are connected if they can communicate with each other by one-hop or multi-hop. The network connectivity is a fundamental concern to ensure that sensing data is transferred to the destination node. The network connectivity problem is closely related to the sensing coverage problem. When the transmission distance is at least twice the sensing range, the set of nodes is connected while their sensing range covers the whole area. Both sensing coverage and network connectivity are necessary to ensure that the area is detected and data can reach the sink.

For random sensor deployment, the requirement for full-coverage (or connectivity) theoretically requires infinitely many (or a massive number of) sensor nodes and is challenging to reach. It will make excessive redundant sensors and increase network costs. Achieving partial connectivity(or coverage) is more realistic and feasible. So the partial connectivity and partial area coverage become the performance measure for the random deployed WSNs. The partial area coverage tolerates the field's monitoring to some extent, leaving the remaining areas uncovered. The partial network connectivity means not all the sensor nodes are connected with the sink.

F. THE PERCOLATION MODEL

Percolation processes were introduced by Broadbent and Hammersley [47] to model the random flow of a fluid through a medium. It can describe the abrupt changes in behavior as a parameter value crosses a threshold. The percolation model is attractive in several areas. Numerous studies have adopted the percolation theory to analyze coverage and/or connectivity in the network domain. It deals with a phase transition phenomenon, where the network exhibits fundamentally different behavior when the node density is below and above some critical node densityλ_0. It means that when node density $\lambda > \lambda_0$, an infinite cluster of overlapping disks appears almost-surely. Glauche *et al.* [48] transformed the problem of finding the critical transmission range of mobile devices to that of determining the critical node neighborhood degree above which an ad hoc network graph is almost-surely connected. In [17], a continuum percolation model which consists of homogeneous disks was adopted to consider the covered area fraction at critical percolation. The Numerical results show that percolation first occurs at covered area fraction $A(r) = 0.575$. For infinite network area, when the Boolean model is used to tackle the connectivity issue, the probability that the network is fully connected is always exactly zero. If the node density λ and the range r are such that $\pi\lambda r^2 > N^*$, for a special constant $N^* \simeq 4.5$, the partial connectivity network is indeed formed by a huge connected component, and the fraction of connected nodes is a deterministic function of the average node degree [49]. For a finite but large area, the fraction of connected nodes is a deterministic function [50].

In this paper, for a required percentage of node connectivity (or area coverage), the sensor's critical density will be determined by reference to the above results. When the density is increased to slightly above it, the probability of meeting the requirement will be very high.

IV. PROBLEM DEFINITION AND OPTIMIZATION MODEL

In this section, we describe the deployment scenario, underlying assumptions, and give the problem definition and constrained optimization model.

A. PROBLEM DEFINITION

The WSNs, considered in this paper, contain two types of nodes: sensor and sink. The sensor is static and equipped with finite energy and ID. It has the functions of sensing the environment, receiving and sending information. The sensing range r_s and transmission radius r_t are fixed. The sink has no limit to energy. When we want to randomly deploy WSNs in a large-scale interesting field, in addition to satisfying some network performance, such as coverage, connection, and lifetime, the network cost must be considered. In this paper, the cost is the comprehensive metrics, defined as for formula 1, which is related to the lifetime, the number of nodes, and the detected area. It is assumed that sensors periodically generate data and transmit data to another sensor or sink. We focus on minimizing the CPAT. The general problem is defined as below.

Definition 1 (MCPAT): There are two types of nodes: sensor and sink. For a given RoI, the Minimum Cost Per Area and Time problem is to find a random nodes deployment strategy to minimize the Cost Per Area and Time under satisfying the requirements of area coverage and network connectivity.

In this problem, the number of sinks and the shape of RoI are not constrained. For simplicity, we consider a particular case in which the RoI is a circular region and a sink deployed in the center of the region. It can be extended to the general problem for large RoI.

Definition 2 (SMCPAT): For a given circular RoI, a sink located in the center of RoI. The Special Minimum Cost Per Area and Time problem is to find a random sensors deployment strategy to minimize the Cost Per Area and Time under satisfying the requirements of area coverage and network connectivity.

B. OPTIMIZATION MODEL

The set $S = \{s_1, s_2 \cdots s_N\}$ is the set of sensors deployed in the RoI that area is A. S_a denotes the set of sensors that are active and connected to sink, $S_a \subseteq S$. The sensors in S_a perform environment detection and data transfer at the time. Based on some policies, S_a can be updated until no sensors of S can be selected. The network lifetime T is defined as the time of work of all S_a. The A_c denotes the area in RoI covered by S_a. For the MCPAT, we can get the optimization model as below. $CPAT = \frac{cn+c^*m}{AT}$.

$$\min \quad CPAT \tag{2}$$

$$\text{s.t.} \quad \frac{A_c}{A} \geq \alpha \tag{3}$$

where α is a threshold value of covered area rate, $0 < \alpha \leq 1$, it depends on the application requirements. When $m = 1, A = \pi R^2$, the model corresponds to the SMCPAT problem, where R is the radius of circular RoI.

For the CPAT is related to network lifetime, the model's solution should include the number and density(location) of nodes and also provide the corresponding network topology structure and routing strategy. In the next section, a random deployment strategy to minimize CPAT will be given.

V. THE RANDOM SENSORS DEPLOYMENT STRATEGY

In this section, we provide a random sensors deployment strategy for the above problem.

A. NETWORK STRUCTURE

We assume the RoI is a circle, and the sensed phenomenon is uniformly distributed over time. To achieve increased network lifetime and the same convention, the suitable position for the sink is the center of the network [51]. The corona based network architecture [52] is adopted. The area is divided into a set of adjacent coronas or concentric circles of radii $R_i, i = 1 \cdots n$. C_i denotes each corona. The width of coronas $C_i^w = R_i - R_{i-1}$ is the transmission radius of sensor r_t. The unequal width coronas structure is not adopted. The reason is that it will increase the hop number of data transmission, which consumes more energy and increases the delay. We assume that a sensor generates l bits of data per unit time to record the environment, and the sensed data are sent to sink at a certain rate by multi-hop transmission mode. Sensors in C_i will forward data generated by themselves and sensors from $C_j((i+1) \leq j \leq n)$ to C_{i-1}. Sensors in C_n only send data generated by themselves to C_{n-1}. The sensors in C_1 can directly send data to the sink. In general, the closer the corona is to the sink, the higher its transport load.

B. ANALYSIS OF DENSITY

For the above network structure, denser nodes should be deployed in the inner coronas to avoid the energy hole problem. The density of each corona will be given in this section. For random deployment networks, many works of literature used theory to discuss network coverage and network connection. The papers [17], [53] give the critical covered area fraction A_c(or critical densityλ_0) at percolation. When the covered area fraction is larger than A_c, almost surely, a Huge Covered Component(HCC) will appear. The covered area fraction is $A = 1 - exp(-\lambda\pi r_s^2)$. However, whether the HCC constitutes a network depends on its connectivity. Percolation theory addresses that if $\pi\lambda r_t^2 > N^*, N^* \simeq 4.5$, then the network is indeed formed by a Huge cOnnected Component(HOC). The fraction of connected nodes $\theta \simeq 1 - exp(-\pi\lambda r_t^2)$, when $\pi\lambda r_t^2$ is large. The covered area of HOC and HCC is different. When $r_t = 2r_s$, the HOC and HCC have the same number of sensors, their covered area is equal. When $r_t > 2r_s$, the number of sensors in HOC is larger than that in HCC. When $r_t < 2r_s$, the number of sensors in HCC is larger than that in HOC. Only the sensed data of sensors in HOC can be sent to the sink. Do not include the disconnected sensors in RoI; the density of sensors in HOC is $\theta\lambda$. The covered area fraction is

$$\begin{aligned} A_r &= 1 - exp(-\theta\lambda\pi r_s^2) \\ &\simeq 1 - exp(-(1 - exp(-\pi\lambda r_t^2))\lambda\pi r_s^2). \end{aligned} \tag{4}$$

Based on the (4), we can estimate the sensor density that satisfes the requirement of the covered area given. It will be a critical density λ_0. The sensor density of the outermost corona is set λ_0. Next, we analyze the density of other coronas. Let A_i denote the area of corona C_i, then

$$A_i = \pi r_t^2(i^2 - (i-1)^2) = \pi r_t^2(2i - 1). \tag{5}$$

The sensed data size(expected value) of corona $D_i = \lambda_0 A_i l$ per unit time. The received data size of each sensor in C_i from outer coronas is

$$RD_i = \frac{\sum_{k=i+1}^{n} D_i}{\lambda_0 A_i} = \frac{l(n^2 - i^2)}{2i - 1}, \tag{6}$$

where we assume that the sensor density is λ_0. The energy consumption of each sensor in C_i per unit time is

$$E_i = le_g + e_r RD_i + e_t(RD_i + l) + e_0. \tag{7}$$

The lifetime of sensor in C_i

$$T_i = \frac{E}{E_i} \tag{8}$$

where E is the initial energy of sensor. Then $T_i^* = T_i$, T_i^* denotes the lifetime of C_i. In order to avoid the energy hole problem and maximize energy utilization, we increase the nodes density of C_i to extend its lifetime such that $T_i^* = T_n$.

$$\lambda_i = \lambda_0 \frac{T_n}{T_i} = \lambda_0 \frac{E_i}{E_n} = \lambda_0 (1 + w\frac{n^2 - i^2}{2i - 1}), \tag{9}$$

where $w = \frac{e_r + e_t}{e_g + e_t + e_0/l}$. It is noted that only the $\lambda_0 A_i$ sensors in C_i generate sensed data. According to the above analysis, it is easy to prove the following theorem.

Theorem 1 (Sensor Density Theorem): It is assumed that the sensed phenomenon is uniformly distributed over time in the circle RoI. The network based on corona architecture is employed. The λ_0 denotes the base sensor density for satisfying the requirement of coverage. The network lifetime is the maximum lifetime of sensor if and only if $\lambda_i = \lambda_0 (1+w\frac{n^2-i^2}{2i-1})$.

Proof: As the above analysis, the maximum lifetime of a sensor is T_n. The lifetime of C_n is T_n. When $\lambda_i = \lambda_0(1+w\frac{n^2-i^2}{2i-1})$, the lifetime of C_i, $T_i^* = T_n$ by using the corresponding wake-up strategy, $i = 1\cdots n$. So the lifetime of the network is T_n.

C. ANALYSIS OF NETWORK COST

The number of sensors decides the network cost. Next, we calculate the number of sensors deployed in RoI according to the density of sensors. The area of C_i,

$$A_i = \pi r_t^2(2i-1) \tag{10}$$

The number of sensors in C_i

$$\begin{aligned} N_i &= \lambda_i A_i \\ &= \lambda_0(1+w\frac{n^2-i^2}{2i-1})\pi r_t^2(2i-1) \\ &= \lambda_0\pi r_t^2((2i-1)+w(n^2-i^2)) \end{aligned} \tag{11}$$

Based on (11), the relation of the number of sensors between two adjacent coronas can be given.

$$\begin{aligned} N_{i+1} &= \lambda_0\pi r_t^2((2(i+1)-1)+w(n^2-(i+1)^2)) \\ &= \lambda_0\pi r_t^2((2i-1)+w(n^2-i^2)) \\ &\quad -\lambda_0\pi r_t^2(w(2i+1)-2) \\ &= N_i - \lambda_0\pi r_t^2(w(2i+1)-2) \end{aligned} \tag{12}$$

It shows that the number of sensors is incremental from outer corona to inner corona. The total number of sensors is:

$$\begin{aligned} N &= \sum_{i=1}^{n} N_i \\ &= \lambda_0\pi r_t^2\sum_{i=1}^{n}((2i-1)+w(n^2-i^2)) \\ &= \lambda_0\pi r_t^2(\sum_{i=1}^{n}(2i-1)+w\sum_{i=1}^{n}(n^2-i^2) \\ &= \lambda_0\pi r_t^2(n^2+w(n^3-\frac{1}{6}n(2n+1)(n+1))) \end{aligned} \tag{13}$$

For single sink networks, the CPAT is:

$$\begin{aligned} CPAT &= \frac{cN+c^*}{\pi r_t^2 n^2 T_n} \\ &= \frac{c\lambda_0\pi r_t^2(n^2+w(n^3-\frac{1}{6}n(2n+1)(n+1)))+c^*}{\pi r_t^2 n^2 T_n} \\ &= \frac{c^*}{\pi r_t^2 n^2 T_n} \\ &\quad + \frac{c\lambda_0(n^2+w(n^3-\frac{1}{6}n(2n+1)(n+1))}{n^2 T_n} \end{aligned} \tag{14}$$

The expression (14) includes two terms. The first term is the cost about the sink, decreasing as the RoI(or n) increases. The second term denotes the cost of sensors and monotonous increase about n. From the expression, we can have a result that there must be an optimal n to minimize the CPAT. It means the optimal area of a single-sink network can be found for minimizing the CPAT. Based on the result, multi-sink networks can be deployed.

Next, we compare the lifetime of the network deployed at the above density to the network deployed uniformly having the same number of sensors. For a uniform network, the density of sensors is:

$$\begin{aligned} \widetilde{\lambda} &= \frac{N}{A} \\ &= \frac{\lambda_0\pi r_t^2(n^2+w(n^3-\frac{1}{6}n(2+1)(n+1)))}{\pi r_t^2 n^2} \\ &= \frac{\lambda_0(n+w(n^2-\frac{1}{6}(2n+1)(n+1)))}{n}. \end{aligned} \tag{15}$$

Under the same wake-up strategy, the relationship between two lifetimes of networks (non-uniform and uniform) is:

$$\begin{aligned} \frac{T_n}{\widetilde{T}} &= \frac{\lambda_1}{\widetilde{\lambda}} \\ &= \frac{\lambda_0(1+w(n^2-1))}{\frac{\lambda_0(n+w(n^2-\frac{1}{6}(2n+1)(n+1)))}{n}} \\ &= \frac{n(1+w(n^2-1))}{n+w(n^2-\frac{1}{6}(2n+1)(n+1))}, \end{aligned} \tag{16}$$

where the $\widetilde{T}$ is the lifetime of uniform networks.

From the definition of CPAT, the ratio of costs between two networks(non-uniform and uniform)is:

$$\frac{CPAT}{\widetilde{CPAT}} = \frac{\widetilde{T}}{T_n} = \frac{n+w(n^2-\frac{1}{6}(2n+1)(n+1))}{n+wn(n^2-1)}. \tag{17}$$

The expression (17) shows that the ratio is less than or equal to 1 and decreases as n increases. Extending this result, we get the following theorem.

Theorem 2 (Minimum Cost Theorem): It is assumed that the sensed phenomenon is uniformly distributed over time in the circle RoI. For the network based on corona architecture, if N_i (11) sensors are uniformly placed inside the C_i corona($i = 1\cdots n, n > 1$), the CPAT reaches a minimum.

Proof. Assuming that there is any other deployment scheme, the number of sensors in C_i is N_i', $i = 1\cdots n, n > 1$. The total number of sensors $N = \sum_{i=1}^{n} N_i' = \sum_{i=1}^{n} N_i$. There must be a corona that $N_i' < N_i$. Then $\lambda_i' < \lambda_i$. From Theorem 1, the lifetime of C_i,$T_i' < T_n$. Since the network lifetime $T' \le T_i'$, so $T' \le T_n$. By definition, the CPAT of this scheme is greater than that of the scheme proposed in the theorem.

D. SENSOR DEPLOYMENT ALGORITHM

In this section, two deployment algorithms are given, single-sink and multi-sink networks. For the single-sink networks, if the radii of a circle RoI $R \ne kr_t$,k is an integer, the width of the outermost corona $C_n^w < r_t$. Several formulas are adjusted as follows.

$$
\begin{aligned}
A_n &= \pi(R^2-(n-1)^2r_t^2)\\
RD_i &= \frac{l((n-1+\beta)^2-i^2)}{2i-1}\\
E_i &= le_g+le_tR_i+(e_r+e_t)(\frac{l((n-1+\beta)^2-i^2)}{2i-1})+e_o\\
\lambda_i &= \lambda_0(1+w\frac{((n-1+\beta)^2-i^2)}{2i-1})
\end{aligned}
\tag{18}
$$

Algorithm 1 Deployment for Single-SINK Network

```
A_r ← α, solve the formula(9) to get base density(λ_0)
n ← ⌈R/r_t⌉
if R mod r_t = 0
    for i from 1 to n
        λ_i ← λ_0(1 + (n^2−i^2)/(2i−1))
        A_i ← π r_t^2 (i^2 − (i − 1)^2)
        N_i ← λ_i A_i
    end for
else
    for i from 1 to n − 1
        λ_i ← λ_0(1 + w((n−1+β)^2−i^2)/(2i−1))
        A_i ← π r_t^2 (i^2 − (i − 1)^2)
        N_i ← λ_i A_i
    end for
    λ_n ← λ_0
    A_n ← π(R^2 − (n − 1)^2 r_t^2)
    N_n ← λ_n A_n
end if
for i from 1 to n
    Scatter randomly N_i sensors over the corona C_i
end for
```

The deployment algorithm of single-sink networks is detailed as follows. The pseudo code of the algorithm is presented in Algorithm 1.

1) According to application requirements of covered area, let $A_r = \alpha$, the critical density(λ_0) is calculated from (4).
2) Divide the circle RoI into n coronas, the width of coronas is

$$
\begin{cases} C_i^w = r_t, & i = 1\cdots n-1,\\ C_n^w \le r_t, \end{cases} \tag{19}
$$

3) Calculate sensor density and the number of sensors in each corona. When $C_n^w = r_t$, the formula (9) is used, otherwise,the (18) is used to calculate λ_i. Further, the N_i can be calculated.
4) Scatter randomly N_i sensors over the corona C_i.

Algorithm 1 is the deployment process for a single sink network. First, the network parameters are calculated, and then the nodes are deployed in each ring, respectively. Its algorithm complexity is O(n). For a single-sink network, the above algorithm can avoid the energy hole problem and maximize energy utilization rate, but can not guarantee the lowest cost. Minimize (14), we can get n^*. This means that when the radii of the circle filed is n^*r_t, the network cost (CPAT) is the lowest. So in order to minimize cost, the multi-sink networks should be deployed for a large RoI. According to the size and shape of the region, it is divided into several circles with an approximate radius n^*r_t, and then the single-sink network is deployed in each circle. The deployment algorithm of multi-sink networks is detailed as follows. The pseudo code of the algorithm is presented in Algorithm 2.

Algorithm 2 Deployment for Multi-Sink Network

```
A_r ← α, solve the formula (9) to get base density(λ_0)
E_n ← l(e_g + e_t), T_n ← E/E_n
Calculate n* by minimizing the (14).
Divide the RoI into k circle field with approximate
        radius n* r_t
for i from 1 to k
    deploy single-sink network in i circle field.
end for
```

1) According to application requirements of covered area, let $A_r = \alpha$, the critical density(λ_0) is calculated from (4).
2) Calculate the n^* by minimizing CPAT (14).
3) Divide the RoI into k circle field with approximate radius n^*r_t.
4) Deploy single-sink network in each circle.

In step 3, the distance(d) between the center of two adjacent circles is theoretically $\sqrt{3}n^*r_t \le d \le 2n^*r_t$ after the region's division. When $d = \sqrt{3}n^*r_t$, the area of overlap region in two adjacent circles is $(\frac{\pi}{3}-\frac{\sqrt{3}}{2})(n^*r_t)^2$. When $d = 2n^*r_t$, the area not covered between three adjacent circles is $(\sqrt{3}-\frac{\pi}{2})(n^*r_t)^2$. The distance can be a tradeoff between performance and cost based on application requirements. Algorithm 2 is the deployment process of a multi-sink network. Firstly, relevant network parameters are calculated, and then nodes are deployed to the single sink network, respectively. Its algorithm complexity is O(kn). In practical application, because of the diversity and irregularity of RoI shape, the division of regions is complicated. The basic principle of division is that the sub-region is as close as possible to the circle area of n^*r_t radius. Since not the focus of this article, it is not discussed in detail.

E. NETWORK TOPOLOGY AND ROUTING STRATEGY

In the network deployed by the above method, the node density and the data transmission load of the different corona are different; the location of the sensors is random. The network topology structure in the network operation is updated continuously. The multi-sink network is composed of multiple single-sink networks, and this section presents the topology control and data routing strategies for the single-sink network. In order to ensure the relative stability of the network topology and reduce the energy consumption and bandwidth overhead caused by updating the topology, all sensors are divided into four categories according to their status: Sensing Nodes(SN), Relay Nodes(RN), sLeeping nodes(LN), and Dead Nodes(DN). The sensing node periodically generates environmental data and transmits it to the relay node. The relay node receives and transmits data to the sink in a multi-hop mode. A node without sensing and relay task is regarded as a sleeping node. When a node exhausts energy, it becomes a dead node. Data is periodically transmitted to the sink. When the proportion of data transferred to the sink in a period is below a certain threshold, the network fails. The data transmission is assumed to be in an ideal state, and signal interference and transmission conflict are not considered. The network topology building and data routing strategy include the following steps.

1) Initialize network. Each node has the positioning function to know its location. Sink broadcasts its location and network parameters (density, number of coronas, etc.). Each node receives this information and calculates the distance to sink and the corona number it is located in. Each node sends its location to the neighbor node and records all the neighbor nodes ID and locations.
2) Select the SN. Select the sensors as SN in each corona separately, so that the SN density in the network area is the critical density λ_0. The number of randomly selected sensors in the ith corona is $\lambda_0 \pi r_t^2(2i-1)$, and the proportion of the total number of sensors in the corona is $\frac{2i-1}{(2i-1)+w(n^2-i^2)}$. Among them, all the nodes in the outermost corona are selected. The selected sensor marks itself as SN type and informs its neighbor nodes. When two adjacent SNs are very close, one can be adjusted to ensure that the two nodes' overlapped area is small.
3) Select the relay node to establish the data route. Each SN selects the nearest non-SN sensor to sink from its neighbor as the next hop node, and the selected sensor is marked as RN. RN selects the next hop node in the same way, and the next hop node of SN and RN in the first corona is the sink.
4) The sensors that are not selected are marked as sleeping node, waiting to be woken up.
5) Through the above steps, the network topology and data routing path are established. Since SNs do not relay data, their lifetime is approximately the same. In a data collection cycle, the transmission data load of each RN is different. In general, the closer the RN is to the sink, the larger its data transmission load is, and the shorter its lifetime is. When the remaining energy of RN is lower than a certain threshold, it dies and informs the neighbor. Then the previous hop node selects the next hop RN from its neighbor nodes. If there are sleeping neighbor nodes, the one closest to the sink is selected as the next hop. If there is no LN, the RN closest to the sink is selected. If there is no LN and RN, the SN closest to the sink is selected.
6) In a data collection cycle, when the proportion of the data received by the sink in the total sensing data is lower than a threshold, the network function fails.

The pseudo code of the network topology and routing algorithm is presented in Algorithm 3.

Algorithm 3 Network Topology Building and Data Routing Strategy

Sink broadcasts its own location and related network parameters(λ_0, n, r_t etc).
Each sensor receives information from the sink and calculates the distance to the sink.
for i from 1 to n.
  Randomly select $\lambda_0 \pi r_t^2(2i-1)$ sensors as SN.
  if The distance between two adjacent SN is less than the threshold.
    then One of them will be reselected.
  end if
end for
for Each SN
  $SN.next \leftarrow s$, s is the neighbor sensor of SN nearest to sink
  s is labeled RN.
  while $RN \neq sink$ and $RN.next = NULL$
    if RN is in first corona
    then $RN.next \leftarrow sink$
    end if
    $RN.next \leftarrow s$,s is the nearest neighbor sensor of SN to sink
    $RN \leftarrow s$ and s is labeled as RN.
 end for
 if RN.rp<p
  then RN is labeled as DN, CRN←RN.pre
  if there are LNs in the neighbors of CRN
    then CRN.next← s, s is the nearest LN neighbor of CRN to sink.
    else ifthere are RNs in the neighbors of CRN
    then CRN.next← s, s is the nearest RN neighbor of CRN to sink.
    else ifthere are SNs in the neighbors of CRN
    then CRN.next← s, s is the nearest SN neighbor of CRN to sink.
    else CRN is labeled as DN.
  end if
 end if

Algorithm 3 presents the construction and update process of network structure and data routing. Its time complexity is $O(n^3)$.

VI. NUMERICAL ANALYSIS AND SIMULATION RESULTS

In this section, the numerical analysis and simulation results for the proposed deployment strategy are presented by Matlab.

A. SIMULATION ENVIRONMENT

We assumed that simulations are based on collision-free MAC protocol without data loss, and the sink can send data directly to the data receiving station.

B. STUDY OF BASE DENSITY

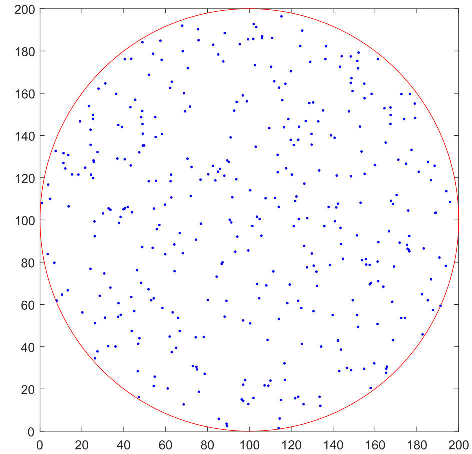
In the above section, we discuss the relationship between the covered area fraction and sensor density, sensing range and transmission distance, and get the (4). Next, based on the application's coverage requirements, the critical density is studied through numerical simulation. The Fig. 1 shows a uniform node deployment, where the sensing area is a circular domain with a radius of 100, the node density is 0.012, $r_s = 5$, $r_t = 10$. Fig. 1a shows a random deployment. Fig. 1b gives the connected component. Fig. 1c presents the covered area of the HOC.

Fig. 2 shows the ratio of the covered area of the huge connected component to RoI, while $r_s = 5$, $r_t = 10$. The red line is the simulation value, and the black line is the theoretical value from (4). From this figure, it can be seen that when the ratio is greater than 0.8, the simulation value is almost the same as the theoretical value, which is consistent with the establishment of (4) when $\pi\lambda r_t^2$ is large. So the expression (4) can be used to calculate the critical density when the covered area requirement is large. The green line is the ratio of the number of nodes in the HOC to the total number of nodes. Like the red line's shape, there is a rapid growth in a particular range, reflecting the penetration phenomenon. Based on these connected nodes, the network will be formed.

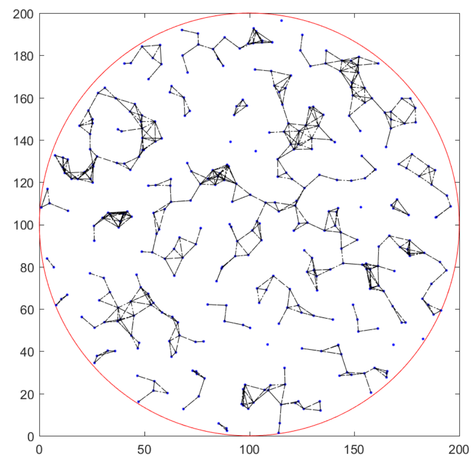
C. DEPLOYMENT SIMULATION

Based on the critical density, the node density and number in each corona can be calculated according to (9) and (11). The assumption of energy consumption is the same as that set in the following chapters. Fig. 3 shows the result when $\lambda_0 = 0.04, R = 60, r_t = 10$. Fig. 3a shows that the density increases rapidly from the outer corona to the inner, and the first corona has the largest increase. This is because the sensors in the first corona have to undertake all other coronas data forwarding tasks and its area is the smallest. From Fig. 3b, the number of sensors also gradually increases, but the increase is getting smaller and smaller. Fig. 4 shows the simulation deployment results.

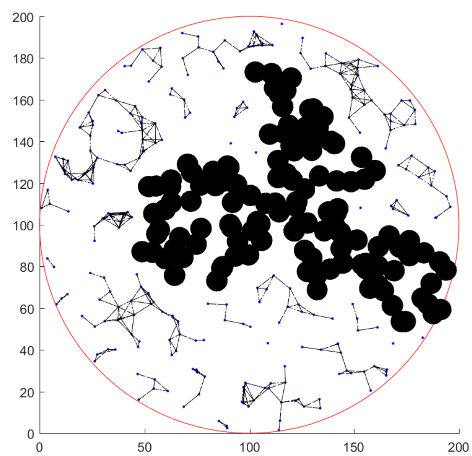
The Fig. 5 compares the density at different numbers of coronas(n). The Fig. 5a shows the density of each corona when n is 2, 4, 6, 8, 10, respectively. The growth of the first corona becomes larger as n increases. The Fig. 5b shows the sensor average density at different n. As n increases, the average density increases linearly. It implies that the cost per unit area of the sensors is increasing. The reason is that the



(a) A uniform node deployment



(b) The connected component



(c) The covered area of HOC

FIGURE 1. A sample of uniform node deployment.

network's total cost includes the sink's cost, and the one sink's cost is much higher than a sensor's cost. In order to study the

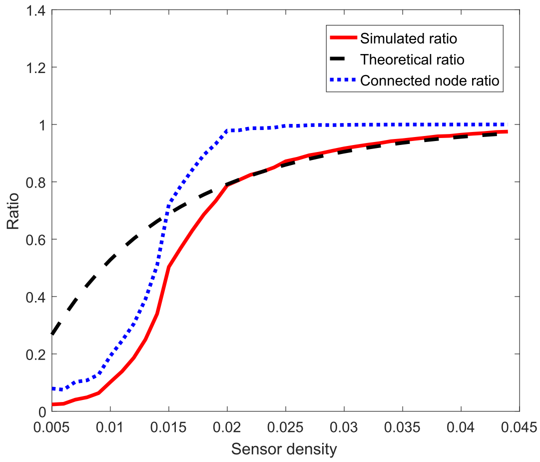
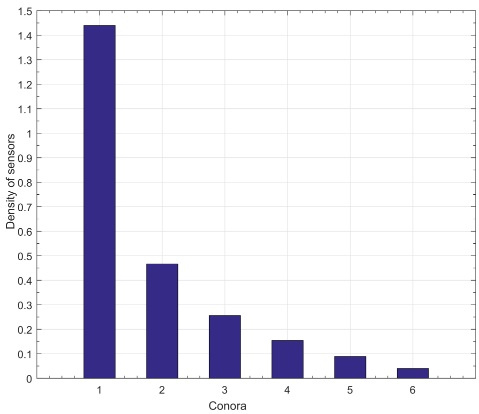
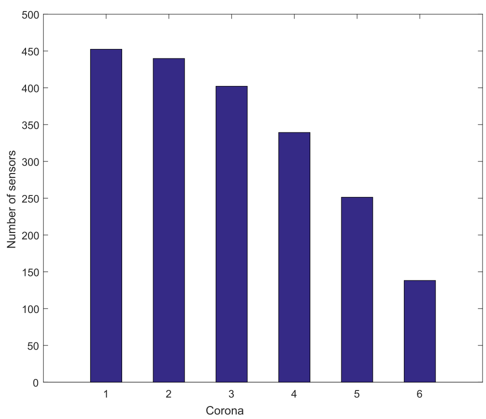


FIGURE 2. The covered area ratio for HOC.



(a) The sensor density in each conora



(b) The number of sensors in each conora

FIGURE 3. The density and number of sensors in each corona.

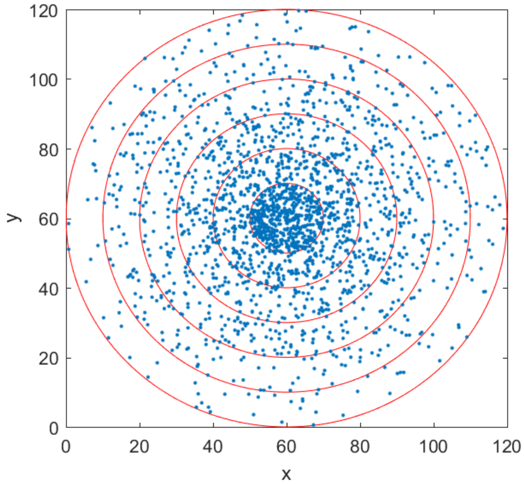
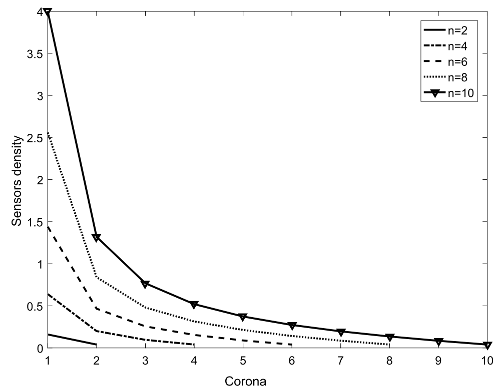
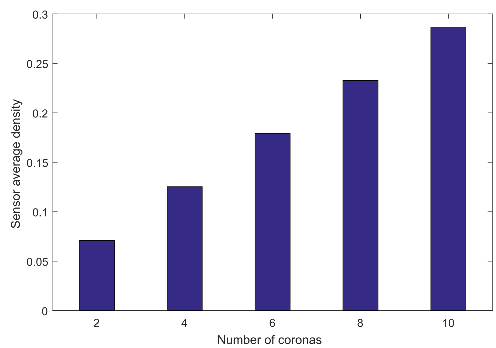


FIGURE 4. Deployment.



(a) The sensor density



(b) Sensor average density

FIGURE 5. Sensors density at different numbers of coronas.

change of the total cost, we assume that the cost of a sensor is 2, and the cost of a sink is 2000. Fig. 6 shows the change in the total cost as the number of corona changes. There must be a specific value of n that minimize the network cost. Under the current assumption, n is 6. It should be noted that this conclusion is drawn from the same theoretical design lifetime of the networks. In general, the theoretical design lifetime and the actual lifetime are in a positive linear relationship. So the above conclusions can guide the design and deployment of the network to minimize costs. That says, when the RoI is large, a multi-sink network should be deployed to reduce the network cost.

D. ROUTING SIMULATION

This section simulates the proposed routing strategy. The nodes are generated randomly under the parameters set

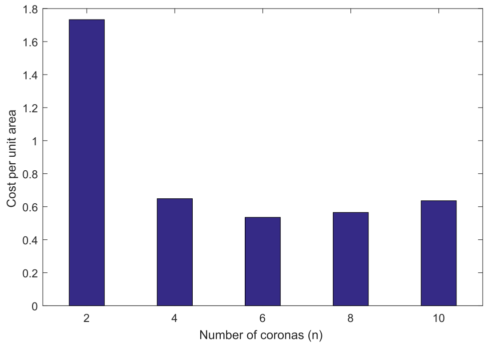


FIGURE 6. Cost per unit area.

previously (Fig. 7a). The sensing nodes are selected according to the critical density, shown as the red circle in Fig. 7b. Fig. 7c shows the initial routes from the sensing nodes to the sink. In the network operation, when a node's energy is less than a certain threshold, it fails, and its previous hop node re-establishes a route to the sink. In Fig. 7b, the green lines represent the re-established routes, and the blue asterisks indicate the failed node.

The simulation has made appropriate adjustments to the routing strategy. When there are only SNs in the neighbors of an SN, to establish a route to the sink, SN is allowed to be next hop node, which makes almost all SNs can establish a route. This adjustment is mainly beacause all nodes in the outermost corona are SN, and the probability of non-SN in the neighbors of these nodes near the outer edge is small. If SN is not allowed as the next hop node, there will be some nodes that no route to sink, resulting in unreasonable waste. Such adjustment will also bring a problem. The lifetime of the SN with dual tasks(sensing and relaying) will be shortened. When it fails, the number of SN is reduced. After an SN fails, its non-SN neighbor can be chosen as the SN to guarantee the SN's amount. Of course, other methods can be adopted to reduce or avoid the SN as the next hop node. For example, in the outermost corona deployment, the node position's outer boundary can be contracted inward by a certain distance, which is less than r_s. This will increase the probability of non-SN nodes' occurrence in the neighbors of the outermost corona nodes. These adjustments will improve the proposed strategy. Since these contents are not the focus and space of this article is limited, they will not be discussed in detail.

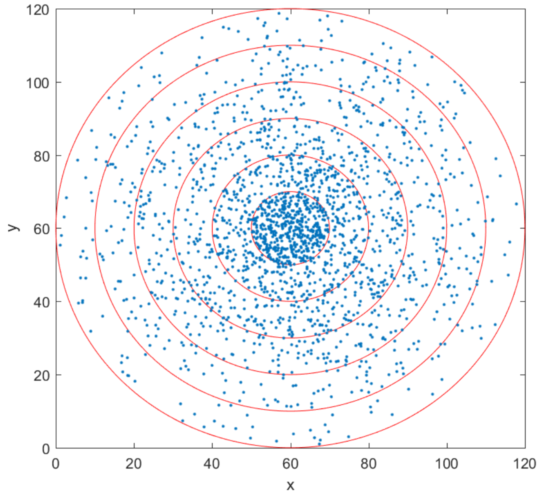
E. PERFORMANCE COMPARISON

In this section, we compare the proposed method with existing random deployment methods, including uniform deployment, normal diffusion, R-random diffusion, and Exponential diffusion [11]. The coverage area ratio and the number of working rounds are simulated. For simplicity, three types of energy consumption, sensing, receiving, and sending, are considered, since other energy consumption has little effect on the comparison results. Assuming that each sensor initially has 50 energy units, the sensing node periodically generates data, and each cycle counts as one round. The amount of data generated by each sensing node per round is counted as one data unit. The energy consumed by a unit of data is 0.1 for sensing, 0.2 for receiving, and 1.5 for sending. For simplicity, the e_0 is ignored. Since e_0 is small and independent of the amount of data transferred, this does not affect the comparison results. The transmission distance of the sensor is 10m, the sensing distance is 5m, and the RoI is a circular area with a radius of Rm. To be comparable, all deployment schemes use the topology and routing strategies proposed in this paper.

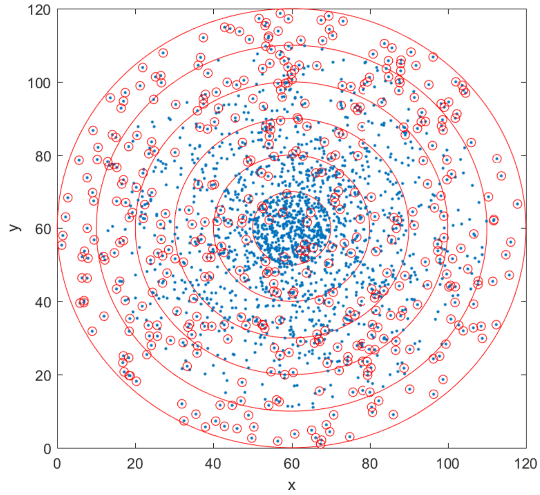
Each method is simulated 30 times randomly. Each network is simulated to run 30 rounds, and the covered area ratio of each round is recorded. Figure 8 gives the average results of the five different deployment methods when R is 60 m. The horizontal axis represents the number of working rounds, and the vertical axis represents the covered area ratio, which is the ratio of the covered area of the sensing nodes whose data are received by the sink to RoI. All networks are single sink networks and contain the same numbe of sensors.

The Fig. 8a is the result when $\lambda_0 = 0.025$, and the Fig. 8b is the result when $\lambda_0 = 0.04$. The changes in the curves in the two figures are similar. The curve of uniform deployment drops sharply after a few rounds, indicating an energy hole problem. The other four non-uniform deployments alleviate this problem. With the increase of working rounds, the ratio decreases gradually. The maximum ratio of normal deployment is less than the R-random method and the proposed method. In the first few rounds, the R-random method's ratio is similar to that of the proposed method. The ratios of two methods drop sharply after several rounds, which indicates that a large number of sensors in the inner corona fail. The proposed method is better than other methods in the covered area ratio.

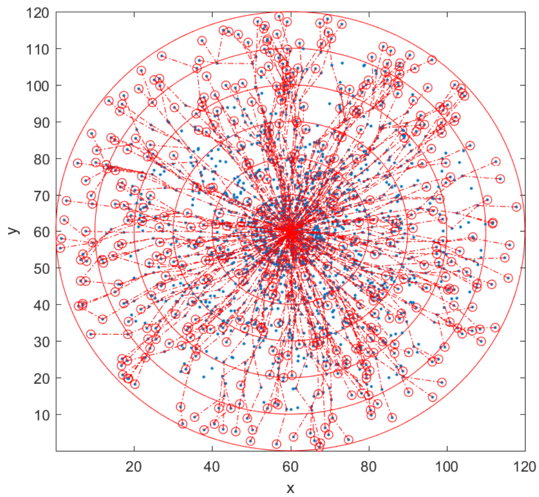
Fig. 9 shows the Cumulative Covered Area Ratio(CCAR) of 30 rounds for five methods. The CCAR is the sum of the covered area ratio of each round. It is difficult to maintain a constant covered area ratio due to the multi-hop and randomness of the network. The ratio will decrease with the increase in the number of working rounds. The CCAR can be used as a comprehensive index to measure the network's coverage and working life. It largely reflects the AT value of CPAT in the design stage. We replace the AT in CPAT with CCAR to get CPAT', which does not affect the comparison results of the various methods. $CPAT' = \frac{cn+c^*m}{A*CCAR}$. Fig. 10 shows the CPAT' of each method. For a large area of detection, the method proposed in this paper will perform better by deploying a multi-sink network. Based on the parameter values previously set, Figure 5 shows that when the number of cycles is 6, the cost is the lowest. When R=104, different methods are simulated. The method proposed in this paper deploy the 3-sink network. The covered area ratio is similar to Figure 9. Fig. 11 shows the CPAT' of different methods. Compared with the other four methods at the two densities, the cost was reduced by 40%, 43.8%, 70.5%, 92.9% (density is 0.04), and 24.1%, 30.6%, 61.6%, 90.6% (density is 0.025), respectively. The simulation reflects the cost under the same



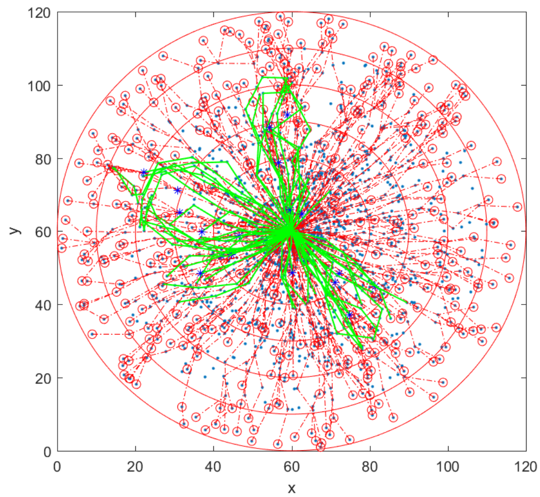
(a) Random node deployment



(b) Sensing nodes

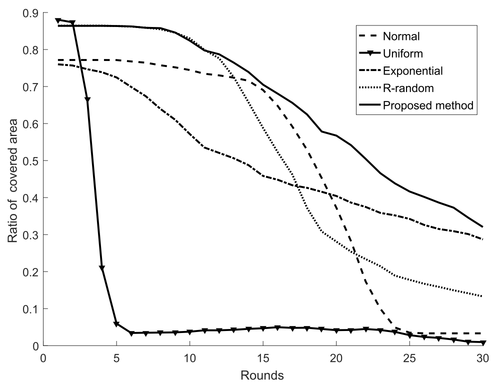


(c) The initial routes

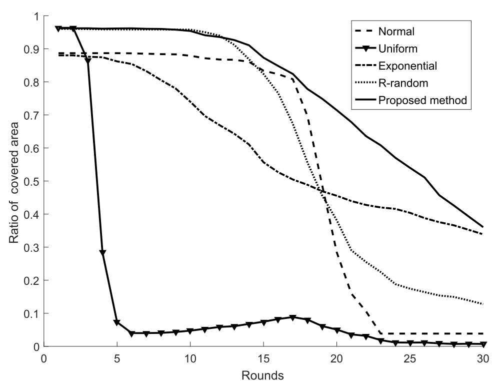


(d) The re-established routes

FIGURE 7. Networks routing simulation.



(a) The result as $\lambda_0 = 0.025$



(b) The result as $\lambda_0 = 0.04$

FIGURE 8. The number of rounds and corresponding ratio of covered area.

detection area without considering the shape and division of the area. For real applications, region shapes are essential to the performance of all aspects of the network. As can be seen from Fig. 10 and 11, with the increase of the detection area,

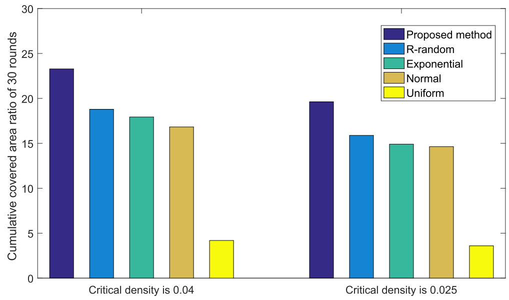


FIGURE 9. Cumulative covered area ratio of 30 rounds.

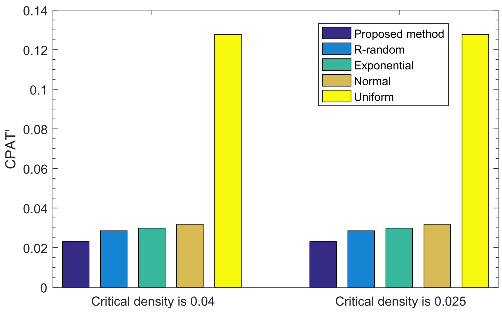


FIGURE 10. Cost comparison when R=60.

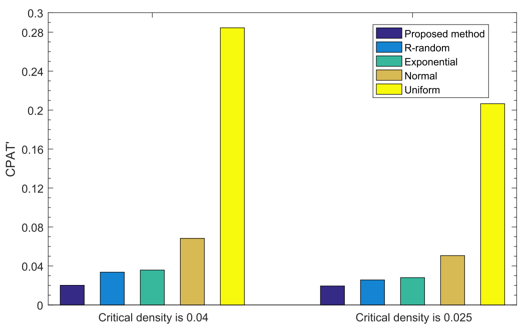


FIGURE 11. Cost comparison when R=104.

the cost of other methods (CPAT) will increase while the cost advantage of the proposed method is distinct.

F. DISCUSSION

The proposed strategy includes three algorithms, the first two are about the deployment process, and the third is construction and update process of the network and data routing. The computation in the first two algorithms determines the deployment parameters, calculated by the given formula. The computation in the third algorithm is mainly to establish and update data routing. It is distributed. Each SN node selects the next hop node from neighbor nodes, which will take some time and consume some energy. Due to the randomness of node location and multi-hop routing, some nodes will fail during network operation, and the network topology will change. It makes it challenging to maintain constant area coverage(α). As a result, the covered area ratio generally decreases unless a large number of redundant nodes are deployed regardless of cost. This paper takes minimizing cost as the network design goal, so it is more practical and feasible to use the cumulative covered area ratio as the measurement index of network coverage. A duty cycling strategy in node-dense areas is required. It is inevitable that more control packets are needed in the network structure and routing update process. Clock synchronization is a common problem faced by many networks, and there are many solutions. Because not our focus, it is not covered in this article.

The proposed method has the following shortcomings. For a large detection area, area division should be carried out before establishing a multi-sink network. The method only gives the scale of a single sink network and the principle of area division, and there is no exact method of division. Area division is another critical issue, and it is closely related to the shape of the area and the actual application. This method needs to throw nodes of different densities in different coronas, which may be difficult in actual operation. The data routing method has a significant impact on energy consumption and network lifetime. The routing scheme proposed in this paper is designed to minimize the number of hops, and reduce the number of route updates and the traffic between neighboring nodes. Its purpose is to decrease energy consumption. Because the node's remaining energy and the current load information are not considered when selecting the next hop node, some relay nodes fail too quickly. In the application, the routing strategy can be adjusted and optimized according to actual needs. In network operation, the construction and update of network structure and data routing need to consume additional energy, which has an impact on the lifetime of nodes. This article does not analyze the impact of this consumption in detail.

VII. CONCLUSION

For some performance requirements, a randomly deployed network often requires many redundant nodes, increasing the network's cost. In this paper, a random deployment strategy is proposed to minimize cost, considering factors such as network coverage, connectivity, and longevity. The problem (MCPAT, SMCPAT)is defined, and relevant parameters($\lambda_0, \lambda_i, N_i$) are determined through theoretical analysis, and deployment method and corresponding topology control and routing strategy are given. Simulation experiments verify the effectiveness of the method. This paper puts forward a new concept of relative comprehensive cost. Based on theoretical analysis, a random deployment strategy is designed. This strategy includes multiple algorithms from network design to operation. It can be used to deploy WSN in a large detection area. First, calculate the network deployment parameters according to the perceptron and sink's attributes and application performance requirements. Then the regional division and node deployment are carried out according to the parameters. In the stage of network construction and data transmission, tasks are carried out in a distributed manner, that is, each node performs network update and data transmission based on local information. To the shortcomings mentioned above, we will further study the following questions in the future: (1) the division of regions, (2) optimizing data routing strategies, (3) establishing WSNs for a practical application using this strategy.

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