Relay Node Deployment Strategies in Heterogeneous Wireless Sensor Networks

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Abstract—In a heterogeneous wireless sensor network (WSN), relay nodes (RNs) are adopted to relay data packets from sensor nodes (SNs) to the base station (BS). The deployment of the RNs can have a significant impact on connectivity and lifetime of a WSN system. This paper studies the effects of random deployment strategies. We first discuss the biased energy consumption rate problem associated with uniform random deployment. This problem leads to insufficient energy utilization and shortened network lifetime. To overcome this problem, we propose two new random deployment strategies, namely, the lifetime-oriented deployment and hybrid deployment. The former solely aims at balancing the energy consumption rates of RNs across the network, thus extending the system lifetime. However, this deployment scheme may not provide sufficient connectivity to SNs when the given number of RNs is relatively small. The latter reconciles the concerns of connectivity and lifetime extension. Both single-hop and multihop communication models are considered in this paper. With a combination of theoretical analysis and simulated evaluation, this study explores the trade-off between connectivity and lifetime extension in the problem of RN deployment. It also provides a guideline for efficient deployment of RNs in a large-scale heterogeneous WSN.

Index Terms—Wireless sensor network, deployment, biased energy consumption rate, system lifetime, connectivity.

1 Introduction

Device deployment is a fundamental issue in WSN design. It determines the limits of many intrinsic properties of a WSN, such as coverage, connectivity, cost, and lifetime. It has been investigated in terms of sensing coverage and/or network connectivity in [1], [2], [3], [4]. However, its significance on lifetime in a randomly deployed network, in which the positions of devices cannot be precisely known or controlled, has been largely unaddressed. Assuming that devices can be deliberately placed on the sensing field, some research efforts have attempted to optimize the device placement with respect to system lifetime [5], [6], [7], [8], [9], [10], [11]. However, the methodologies and solutions therein are not applicable in situations where deliberate placement is not feasible. The infeasibility usually occurs in two types of situation, one where the number of devices is very large, and the other where the application environment is not completely accessible. In these situations, a well-designed deployment density function becomes a viable approach to efficient network provisioning [12], [13], [14].

Uniform random deployment is the most commonly considered random deployment strategy in the literature. However, it is inefficient from an energy perspective due to the biased energy consumption rate (BECR) phenomenon in two scenarios, described as follows: Consider a WSN composed of uniformly deployed sensor nodes (SNs) and relay nodes (RNs) in which traffic originates at SNs and is sent to the base station (BS) via RNs. Assume that the traffic is uniformly generated over the sensing field and the initial energy is identical on every RN. In the first scenario, where all RNs transmit data to the BS in one hop (single-hop heterogeneous WSN) by adjusting their transmission power, illustrated in Fig. 1a, the RNs which are farther away from the BS will deplete energy faster than the RNs closer to the BS due to the larger transmission distance. As such, the nodes farther from the BS become unusable, while a large portion of energy is still left on those close to the BS. In contrast, in the second scenario, where RNs adopt a fixed transmission power[1] and transmit data to the BS via multiple intermediate RNs (multihop heterogeneous WSN), illustrated in Fig. 1b, RNs closer to the BS will consume energy faster than RNs farther away from the BS. The reason is because traffic is built up on RNs closer to the BS as it is relayed from far to near. As such, they become unusable earlier than those far from the BS. It is essential to realize that the problem in the second scenario cannot be solved by any energy-efficient routing protocol. For example, the one-hop neighbors, as a group, will inevitably be exhausted sooner than the RNs using them for traffic relay since all traffic has to go through that set to the BS no matter which routing protocol is used [15]. Partly, for this reason, the study in this paper is not coupled with any particular routing scheme. It only assumes that relay paths are always formed from far to near to the BS, a property which is

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1. If RNs can adjust their transmission power, the BECR problem can be alleviated by efficient traffic distribution [8].

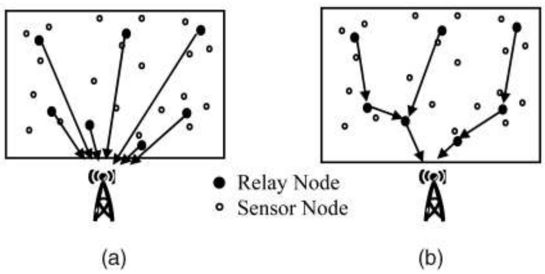

Fig. 1. BECR problem in heterogeneous WSNs. (a) Single-hop network. (b) Multihop network.

generally satisfied by most existing routing schemes [16]. In Section 5, we adopt the classic Bellman-Ford algorithm in our performance evaluation.

Both the single-hop and multihop models represent practical system scenarios. To solve the BECR problem associated with uniform random deployment, we propose two novel random deployment strategies for RNs in both communication models, namely, lifetime-oriented deployment and hybrid deployment. We then analyze and compare the three deployment strategies (uniform, lifetime-oriented, and hybrid). Both theoretical analysis and simulated evaluation show that the new deployment strategies can effectively alleviate the BECR problem and extend the system lifetime. To the best of our knowledge, this is the first effort to optimize the random device deployment (by the density function) in order to extend the lifetime of a large-scale heterogeneous WSN.

The remainder of this paper is organized as follows: In Section 2, related works are outlined. In Section 3, the system models are described. In Section 4, random deployment strategies are proposed and the impact of deployment on connectivity and lifetime is discussed. In Section 5, the performance of the deployment strategies is evaluated and compared. In Section 6, we discuss some practical issues, such as the extensibility of our work and the implementation methods. The paper is concluded in Section 7.

2 Related Work

Due to its fundamental importance on the properties of a WSN, device deployment has attracted increasing amount of interest in academia. A significant amount of research has studied the deployment problem in terms of sensing coverage and/or network connectivity. In [1], asymptotic sensing coverage probabilities are derived for a randomly deployed WSN. In [2], [3], [4], optimal (or near-optimal) sensor deployment patterns are proposed to provide both coverage and connectivity in all sorts of scenarios of sensing radius and communication radius.

A few research efforts have examined the deployment problem from a system lifetime perspective. The majority of the works can be classified into two types based on how devices would be placed, i.e., the deterministic placement [5], [6], [7], [8], [9], [10], [11] and the random deployment [12], [13], [14], [15].

Deterministic placement is applicable in circumstances where the number of devices involved is small to medium, and the sensing field is human accessible. The research in [5] aims to optimize the placement of the BS for maximizing the network lifetime when the positions of sensor nodes and application nodes (cluster heads) are given. The research in [6], [7] is concerned with designing the optimal RN placement using a minimum number of RNs with the constraints of lifetime and connectivity. The research in [8] addresses the joint design problem of energy provisioning and (additional) RN placement. The design problem is first formulated as a mixed-integer nonlinear programming problem, and a heuristic algorithm is derived to solve it. The research in [9] formulates and solves the problem of assigning positions and initial energy levels to the RNs and concurrently positioning the SNs into clusters assigned to individual RNs aiming at maximizing the monitoring lifetime of the two-level WSN subject to a total energy budget. Two studies address the lifetime-oriented SN placement problem in a homogeneous WSN. The research in [10] proposes strategic placement scheme of SNs in linear networks. The necessary distance between neighboring SNs is obtained in order to achieve a specified lifetime. The basic observation is that nodes closer to the sink have shorter mutual distance. The research in [11] addresses the joint optimization problem of SN placement and topology construction under the sensing quality (measured by the distortion of the reconstructed sensed signal) constraints. However, as the problem formulations and their solutions in these works depend on the exact positions and/or traffic of devices, the methodologies therein are not applicable to large-scale randomly deployed networks.

Random deployment according to a density function is more applicable in circumstances where the sensing field is hostile or inaccessible to humans, or the sensing field is so large that a great number of devices are deployed. The research in [12] determines the densities of SNs in a homogeneous WSN by solving the optimization problem of maximizing the coverage percentage under the constraints that the traffic loads among SNs at different distance are equal. The research in [13] is to find the SN deployment density which requires the minimum total number of deployed SNs subject to constraints on the network lifetime and monitoring quality. The research in [14] first discusses the BECR phenomenon in a multihop WSN. It further addresses the joint problem of RN deployment and transmission power control in order to extend the system lifetime. The research in [15] provides a theoretical study of the uneven energy depletion problem. It derives the optimal width of coronas region of a WSN so as to minimize the total energy consumption along the routing path when nodes use a fixed transmission power. To maximize the network lifetime, it also derives a power control strategy based on coronas division of the network. All power control schemes in [13], [14], [15] assume the availability of location information on individual devices.

Our research is different from the previous works in a few aspects. Our work aims to develop RN deployment density functions in order to overcome the BECR problem and extend the system lifetime assuming that the sensing fidelity is ensured by the deployment of SNs, which have been intensively studied in literature, including [1], [2], [3], [4]. In addition, we consider that the network is organized in a hierarchical structure, which has been identified with many advantages over the flat network, such as scalability, enabling data aggregation, etc. In addition, no location information is required in our system.

3 System Models

In this paper, we assume that traffic is periodically generated on SNs and relayed back to the BS. The time-driven delivery method is suitable for applications that require periodic data monitoring. However, the research can also be applied to applications using event-driven data reporting, as long as traffic is generated at the same rate statistically across the network. We next introduce the network model, energy model, and lifetime model in detail.

3.1 Network Model

We assume that a large-scale heterogeneous WSN on a sensing field A is composed of three types of devices: SNs, RNs, and a BS. An SN senses the environment, generates data, and periodically transmits the data to an active RN, which functions as a cluster head (CH), in a single hop. It has limited energy and a fixed transmission radius r_{SN}. We consider a realistic channel model where an SN can be connected to an RN with probability p_c, if they are within a distance of r_{SN}. The value of p_c depends on the channel condition, and it can be derived for a specific deployment. An SN has no relaying function or at least traffic relaying is not a routine function of an SN for the following reasons. First, relaying traffic demands high intelligence, such as security and routing, which leads to higher device cost. Second, extra communication leads to faster energy dissipation. If the number of hops on a relaying path increases, this effect is aggravated due to traffic accumulation. For a large-scale, randomly deployed WSN, it makes more sense for SNs to be simple, low-cost devices. One example of such an SN is the Reduced Function Device (RFD) defined in the IEEE802.15.4 standard [17]. Throughout the paper, we assume that N_{SN} SNs are randomly deployed in the network according to the uniform distribution over A and work together to meet the coverage requirement. This research can be extended to the case when SNs are redundant and work in shifts as long as the positions of on-duty SNs are randomly or evenly spread in the network. In this case, N_{SN} represents the number of active SNs. The research can also be extended to the case when the traffic is not periodic, as long as the traffic is generated uniformly in the network.

An RN is also energy constrained. An RN works as a CH when active, which groups the SNs in its proximity into a cluster. It also coordinates and schedules the MAC layer access within its cluster so that the energy overhead, e.g., retransmissions due to collisions, is minimized. After receiving the data from SNs, it aggregates the traffic. The aggregation diminishes the redundant information from multiple nodes and reduces the network traffic. In the case of the single-hop communication model, an RN transmits data to the BS directly by adjusting its transmission power in order to avoid energy wastage. In the case of the multihop communication model, an RN transmits data to its next hop RN within its fixed transmission range r_{RN}, where typically r_{RN} is a few times larger than r_{SN}. The aggregated traffic won't be aggregated again while passing through other RNs. We assume that the traffic is light compared with the available bandwidth, or the traffic is well scheduled so that there is no traffic congestion in the network. N_{RN} RNs are to be randomly deployed according to some strategy.

We assume that one BS is fixed somewhere (e.g., the corner or center) in the sensing field. Without loss of generality, the position of the BS is marked as point (0, 0).

3.2 Energy Model

The energy spent by an SN for transmitting one packet to RNs is fixed as the transmission radius and packet lengths are fixed. In one round of data collection, the energy spent by an active RN consists of two parts, namely, the energy used for intracluster communication and data processing, denoted by E_{intra}, and in the case of the multihop communication model, the energy used for intercluster traffic relay, denoted by E_{inter}.

Consider an active RN having n member SNs. The energy E_{intra} is composed of three parts, namely, the energy cost of receiving n packets of length l, denoted by $E_{RX}(l,n)$, the energy cost of transmitting the aggregated packet of length l_{AG} to its next hop RN or the BS over a distance d, denoted by $E_{AG}(l_{AG},d)$, and the energy cost of aggregating n packets of length l, denoted by $E_{AG}(l,n)$. Adopting an energy model similar to that in [5], we have

$$E_{RX}(l,n) = nl\beta, \tag{1}$$

$$E_{TX}(l_{AG},d) = l_{AG}(\alpha_1 + \alpha_2 d^m), \tag{2}$$

$$E_{AG}(l,n) = nl\gamma, \tag{3}$$

where β, α_1, α_2, m, and γ are the energy-related parameters. Letting g be the aggregation ratio, the length of the aggregated packet from n packets is

$$l_{AG}(l,n) = ngl. \tag{4}$$

Replacing l_{AG} in (2) by (4), and adding (1), (2), and (3), we have

$$E_{\text{intra}} = (c_1 + g\alpha_2 d^m)nl, \text{ where } c_1 = (\beta + g\alpha_1 + \gamma). \tag{5}$$

On the other hand, the energy spent on intercluster relay E_{inter} consists of two parts, namely, the energy cost of receiving packets of total length l_{relay} and transmitting them (as they are) over the distance rRN:

$$E_{\text{inter}} = c_2 l_{\text{relay}}, \text{ where } c_2 = \beta + \alpha_1 + \alpha_2 r_{RN}^m. \tag{6}$$

Thus, the total energy spent by an active RN in one round of data collection is

$$E_{RN}(d, l_{\text{relay}}) = (c_1 + g\alpha_2 d^m)nl + c_2 l_{\text{relay},} \tag{7}$$

where in the case of single-hop communication, $l_{\text{relay}} = 0$ and d is the distance from the RN to the BS, and in the case of multihop communication with fixed transmission range, $d = r_{RN}$ and l_{relay} may be positive.

3.3 Usability and Lifetime Model

The usability of a WSN is determined by both coverage and connectivity. Coverage has two aspects, namely, coverage area and coverage degree [18]. In this research, they are ensured by the given SN deployment. Connectivity refers to how much of the generated data can ultimately arrive at the BS. It can be measured by the percentage of SNs that can connect to the BS via RNs. As such, coverage provided by SNs and connectivity provided by RNs ultimately determines the effective coverage. As RNs get drained of energy, the connectivity becomes gradually weaker and so does the effective coverage. This process is called *coverage aging* in [18]. As this research aims to extend the system lifetime from a connectivity perspective (topological lifetime in [5]), we define the system lifetime as the number of data collection rounds before the percentage of connected SNs is degraded to a given threshold q. We assume that SNs can function long enough (or have effective duty cycles) so that coverage is not hindered.

It is obvious that the percentage of SNs with connectivity in a newly deployed network should not be less than q in order that the network functions. We can achieve this by ensuring that the probability that any SN connects to at least one RN is not less than a value σ_0. The relationship between q and σ_0 is presented in the Appendix. In the following, the connectivity requirement is specified by the individual node connectivity probability σ_0.

4 Random Deployment Strategies

In this section, we propose and examine deployment solutions for the following problem. Given a WSN as modeled in Section 3, how should one deploy a given number N_{RN} of RNs so that the network lifetime is maximized? We will answer the same problem in both single-hop and multihop WSNs. In the following, we use polar coordinates to specify locations on the sensing field.

4.1 Single-Hop Communication Case

In this part, we will first study the pros and cons of the connectivity-oriented deployment strategy. We then propose two novel deployment strategies, namely, lifetime-oriented deployment and hybrid deployment.

4.1.1 Connectivity-Oriented Deployment

Uniform deployment is the mostly used deployment model in the literature [11], [19], [20], [21], [22], [23]. Assume that N_{RN} RNs are deployed uniformly in a sensing site A of area $|A|$. For any SN, the probability that it can reach at least one RN in one hop is

$$p_R = 1 - \left(1 - \pi r_{SN}^2 p_c/|A|\right)^{N_{RN}}. \tag{8}$$

If a connectivity probability σ_0 for any SN is required, i.e., $p_R \geq \sigma_0$, the minimum number of RNs is expressed as

$$N_{RN}^{u\{\min\}} = \ln(1-\sigma_0)/\ln\left(1 - \pi r_{SN}^2 p_c/|A|\right). \tag{9}$$

Compared with other random deployments, this strategy provides identical and maximal connectivity everywhere in the WSN. In other words, for a given connectivity requirement σ_0, this strategy will require the least number of RNs (illustrated in Section 5). We, therefore, refer to it as the Connectivity-Oriented Deployment strategy. However, due to the BECR phenomenon discussed above, it suffers fundamentally from an energy efficiency perspective.

4.1.2 Lifetime-Oriented Deployment

We also refer to this strategy as a weighted random deployment. Consider two regions of a WSN: one far from the BS and another close to the BS. Assume that there is the same number of nodes (SNs and RNs) in each of them. As the active RNs in the farther region dissipate energy faster than their peers in the closer region due to the longer transmission range, the overall system becomes unusable even though much energy is left in RNs in the near region. To allow nodes in both regions to function for the same length of time, the node deployment density should reflect the different energy dissipation rates. That is, more RNs should be deployed as one gets farther from the BS. When one CH dies, another RN can take over its role.

Denote the integral of $E_{RN}(d,0)$ over the sensing area A by $D = \int_A E_{RN}(u,0)ududv$. For the nodes in different regions of the network to function for the same period, the RN deployment density at a point $(d,\theta) \in A$ should be proportional to the energy dissipation rate of an active RN at a distance d from the BS. As such, the RN deployment density function is

$$f(d,\theta) = E_{RN}(d,0)/D = (c_1 + g\alpha_2 d^m)nl/D \quad \text{if } (d,\theta) \in A \tag{10}$$

and $f(d,\theta) = 0$ otherwise. If N_{RN} RNs are deployed according to the density function (10), the probability that an SN at point (d,θ) can reach one or more RNs in one hop is

$$p_R(d,\theta) = 1 - \left(1 - p_c \int_{O(d,\theta)} f(u,v)ududv\right)^{N_{RN}}, \tag{11}$$

where $O(d,\theta)$ is a circle centered at (d,θ) with radius r_{SN}. If r_{SN} is relatively small, the probability can be approximated by

$$p_R(d,\theta) \approx 1 - \left(1 - \pi r_{SN}^2 p_c f(d,\theta)\right)^{N_{RN}}. \tag{12}$$

Assume that the connectivity σ_0 is required. Then, letting $p_R(d,\theta) = \sigma_0$ and using the approximation in (12), we have

$$1 - \left(1 - \pi r_{SN}^2 p_c f(d,\theta)\right)^{N_{RN}} = \sigma_0. \tag{13}$$

Plugging (10) into (13) and solving for d, we get

$$d_0 = \left[\left(\frac{D \cdot \left(1 - (1-\sigma_0)^{1/N_{RN}}\right)}{ng\alpha_2 l\pi r_{SN}^2 p_c} - \frac{c_1}{g\alpha_2}\right)\right]^{1/m}. \tag{14}$$

Formula (14) defines a cutoff distance in the sensing area. We define the region B as

$$B = \{(d,\theta) \mid (d,\theta) \in A, d < d_0\}. \tag{15}$$

In this region, the probability of connectivity of an SN is less than σ_0, while an SN outside of B has connectivity probability higher than σ_0. Assuming a square sensing area with the BS at the center, the cutoff circle and region B are illustrated in Fig. 2.

If we set the right side of (14) equal to zero and solve for N_{RN}, we have

$$N_{RN}^{w\{\min\}} = \ln(1-\sigma_0)/\ln\left(1 - c_1 nl\pi r_{SN}^2 p_c/D\right). \tag{16}$$

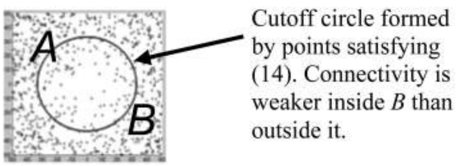

Fig. 2. An illustration of weighted random deployment.

That is, if N_{RN} is less than $N_{RN}^{w\{\min\}}$, the deployment according to (10) will not be able to meet the connectivity requirement in the subarea inside the cutoff circle.

Note that in order to obtain a numerical solution to a specific application scenario, one does not need to evaluate the number of SNs associated with one RN, n, which appears in many formulas above since it will be canceled out from the denominator and numerator.

4.1.3 Hybrid Deployment

The weighted random deployment of RNs according to the density function (10) can counteract the BECR phenomenon. However, this benefit will be fully realized only if the connectivity of SNs is satisfied in the network. If the number of given RNs, N_{RN}, is less than $N_{RN}^{w\{\min\}}$, the number of SNs without connectivity may be too high for the network to function properly.

The idea of the hybrid deployment is to optimize RN deployment by balancing the concerns of connectivity and lifetime extension. If $N_{RN} < N_{RN}^{u\{\min\}}$, there is no way to guarantee the connectivity in the first place. If $N_{RN} \geq N_{RN}^{w\{\min\}}$, the weighted random deployment as defined by (10) can provide sufficient connectivity. If $N_{RN}^{u\{\min\}} \leq N_{RN} < N_{RN}^{w\{\min\}}$, the weighted random deployment alone will not be able to satisfy the connectivity. In this case, the hybrid deployment tries to maximize the system lifetime while satisfying the connectivity requirement. To this end, the hybrid deployment is designed in two steps. First, we design the deployment of N_{RN}^{l} RNs to extend the lifetime in a weighted random manner defined by (10). Since the connectivity of an SN in the weak connectivity region B is less than σ_0, in the second step, we arrange the deployment of N_{RN}^{c} RNs exclusively in B so as to meet the connectivity requirement everywhere in the network (overall, the RNs in B are deployed uniformly when the RNs deployed in the two steps are combined together). The number of RNs deployed in the two steps should be equal to the given number N_{RN}. We next study how N_{RN} should be optimally split between N_{RN}^{l} and N_{RN}^{c}.

Allocation of RNs for the two steps is a constrained optimization problem. As N_{RN}^{l} increases, N_{RN}^{c} has to be decreased. However, if N_{RN}^{c} is too small, the connectivity of the sparse area of the network is at risk. In the following, we consider an arbitrary $n_{RN}^{1} < N_{RN}$ for the first step. To satisfy the connectivity in region B, we derive the number of RNs needed in the second step n_{RN}^{c} (enhance connectivity in region B) as a function of n_{RN}^{l}. By summing n_{RN}^{l} and n_{RN}^{c} (function of n_{RN}^{l}), we obtain the total number of RNs n_{RN} as a function of n_{RN}^{l}. We prove that n_{RN} is a nondecreasing function of n_{RN}^{l}. Therefore, we can easily solve for N_{RN}^{l} for a given N_{RN} numerically.

Assume that n_{RN}^{l} RNs have been deployed according to (10). We define the RN density at a position (d, θ) as the product of the number of RNs deployed and the density function $f(d, \theta)$. To make the connectivity in B meet the minimum requirement, the RN density in B should be leveled up to the RN density level of points (d_0, θ) on the boundary of B. The number of RNs needed in the second step is

$$n_{RN}^{c} = \left| \int_B \left(n_{RN}^{l} \cdot f(d_0, v) - n_{RN}^{l} \cdot f(u, v) \right) ududv \right|. \tag{17}$$

Plugging (10) into (17), we have

$$n_{RN}^{c} = \left| \frac{ngl\alpha_2 n_{RN}^{l}}{D} \int_B \left(d_0^m - u^m \right) ududv \right|. \tag{18}$$

Summing n_{RN}^{l} and n_{RN}^{c}, the total number of RNs deployed is

$$n_{RN} = n_{RN}^{l} + \left| \frac{ngl\alpha_2 n_{RN}^{l}}{D} \int_B \left(d_0^m - u^m \right) ududv \right|. \tag{19}$$

Lemma 1. *n_{RN} is an nondecreasing function of n_{RN}^{l}.*

Proof. See the Appendix.

In the second step, $N_{RN}^{c} = N_{RN} - N_{RN}^{l}$ RNs will be deployed in the region B according to the density function in (20):

$$g(d, \theta) = \begin{cases} \dfrac{f(d_0, \theta) - f(d, \theta)}{\int_B (f(d_0, \theta) - f(u, v)) ududv}, & \text{if } (d, \theta) \in B, \\ 0, & \text{otherwise.} \end{cases} \tag{20}$$

After the second step, the RN density becomes uniform everywhere in B and the connectivity is satisfied everywhere. Finally, the overall deployment density function for one-time deployment can be written as

$$h(d, \theta) = \begin{cases} \dfrac{f(d_0, \theta)}{f(d_0, \theta)|B| + \int_{A-B} f(u, v) ududv}, & \text{if } (d, \theta) \in B, \\ \dfrac{f(d, \theta)}{f(d_0, \theta)|B| + \int_{A-B} f(u, v) ududv}, & \text{if } (d, \theta) \in A - B. \end{cases} \tag{21}$$

4.2 Multihop Communication Case

In this part, we study the three random deployment strategies with the multihop communication model.

4.2.1 Connectivity-Oriented Deployment

The connectivity-oriented deployment in the multihop communication case is the same as the one in the single-hop case, in terms of the density function and connectivity property. It suffers fundamentally from an energy efficiency perspective due to the BECR phenomenon.

4.2.2 Lifetime-Oriented Deployment

Due to the aggregation effect of traffic relaying in the multihop communication model, deriving an optimal density function is more challenging than in the single-hop case. We present a derivation of a heuristic suboptimal deployment density function. Readers could fast forward to

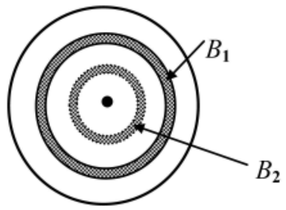

Fig. 3. A sensing site: the density function is proportional to the energy consumption rate and inversely proportional to the size of areas.

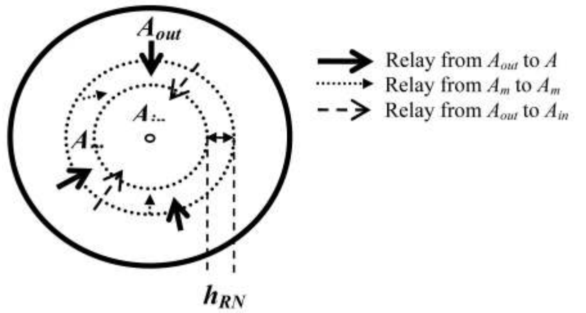

Fig. 4. The physical meaning of the effective radius of RNs.

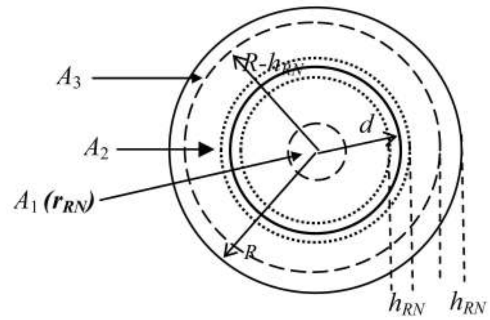

Fig. 5. Partitioning of a sensing site.

(36) for final expressions. We show that the lifetime is increased by up to more than three times by using the heuristic weighted deployment compared to the uniform deployment in our experimental setup. We first consider a circular sensing field of radius R, with the BS fixed at the center. We discuss how to extend the methodology to an arbitrary convex sensing field in Section 6.

The average deployment density in a given area should depend on two factors, namely, the average total energy consumption rate in the area and the size of the area. The energy consumption rate of an area is the total energy consumed by RNs in the area per round of data collection. To overcome the BECR problem, the average density over an area should be proportional to the energy consumption rate and inversely proportional to the size of the area. For example, in Fig. 3, consider two arbitrary shells B_1 and B_2 with the BS at the center. The size of B_1 is larger than that of B_2. Due to the BECR phenomenon, suppose that RNs in B_1 and B_2 have the same energy consumption per round. Then, B_2 should have higher deployment density so that the expected numbers of RNs are the same in the two areas.

We therefore define the *Energy Consumption Intensity* (ECI) of an area as the ratio of the energy consumption rate of the area to the size of the area. For an arbitrary point (d, θ) and a small positive value ε, we can form a disk of radius ε with (d, θ) at the center. We define the ECI of position (d, θ), i.e., ECI (d, θ) as the limit of the ECI of the disk as ε goes to 0. In fact, as the traffic is symmetric with respect to the BS, ECI (d, θ) does not depend on θ. The concept of ECI (d, θ) is the basis for deriving the weighted random deployment density function. The principle is that the density function should be proportional to the ECI at any position.

To obtain the ECI, we next derive the amount of intercluster traffic and intracluster traffic at different parts of the network. We first define a parameter h_{RN} as $h_{RN} = h^* r_{RN}$, where h is between 0 and 1. In Fig. 4, we construct the shell A_m of width h_{RN} lying between the two dotted circles in the sensing field. The area which is outside of A_m (farther from the BS) is referred to as A_{out}, and the area which is inside of A_m (closer to the BS) is referred to as A_m. Three types of traffic relay (between RNs) are of interest: first from A_{out} to A_m, second from A_m to A_m, and third from A_{out} to A_m directly. When $h = 1$, the direct relay from A_{out} to A_m does not exist and some relay happens from RNs in A_m to other RNs in A_m. As h becomes smaller (the width of the shell decreases), the relay from A_{out} to A_m directly becomes more common and so more traffic from RNs in A_{out} will not be relayed by RNs in A_m. At the same time, less traffic from RNs in A_m will be relayed to other RNs in A_m. By empirically choosing the value of h appropriately, the amount of traffic relayed from A_{out} to A_m directly and the amount of traffic relayed between RNs inside the shell A_m are largely canceled out by each other. In other words, the traffic in the two directions reaches equilibrium. As such, we can approximate the volume of intercluster traffic relayed by RNs in the shell A_m by all traffic generated by RNs in A_{out}. We will explore the optimal value of h in Section 5. Also, the average intracluster traffic volume handled by the RNs in any subarea is proportional to the size of the subarea under consideration. That is, the intracluster traffic handled by RNs in the shell A_m is the traffic originated by SNs located in the same shell. Following the same logic, the relay traffic transmitted from A_{out} to A_m is the sum of the aggregated traffic generated by SNs in A_{out}. The approximations on the intercluster and intracluster traffic volume of the shell A_m are the basis for the following derivation.

With h_{RN}, we partition a sensing field with radius R into three areas, as shown in Fig. 5. The part which is surrounded by the inner broken circle of radius r_{RN} is the first area, denoted by A_1. In this area, an RN is able to transmit to the BS in one hop. The shell between the two broken circles of radius of $R - h_{RN}$ and r_{RN}, respectively, is the second area, denoted by A_2. In this area, traffic is relayed from far to near. The remaining part, which is between the bounding solid circle of radius R and the broken circle of radius $R - h_{RN}$, is the third area, denoted by A_3. The intercluster relay traffic is negligible in area A_3. The three areas are defined as

$$A_1 = \{(d, \theta) | 0 \le d \le \min(r_{RN}, R), 0 \le \theta \le 2\pi\}, \qquad (22)$$

$$A_2 = \begin{cases} \{(d, \theta) | r_{RN} < d \\ \quad \le R - h_{RN}, 0 \le \theta \le 2\pi\}, & \text{if } R > r_{RN} + h_{RN}, \\ \phi, & \text{otherwise}, \end{cases} \qquad (23)$$

$$A_3 = \begin{cases} \{(d,\theta) | \max(r_{RN}, R-h_{RN}) < d \le R, \\ \quad 0 \le \theta \le 2\pi\}, & \text{if } R > r_{RN}, \\ \phi, & \text{otherwise.} \end{cases} \tag{24}$$

Note that if $R \le r_{RN}$, A_2 and A_3 shrink to null sets, and if $r_{RN} < R \le h_{RN} + r_{RN}$, A_2 shrinks to a null set. Without loss of generality, we consider the case where $R > h_{RN} + r_{RN}$. The other two cases are easily addressed following the same line of logic.

In A_1, the expected number of SNs is $N_{SN} r_{RN}^2 / R^2$. Substituting for n in (5), the expected total energy spent on intracluster communication by all RNs in A_1 is

$$E_{\text{intra}}^{(1)} = \left(c_1 + g\alpha_2 r_{RN}^m\right) N_{SN} l r_{RN}^2 / R^2. \tag{25}$$

All traffic generated by SNs outside of A_1 must be relayed by an RN in A_1 to reach the BS. The expected traffic relayed by RNs in A_1 is $gN_{SN} l (R^2 - r_{RN}^2)/R^2$. Substituting for l_{relay} in (6), the expected total energy spent on intercluster relay by RNs in A_1 is

$$E_{\text{inter}}^{(1)} = c_2 g N_{SN} l \left(R^2 - r_{RN}^2\right)/R^2. \tag{26}$$

We make the approximation that the ECI at any position (d,θ) in A_1 is the same and so is given by

$$\begin{aligned} \text{ECI}^{(1)}(d,\theta) &= \left(\frac{E_{\text{intra}}^{(1)} + E_{\text{inter}}^{(1)}}{\pi r_{RN}^2}\right) \\ &= \frac{N_{SN} l}{\pi R^2}\left(c_1 + g\alpha_2 r_{RN}^m + c_2 g\left(\frac{R^2}{r_{RN}^2} - 1\right)\right). \end{aligned} \tag{27}$$

The integral of $\text{ECI}^{(1)}(d,\theta)$ over A_1, denoted by $J^{(1)}$, is

$$J^{(1)} = \frac{N_{SN} l}{R^2}\left(c_1 r_{RN}^2 + g\alpha_2 r_{RN}^{2+m} + c_2 g\left(R^2 - r_{RN}^2\right)\right). \tag{28}$$

In A_2, the ECI at different positions might be largely differentiated, as RNs at different positions relay different amounts of traffic. We propose to approximate the ECI at point (d,θ) by the ECI of the shell between the two dotted circles of radius $(d - h_{RN}/2)$ and $(d + h_{RN}/2)$ (see Fig. 5), which is calculated as the sum of the energy consumption for intracluster communication $E_{\text{intra}}^{(2)}(d)$ and the energy consumption for the intercluster relay $E_{\text{inter}}^{(2)}(d)$, by RNs in the shell, divided by the size of the shell, i.e.,

$$\text{ECI}^{(2)}(d,\theta) = \left(\frac{E_{\text{intra}}^{(2)}(d) + E_{\text{inter}}^{(2)}(d)}{\pi\left((d + h_{RN}/2)^2 - (d - h_{RN}/2)^2\right)}\right). \tag{29}$$

Similar to (25), the energy consumption for intracluster traffic in the shell for each round of data collection is approximated as

$$E_{\text{intra}}^{(2)}(d) = \frac{2\left(c_1 + g\alpha_2 r_{RN}^m\right) N_{SN} l d h_{RN}}{R^2}. \tag{30}$$

The energy consumption for intercluster traffic in the shell for each round of data collection can be approximated by

$$E_{\text{inter}}^{(2)}(d) = c_2 g N_{SN} l \left(\frac{R^2 - (d + h_{RN}/2)^2}{R^2}\right). \tag{31}$$

Plugging (30) and (31) into (29), we have

$$\begin{aligned} \text{ECI}^{(2)}(d,\theta) = \frac{N_{SN} l}{\pi R^2}\Bigg\lfloor c_1 + g\alpha_2 r_{RN}^m \\ + \frac{c_2 g}{2 d h_{RN}}\left(R^2 - \left(d + \frac{h_{RN}}{2}\right)^2\right)\Bigg\rfloor. \end{aligned} \tag{32}$$

The integral of $\text{ECI}^{(2)}(d,\theta)$ over A_2, denoted by $J^{(2)}$, is

$$J^{(2)} = \frac{N_{SN} l}{R^2}\left[\begin{array}{c} \left(c_1 + g\alpha_2 r_{RN}^m\right)\left((R - h_{RN})^2 - r_{RN}^2\right) + c_2 g \\ \left(R^2(R - h_{RN} - r_{RN}) + \frac{(2r_{RN} + h_{RN})^3 - (2R - h_{RN})^3}{24}\right) \end{array}\right]. \tag{33}$$

For A_3, the traffic of intercluster relaying is negligible. Similar to A_1, the ECI at any position (d,θ) in A_3 is

$$\text{ECI}^{(3)}(d,\theta) = \frac{\left(c_1 + g\alpha_2 r_{RN}^m\right) N_{SN} l}{\pi R^2}. \tag{34}$$

The integral of $\text{ECI}^{(3)}(d,\theta)$ over A_3, denoted by $J^{(3)}$, is

$$J^{(3)} = \frac{\left(c_1 + g\alpha_2 r_{RN}^m\right) N_{SN} l (2R - h_{RN}) h_{RN}}{R^2}. \tag{35}$$

Let $J = J^{(1)} + J^{(2)} + J^{(3)}$. We propose the density function for the three areas as follows:

$$f(d,\theta) = \begin{cases} \text{ECI}^{(1)}(d,\theta)/J, & \text{if } (d,\theta) \in A_1, \\ \text{ECI}^{(2)}(d,\theta)/J, & \text{if } (d,\theta) \in A_2, \\ \text{ECI}^{(3)}(d,\theta)/J & \text{if } (d,\theta) \in A_3. \end{cases} \tag{36}$$

In the following, we discuss the properties of the deployment density in (36) in terms of connectivity. If N_{RN} RNs are deployed according to the density function in (36), we use (12) to approximate the probability that an SN, at point (d,θ), can reach one or more RNs in one hop. For an SN whose transmission disk is in A_i, for $i = 1, 2, 3$, the connectivity probability is

$$p_R^{(i)}(d,\theta) = 1 - \left(1 - \pi r_{SN}^2 \text{p}_\text{c} \text{ECI}^{(i)}(d,\theta)/J\right)^{N_{RN}}. \tag{37}$$

In A_1, if a connectivity probability σ_0 is required, letting $p_R^{(1)}(d,\theta) = \sigma_0$ and solving for N_{RN}, we have

$$N_{RN}^{w\{\min 1\}} = \ln(1 - \sigma_0)/\ln\left(1 - \pi r_{SN}^2 \text{p}_\text{c} \text{ECI}^{(1)}(d,\theta)/J\right). \tag{38}$$

If $N_{RN} \ge N_{RN}^{w\{\min 1\}}$, the deployment according to (36) will be able to meet the connectivity requirement in A_1.

Now, $p_R^{(2)}(d,\theta)$ is a decreasing function in $[r_{RN}, R - h_{RN}]$. Thus, an SN at distance $R - h_{RN}$ has the least connectivity probability $p_R^{(2)}(R - h_{RN},\theta)$, while an SN at distance r_{RN} from the BS has the highest connectivity probability $p_R^{(2)}(r_{RN},\theta)$. Following (38), we set

$$N_{RN}^{w\{\min 2\}} = \ln(1 - \sigma_0)/\ln\left(1 - \pi r_{SN}^2 \text{p}_\text{c} \text{ECI}^{(2)}(R - h_{RN},\theta)/J\right), \tag{39}$$

$$N_{RN}^{w\{\min 2-\}} = \ln(1 - \sigma_0)/\ln\left(1 - \pi r_{SN}^2 \text{p}_\text{c} \text{ECI}^{(2)}(r_{RN},\theta)/J\right). \tag{40}$$

If $N_{RN} < N_{RN}^{w\{\min 2-\}}$, the deployment according to (36) will not be able to meet the connectivity requirement

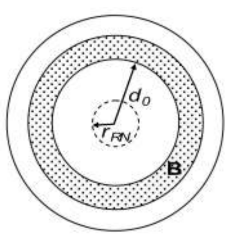

Fig. 6. The connectivity in B is not satisfied.

anywhere in A_2, while if $N_{RN} \geq N_{RN}^{w\{\min 2\}}$, the connectivity requirement is met everywhere in A_2. If $N_{RN}^{w\{\min 2-\}} \leq N_{RN} < N_{RN}^{w\{\min 2\}}$, the connectivity requirement is only partially met in A_2. In this case, letting $p_R^{(2)}(d,\theta) = \sigma_0$, we can solve for d using Newton's method since $p_R^{(2)}(d,\theta)$ is a decreasing function of d on $[r_{RN}, R - h_{RN}]$. The solution d_0 defines a cutoff distance inside the sensing area A_2. We define the region B as

$$B = \{(d,\theta) | d_0 < d \leq R - h_{RN}\}. \tag{41}$$

In the region B, the connectivity probability of an SN is less than σ_0, while in $A_2 - B$, an SN has connectivity probability at least σ_0. The cutoff circle and region B (tinted area) are illustrated in Fig. 6.

For A_3, we similarly define

$$N_{RN}^{w\{\min 3\}} = \ln(1-\sigma_0) / \ln\left(1 - \pi r_{SN}^2 \mathrm{p_c} \mathrm{ECI}^{(3)}(d,\theta)/J\right). \tag{42}$$

Then, letting $N_{RN}^{w\{\min\}} = \max\{N_{RN}^{w\{\min 1\}}, N_{RN}^{w\{\min 2\}}, N_{RN}^{w\{\min 3\}}\}$, if $N_{RN} \geq N_{RN}^{w\{\min\}}$ the connectivity of SNs is satisfied everywhere in the network.

4.2.3 Hybrid Deployment

For the same reason as stated in Section 4.1.3, we design a hybrid deployment for the multihop communication case. As in Section 4.1.3, the hybrid deployment is designed in two steps, where allocation of RNs for the two steps is a constrained optimization problem: as N_{RN}^l increases, N_{RN}^c has to be decreased. We next derive n_{RN}^c as a function of n_{RN}^l. In set A_1, the number of RNs needed is

$$n_{RN}^{c1} = \max\left(0, \ln(1-\sigma_0)/\ln\left(1 - r_{SN}^2/r_{RN}^2\right) - n_{RN}^l J^{(1)}/J\right). \tag{43}$$

Similarly, in A_3, the number needed is

$$\begin{aligned} n_{RN}^{c3} = \max\big(0, &\ln(1-\sigma_0)/\ln\left(1 - r_{SN}^2/\left(2Rh_{RN} - h_{RN}^2\right)\right) \\ &- n_{RN}^l J^{(3)}/J\big). \end{aligned} \tag{44}$$

For set A_2, we examine the compensation deployment in two cases. The first case is $N_{RN}^{w\{\min 2-\}} \leq N_{RN} < N_{RN}^{w\{\min 2\}}$ and the second case is $N_{RN} < N_{RN}^{w\{\min 2-\}}$. In the first case, the connectivity is partially satisfied in A_2. We define the RN density at a position (d,θ) as the product of the number of RNs deployed and the density function $f(d,\theta)$. To make the connectivity in set B in (41) meet the minimum requirement, the RN density in B should be leveled up to the RN density level of points (d_0,θ) on the boundary of B. The number of RNs needed in the second step is

$$n_{RN}^{c2} = \left| \int_B \left(n_{RN}^l \cdot f(d_0, v) - n_{RN}^l \cdot f(u,v)\right) ududv \right|. \tag{45}$$

Plugging (29) and (36) into (45), we have

$$n_{RN}^{c2} = \left| \begin{array}{l} \frac{c_2 g n_{RN}^l N_{SN} l}{R^2 J h_{RN}} \left(\frac{((R-h_{RN})^2 - d_0^2)(R^2 - (d_0 + h_{RN}/2)^2)}{2d_0} \right) - \\ \frac{c_2 g n_{RN}^l N_{SN} l}{R^2 J h_{RN}} \left(R^2(R - h_{RN} - d_0) + \frac{(2d_0 + h_{RN})^3 - (2R - h_{RN})^3}{24} \right) \end{array} \right|. \tag{46-1}$$

In the second case, the connectivity is not satisfied anywhere in A_2. The number of RNs in the second step is

$$n_{RN}^{c2} = \left\lceil \left(N_{RN}^{u\{\min\}} - n_{RN}^l\right) \frac{\left((R - h_{RN})^2 - r_{RN}^2\right)}{R^2} \right\rceil. \tag{46-2}$$

By summing n_{RN}^l and n_{RN}^{ci}, the total number of RNs deployed is $n_{RN} = n_{RN}^l + n_{RN}^{c1} + n_{RN}^{c2} + n_{RN}^{c3}$.

Lemma 2. *n_{RN} is a nondecreasing function of n_{RN}^l.*

Proof. See the Appendix.

For the compensation deployment, the number of RNs for each part can be calculated using (43), (44), and (46). The density function for areas A_1 and A_3 is uniform. The density function for the region B in A_2 in the first case is

$$g(d,\theta) = \frac{f(d_0,\theta) - f(d,\theta)}{\int_0^{2\pi}\int_{d_0}^{R-h_{RN}} (f(d_0,\theta) - f(u,v)) ududv}. \tag{47-1}$$

In the second case, the density function for all of A_2 is

$$g(d,\theta) = \frac{N_{RN}^{u\{\min\}}/\pi R^2 - n_{RN}^l f(d,\theta)}{\int_0^{2\pi}\int_{d_0}^{R-h_{RN}} (N_{RN}^{u\{\min\}}/\pi R^2 - n_{RN}^l f(u,v)) ududv}. \tag{47-2}$$

After the second step, the RN density becomes uniform everywhere in B and the connectivity is satisfied everywhere.

5 Performance Evaluation

In this section, we will evaluate the three deployment strategies using simulations. We are interested in the energy utilization and the system lifetime of the different deployment strategies. Therefore, two metrics are used to measure the performance. The first is the utilization of energy in the system, i.e., the ratio of the total consumed energy of RNs to the total initial energy. The other metric, denoted by Normalized DCR, is the number of data collection rounds normalized to the initial energy of an RN (the unit is Joule) before the network lifetime expires.

As RNs are densely deployed, energy is wasted if all of them work simultaneously. A clustering algorithm is used to select CHs from redundant RNs so that some RNs can connect all SNs, while other RNs go to sleep. Most existing clustering algorithms are designed for homogenous networks and they assign the role of CH to identical nodes in rotation [19], [20], [21], [22], [23]. Such schemes cannot be directly applied or extended to the case of heterogeneous networks. To conduct a convincing performance evaluation

TABLE 1
The Parameters of the Simulated WSN

α_1	50e-9 (J/bit)	m	2
α_2	10e-12 (J/bit/m^2)	g	0.2
β	50e-9 (J/bit)	γ	1e-12 (J/bit)
N_{SN}	10,000	R	500 (m)
r_{RN}	90 (m)	r_{SN}	30 (m)
q	0.8	σ_0	0.84
l	2000 (bits)	p_c	1

and a fair comparison of the deployment strategies, we propose a simple and effective idealized clustering scheme for heterogeneous WSNs.

5.1 Clustering Scheme

Assuming that every RN sets up a neighboring SN table upon initialization, the operation of our scheme is briefly described as follows:

1. An RN is elected as a CH if it covers the most uncovered SNs, and broadcasts an ADVERTISEMENT message to its neighboring RNs.
2. An RN goes to sleep if all of its neighboring SNs are present in one of received ADVERTISEMENT messages, which indicates that all neighboring SNs are served by some CH.
3. A CH keeps functioning until its energy is exhausted. In this case, the clustering scheme is locally invoked to select other CHs. The election gives preference to the RNs which cover the most uncovered SNs.
4. Depleted RNs will not be involved in any further operations.

The scheme has the following desirable properties. First, it ensures that each SN is able to reach a CH, unless all neighboring RNs are out of energy. Second, the clustering scheme tries to minimize the number of CHs. Third, the CH duty cycle is rotated in an on-demand manner. Only a CH which is going out of energy needs to invoke a local CH selection procedure.

After CHs have been locally selected in the network to connect SNs directly, the CHs execute the Bellman-Ford algorithm to set up the paths to the BS. For simplicity, we use a constant link cost so that the shortest paths correspond to minimum hop paths. If there are two or more shortest paths to the BS, the one with less traffic is chosen. We realize that energy-aware routing schemes may extend the lifetime of a network. However, the same applies to other deployment methods. We choose to use a simple and generic routing protocol to emphasize the effect of deployment strategies.

5.2 Simulation Setup

We simulate a WSN of 10,000 SNs on a disk sensing field with radius 500 m in which the BS is located at the center. The parameters used in the simulations are listed in Table 1.

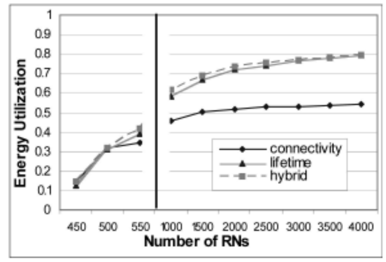

Fig. 7. Comparison of three deployment strategies by energy utilization in the single-hop case.

Therein, σ_0 is calculated to ensure (with probability greater than 0.9999) that the ratio of total connected SNs in an initial deployment is not less than q. We are interested in relative performance, and hence, the channel condition parameter p_c is set to 1 for clarity. Our offline analysis shows that the relative performance of the compared schemes would be similar. All experimental results presented are the average of 30 runs.

5.3 Comparison of Deployment Strategies in the Single-Hop Case

In this section, we explore and compare the performance of the three strategies in the single-hop communication case, as derived in Section 4.1. The three strategies are conducted on the same network, while N_{RN} varies from 450 to 4,000. The minimum numbers of RNs required to guarantee connectivity with a high probability (beyond 0.9999) in the connectivity-oriented deployment and the lifetime-oriented deployment are 509 (9) and 2,630 (16), respectively. Figs. 7 and 8 present, respectively, the average energy utilization and system lifetime (Normalized DCR) by using the three strategies.

As can be seen in Figs. 7 and 8, the hybrid deployment strategy performs uniformly better than the connectivity-oriented deployment in terms of both energy utilization and normalized system lifetime, while its performance is also better than that of the lifetime-oriented deployment strategy. When the number of RNs is between 450 and 1,000, the hybrid deployment can extend the lifetime by 5-15 percent as compared to the lifetime-oriented deployment.

For the connectivity-oriented deployment, when $N_{RN} = 450$, the energy utilization is only 14 percent and the DCR is only 21. The energy utilization climbs up to 32, 34, 45, and 50 percent when N_{RN} increases to 500, 550, 1,000, and 1,500, respectively. Correspondingly, the normalized DCR increases to 49, 56, 124, and 196. After that, the growth of energy utilization becomes much slower as the number

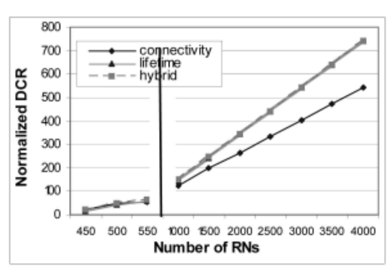

Fig. 8. Comparison of three deployment strategies by DCR in the single-hop case.

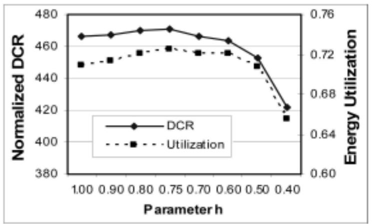

Fig. 9. Comparison of the lifetime-oriented deployments with different h by energy utilization and DCR.

of RNs increases. The energy utilization reaches 54 percent when $N_{RN} = 4{,}000$.

For the connectivity-oriented deployment, when $N_{RN} = 450$, the energy utilization is only 14 percent and the DCR is only 21. The energy utilization climbs up to 32, 34, 45, and 50 percent when N_{RN} increases to 500, 550, 1,000, and 1,500, respectively. Correspondingly, the normalized DCR increases to 49, 56, 124, and 196. After that, the growth of energy utilization becomes much slower as the number of RNs increases. The energy utilization reaches 54 percent when $N_{RN} = 4{,}000$.

In our experiments, when N_{RN} is small, the lifetime-oriented deployment provides shorter lifetime and lower energy utilization than the connectivity-oriented deployment, since it provides only weak connectivity in the part of the sensing field nearer to the BS. For example, when $N_{RN} = 450$, in the 30 runs, the connectivity is so poor in some cases that the deployment does not function at all. On the other hand, one should perhaps not expect improved energy utilization or extended system lifetime when the number of deployed sensors cannot even provide the desired connectivity using the connectivity-oriented deployment. When the number of RNs gets larger, the lifetime-oriented deployment enjoys fast performance improvement and outperforms the connectivity-oriented strategy on both lifetime and energy utilization. When $N_{RN} = 4{,}000$, the lifetime-oriented deployment provides a normalized DCR lifetime of 741 and energy utilization of 79 percent, compared with a normalized DCR of 543 and energy utilization of 54 percent in case of the connectivity-oriented deployment. Both measurements are improved by more than 35 percent. Of course, using the lifetime-oriented deployment, the desired connectivity is not achieved until at least 2,630 RNs are deployed.

In these experiments, the hybrid deployment is the preferred deployment strategy of the three, as it provides both energy efficiency and lifetime extension at least as good as that provided by the lifetime-oriented deployment, while also satisfying the connectivity requirement whenever the connectivity-oriented deployment does so. When $N_{RN} \leq 509$, the hybrid deployment is equal to the connectivity-oriented deployment as the number of RNs allocated for the first step will be 0. All RNs are used to meet the minimal connectivity (Section 4.1.3). When $509 < N_{RN} < 2{,}630$, the hybrid deployment provides better performance than the lifetime-oriented deployment since it reconciles the needs of lifetime extension and connectivity. The advantage becomes less significant as N_{RN} increases due to the fact that the connectivity issue becomes a less serious problem as N_{RN} approaches 2,630. When $N_{RN} > 2{,}630$, the hybrid deployment is reduced to the lifetime-oriented deployment.

TABLE 2
Key Properties of Deployment Strategies

$N_{RN}^{u\{\min\}}$	509	$N_{RN}^{w\{\min 1\}}$	98
$N_{RN}^{w\{\min 2\}}$	1181	$N_{RN}^{w\{\min 3\}}$	1495

We remark that for all the deployment strategies, the energy utilization appears to approach a saturation level as the number of RNs increases, while the normalized DCR grows approximately linearly. Under this observation, the performance of the connectivity-oriented deployment can be characterized as having a lower energy utilization saturation level and a smaller DCR growth slope compared to the lifetime-oriented or hybrid deployment performance curves. The energy wastage from the connectivity-oriented deployment, exemplified by its low-energy utilization saturation level, is due to the BECR problem.

5.4 Comparison of Deployment Strategies in the Multihop Case

The derivation of the lifetime-oriented deployment in Section 4.2.2 depends on an ad hoc parameter h. We first investigate how this design parameter affects the performance of the lifetime-oriented deployment strategy and determine the best value for the simulation setup above. We then present and discuss some simulation results on the performance of the three deployment strategies.

5.4.1 Impact of the Parameter h

We implement the lifetime-oriented deployment strategy using different values of h from 0.4 to 1.0. To make the comparison fair and effective, the number of RNs to be deployed is set to 2,500, which is greater than $N_{RN}^{w\{\min\}}$ for all cases ($N_{RN}^{w\{\min\}}$ is a function of h). In other words, with 2,500 RNs deployed by the weighted density function, the connectivity requirement is satisfied for all cases. The results are presented in Fig. 9.

The results for both the energy utilization and the system lifetime (Normalized DCR) indicate the same trend. First of all, the weighted random deployment performs the best at $h = 0.75$ for the given setup. Generally speaking, the performance varies slightly when h is between 0.6 and 1. From 0.75 to 1, the performance of the weighted random deployment degrades gradually as h increases. From 0.75 to 0.40, the performance degrades as h decreases and the drop accelerates for $h \leq 0.5$. We expect that the drop will continue as h decreases further. In the experiments which follow, we always use $h = 0.75$ for the weighted random strategy and corresponding hybrid strategy.

5.4.2 Comparison of Deployment Strategies

In this section, we explore and compare the performance of each of the strategies from Section 4.2. Some key properties of the connectivity-oriented deployment and the weighted deployment (when $h = 0.75$) are given in Table 2. Each of the three strategies is always implemented on the same network and we increase N_{RN} from 509 to 3,000. (According

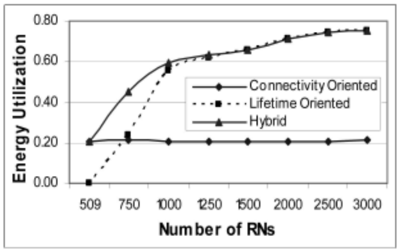

Fig. 10. Comparison of three deployment strategies by energy utilization in the multihop case.

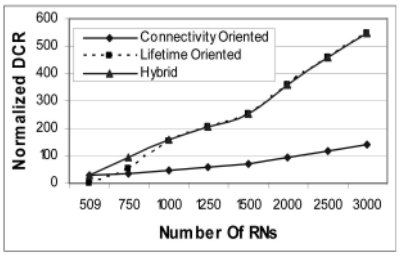

Fig. 11. Comparison of three deployment strategies by DCR in the multihop case.

to (9), if the number of RNs is less than 509, none of the strategies can provide a fully functioning network upon start-up with high probability.)

Figs. 10 and 11 present the results for the average energy utilization and Normalized DCR by using the three strategies.

For the connectivity-oriented deployment, the energy utilization is almost unchanged at around 21 percent as the number of RNs increases from 509 to 3,000. The energy wastage due to the BECR problem is clearly exemplified. The Normalized DCR does increase, in an approximately linear fashion, as the number of RNs increases, though the increase is slow relative to the other strategies. The overall poor performance of the connectivity-oriented deployment illustrates the critical importance of the RNs closer to the BS when using multihop transmission.

In contrast, since the weighted density function reflects the energy consumption at different locations, not only from the local traffic, but also from the traffic relayed from far to near, the lifetime-oriented deployment exhibits much better performance as N_{RN} increases. The energy utilization increases rapidly from 24 percent when $N_{RN} = 750$ to 66 percent when $N_{RN} = 1{,}500$. The rate of increase becomes less when $N_{RN} > 1{,}500$ and reaches 75 percent when $N_{RN} = 3{,}000$. Its benefits to the Normalized DCR are better realized when N_{RN} is larger and the connectivity is provided with high probability. As a result, the Normalized DCR increases much faster than for the connectivity-oriented deployment as N_{RN} gets larger. When $N_{RN} = 3{,}000$, the utilization of the lifetime-oriented deployment is more than three times of that of the connectivity-oriented deployment, and similarly, for the Normalized DCR. However, when $N_{RN} = 509$, the deployment according to the weighted random density function cannot satisfy the connectivity requirement, and the initial network is unusable.

As in the single-hop case, the hybrid deployment is the preferred deployment strategy of the three. When $N_{RN} = 509$, the hybrid deployment is equal to the connectivity-oriented deployment as the number of RNs

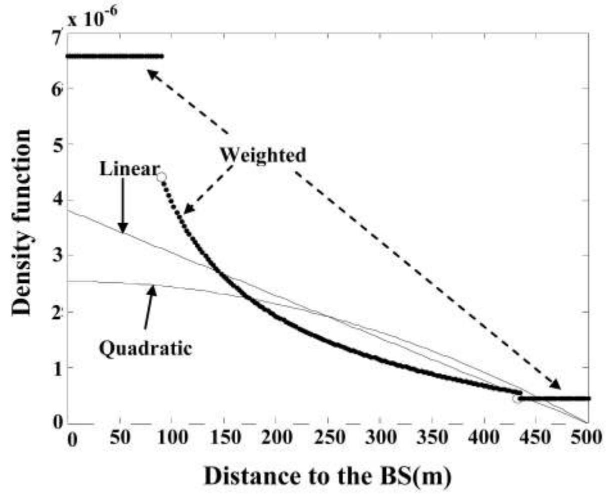

Fig. 12. Three deployment density functions.

allocated for the first step is 0. In this case, all RNs are used to meet the minimal connectivity (Section 4.2.3). When $509 < N_{RN} < 1{,}500$, the hybrid deployment provides better performance than the lifetime-oriented deployment since it reconciles the needs of lifetime extension with the connectivity. The advantage becomes less significant as N_{RN} increases due to the fact that the connectivity issue becomes a less serious problem as N_{RN} approaches $N_{RN}^{w\{\min\}} = 1{,}495$. When $N_{RN} > N_{RN}^{w\{\min\}}$, there is no difference between the hybrid deployment and lifetime-oriented deployment.

The general trend of the weighted density function is that positions farther away from the BS receive less density. It may be that there exist other decreasing functions in a simple form that can provide similar performance. If so, one can avoid going through the derivations of Section 4.2.2. We investigate this by considering two decreasing functions of simple form as optional deployment density functions. We conduct experiments using them and compare the results with those of the weighted density function.

The first is a quadratic density function. Consider a shell of width ε (a small value) at distance d. A quick estimate of the traffic passing by the RNs in the shell is approximately equal to the traffic generated from SNs farther than d (from the BS). The expected number of SNs whose distance from the BS is equal to or greater than d is proportional to $(R^{2-}d^2)$, and so is the traffic volume passing by the shell. We, therefore, propose a quadratic density function given by

$$f(d, \theta) = \frac{2(R^2 - d^2)}{\pi R^4}. \tag{48}$$

Interestingly, this density function is equivalent to the density function (14) given in [14].

Another simple function we consider is the linear density function given by

$$f(d, \theta) = \frac{3(R - d)}{\pi R^3}. \tag{49}$$

We implement the deployment according to the density functions (36), (48), and (49) with 2,000, 2,500, and 3,000 RNs. The density functions are first plotted and compared in Fig. 12. Results are presented in Figs. 13 and 14.

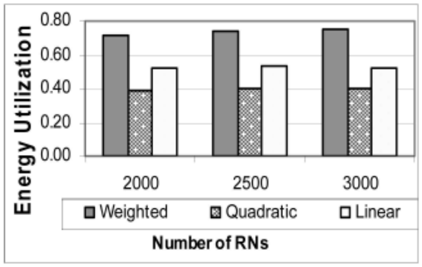

Fig. 13. Comparison of three density functions by energy utilization.

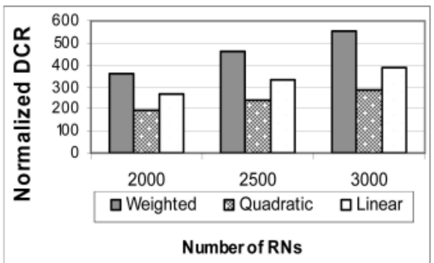

Fig. 14. Comparison of three density functions by DCR.

Generally speaking, the weighted density function given by (36) performs the best of the three functions in all cases. Both the linear density function and quadratic function overcome the BECR problem to some degree. However, the performance of the linear function performs always better than the quadratic function. Actually, (32), which determines the deployment in A_2 (from radius 90 to 432.5 m), is composed of a linear function of d and a inverse function of d. It partially explains the advantage of the linear function over the quadratic function.

6 Practical Issues

In this section, we address two practical issues with random deployment strategies. We first discuss how to apply the derivations in Section 4 to a sensing field of a more general shape. We then briefly discuss the implementation of random deployment strategies in practice.

6.1 General Sensing Field

We first remark that the validity of the derivations for the deployment strategies in the single-hop communication case is not limited to any particular shape of the sensing field. On the other hand, the derivations in Sections 4.2.2 and 4.2.3 assume a sensing field which is a disk with the BS at the center. However, the method and the derivations can be extended to the case where the sensing field is of arbitrary convex shape and the BS is at an arbitrary position or even outside the sensing field, as long as RNs can be deployed anywhere on the same planar (not restricted to the sensing field). For example, in Fig. 15a, SNs are uniformly deployed in a sensing field S, represented by the solid irregularly shaped region, and the BS is outside of S. In such a case, draw two lines (broken lines in Fig. 15a) from the BS tangent to the boundary of S. Thus, we can determine an RN deployment density function for the area surrounded by the irregular curve and the tangent lines, denoted by S', which encompasses the sensing field S. We first derive the ECI of

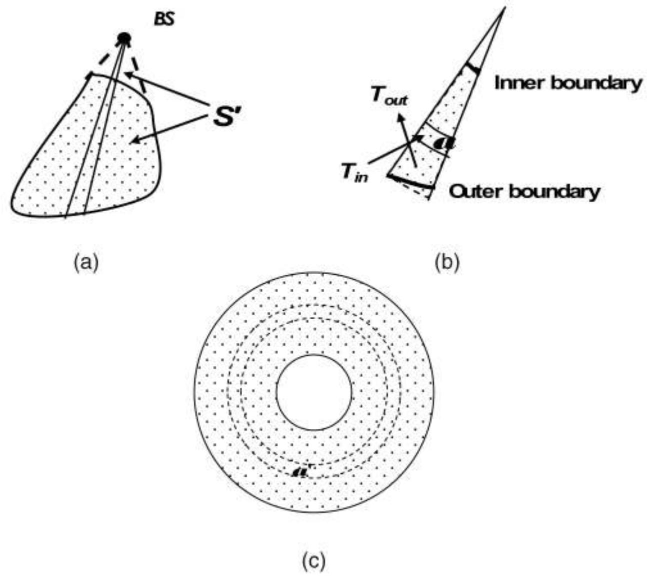

Fig. 15. Irregularly shaped sensing site with the BS is outside of it. (a) RNs are to be deployed in S'. (b) A wedge contains a slide out of S'. (c) The wedge is expanded to a full disk.

each position in S', which indicates the expected energy consumption rate. The overall deployment density function is the ECI divided by the integral of ECI over S'.

To find the ECI function, we start by cutting S' into "pie slices" by drawing line segments from the BS to the boundary of S' such that in any given slice, the points on the same boundary of S (there are two boundaries in Fig. 15b) are all at a similar distance from the BS. As such, we can approximate the intersection of a slice with S' by an arced wedge which just contains the intersection, as magnified in Fig. 15b. In order to obtain the ECI for a point a in Fig. 15b, we first construct a (in-wedge) shell around a of width h_{RN} so that a has an equal distance to the two sides of the shell, similar to Fig. 5. The energy consumption of RNs inside the wedge is due to the local intracluster traffic, and the intercluster traffic from the area which are further away, either inside or outside of the wedge. Note that, in practice, traffic inside the wedge would be partially routed through RNs outside the wedge. On the other hand, some traffic outside the wedge will be routed through the RNs in the shell. We argue that these two inverse traffic flows would be largely canceled out. Therefore, we can approximate that the energy consumption at points in the wedge is due to receiving, transmitting, and relaying information from (some) sensors contained in wedge, but not from sensors outside the wedge. Now imagine expanding the wedge into a disk, as denoted by the dotted circle in Fig. 15c. As the traffic amount increases proportionally to the size of the field, in other words, when the wedge is expanded into a full disk, the energy consumption rate and the area are amplified by the same factor. According to (25)-(34), the ECI of the shell around a in Fig. 15b is equal to the ECI of the shell centered at a' in Fig. 15c as long as their distances to the BS are the same. As we use the ECI of the shell to approximate the ECI of the point, the ECI at the point a in Fig. 15b is the same as the ECI at the point a' in Fig. 15c. The ECI function as derived in (25)-(34) in Section 4.1.2 can now be used for the disk in Fig. 15c without

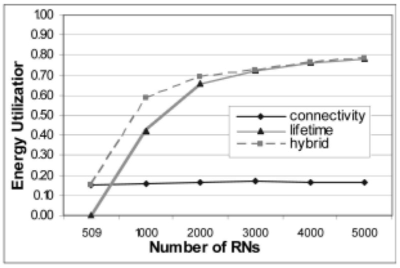

Fig. 16. Comparison of three deployment strategies by energy utilization with the square sensing field (multihop communication).

modification except for the nonsensing subarea between the S area and the BS. For the nonsensing part, the derivation is essentially the same; except that the expected intracluster traffic comes from this part is 0.

The hybrid deployment can be further derived once the weighted density function is determined. As the Lemma 2 holds for any disk sensing field, we argue that it also holds for any wedges, except that the exact number of RNs scales with the angle of the wedge. Therefore, Lemma 2 holds for any convex sensing field which can be seen as a combination of a group of wedges. Therefore, to construct the hybrid deployment density function, we can start from a small n^l_{RN} and construct the lifetime-oriented deployment density function, and then, evaluate the number of RNs, n^c_{RN}, required to compensate for the connectivity and the respective deployment density function. We then increment n^l_{RN} iteratively until the sum of n^l_{RN} and n^c_{RN} is equal to a given number N_{RN}.

To verify this idea, a group of experiments is conducted on a square sensing field. The side length is set to be 886.2 so that the area of the square field is the same as that of the disk field considered in Section 5. The BS is fixed at the middle of one edge. All other parameters are kept the same as in Section 5. Figs. 16 and 17 present the results of the three strategies. We observe that the performance improvement by the lifetime-oriented deployment and hybrid deployment over the connectivity-oriented deployment is more significant in the case of the square field compared to that in the case of the disk field. This may be due to the greater radial asymmetry of the square, and therefore, a higher degree of unbalance in the energy consumption rates.

6.2 Implementation

A few methods can be used, in practice, to implement random deployment as dictated by a density function. One is a variable rate leaky bucket method. For example, consider a transportation tool used to deploy N_{RN} RNs on a row-by-row basis. The transportation tool will keep track of the integral of the density function over the area it has swiped. If the increment of the integral reaches $1/N_{RN}$, the transportation tool drops one RN. As well, the movement of the RNs in the direction of inertia when traveling from the transportation tool to the sensing field should be taken into consideration. Fig. 18 demonstrates the variable rate leaky bucket method.

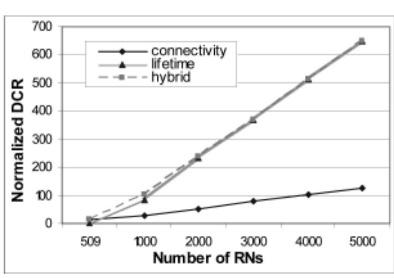

Fig. 17. Comparison of three deployment strategies by DCR with the square sensing field (multihop communication).

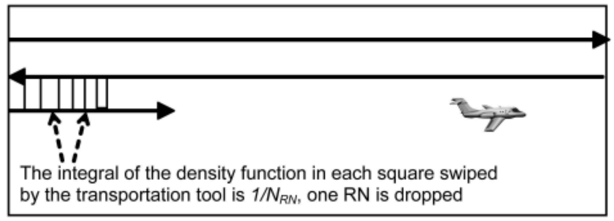

Fig. 18. An illustration of the variable rate leaky bucket method.

7 Conclusion

Device deployment is a fundamental issue in WSNs. The number and positions of devices determine the usability of a system in terms of coverage, connectivity, lifetime, cost, etc. In this paper, we study the impacts of random device deployment on connectivity and lifetime in a large-scale heterogeneous WSN. We first examine the BECR problem with the uniform random deployment in both single-hop and multihop WSNs. This problem results in low-energy utilization of RNs and unnecessarily short system lifetime. To overcome the BECR problem, we propose two novel deployment strategies for each case, namely, lifetime-oriented deployment and hybrid deployment (balancing connectivity and lifetime goals). The performance study of the deployment strategies shows that the new strategies have significant advantages to the connectivity-oriented deployment, which is the only random deployment strategy used in the literature. When the number of RNs is relatively small, the hybrid deployment is the preferred solution as it reconciles the concerns of lifetime with connectivity. When the number of RNs is large, the hybrid deployment is the same as the lifetime deployment, and they both significantly outperform the connectivity-oriented deployment. This paper provides a guideline for random deployment of typical large-scale heterogeneous WSNs.

Appendix

The Relationship between q and σ_0

If the connection probability of any individual SN is σ, the probability that x out of N_{SN} SNs are connected has the binomial distribution with parameter (N_{SN}, σ_0). When $N_{SN}\sigma$ and $N_{SN}(1-\sigma)$ are big enough, this binomial distribution can be approximated by the normal distribution with mean $N_{SN}\sigma$ and standard deviation $\sqrt{N_{SN}\sigma(1-\sigma)}$. If we want the deployment to satisfy the functionality threshold q with a high probability (say 0.9999 and above), the minimum connection probability of any individual SN, denoted by σ_0, can be obtained as a function of q.

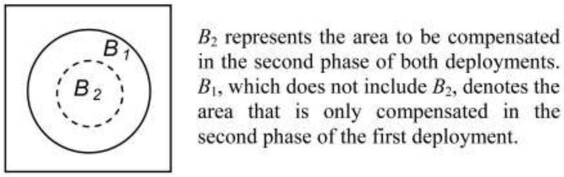

Fig. 19. Comparison of two deployments.

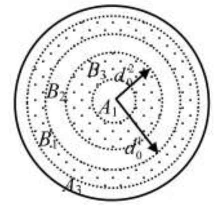

Fig. 20. Comparison of two hybrid deployments.

Proof of Lemma 1. Pick two integer numbers n_{RN}^{l1} and n_{RN}^{l2}, where $n_{RN}^{l1} < n_{RN}^{l2}$. Consider two deployments in which n_{RN}^{l1} and n_{RN}^{l2} RNs are deployed in the first step, respectively. We have the following cases:

1. If both deployments satisfy the connectivity requirement, i.e., $n_{RN}^{l2} > n_{RN}^{l1} \geq N_{RN}^{w\{\min\}}$, no RNs are needed for the second step, and the argument holds.
2. If the first deployment does not meet the connectivity requirement, while the second one does, then $n_{RN}^{c1} \leq N_{RN}^{w\{\min\}} - n_{RN}^{l1} \leq n_{RN}^{l2} - n_{RN}^{l1}$ RNs are needed to be deployed to compensate for the density in the sparse areas, and the argument holds.
3. If both deployments do not satisfy the connectivity requirement, then deploy n_{RN}^{c1} and n_{RN}^{c2} RNs, respectively, to satisfy the connectivity requirements according to (18). As illustrated in Fig. 19, the average number of RNs in the area B_2 (B area for the second deployment) is the same for both deployments as they just meet the connectivity requirement. The number of RNs from the second deployment in the area B_1 (B area for the first deployment excluding B_2) is more than that from the first deployment since the first deployment just meets the connectivity requirement, and the second deployment provides better connectivity. In the rest of the area, the number of RNs is determined by the first step of each deployment only and the first deployment will have fewer RNs. Summing the numbers of RNs in the three parts, the argument holds. □

Proof of Lemma 2. Pick two integers n_{RN}^{l1} and n_{RN}^{l2}, where $n_{RN}^{l1} > n_{RN}^{l2}$. Consider two deployments in which n_{RN}^{l1} and n_{RN}^{l2} CHs are deployed in the first step, respectively. We have the following cases:

1. If both deployments satisfy the connectivity requirement, i.e., $n_{RN}^{l1} > n_{RN}^{l2} \geq N_{RN}^{w\{\min\}}$, then no RNs are needed for the second step, and the argument holds.
2. If the second deployment does not meet the connectivity requirement, while the first one does, then $n_{RN}^{c2} \leq N_{RN}^{w\{\min\}} - n_{RN}^{l2} \leq n_{RN}^{l1} - n_{RN}^{l2}$ RNs are needed to be deployed to compensate for the density in the sparse areas, and the argument holds.
3. If both deployments do not satisfy the connectivity requirement, then deploy n_{RN}^{c1} and n_{RN}^{c2} RNs, respectively, to satisfy the connectivity requirements according to (43), (44), and (46). As illustrated in Fig. 20, a sensing field is partitioned into A_1, A_2, and A_3 as in Section 4.2.2 (see (22)-(24) and Fig. 5). The area A_2 is further cut into three parts B_1, B_2, and B_3, where B_1 is the B area for the first deployment (41), B_1 and B_2 together are the B area for the second deployment, and B_3 is the rest of A_2. The expected number of RNs in B_1 is the same for both deployments since both deployments just meet the connectivity requirement. The expected number of RNs in B_2 of the first deployment is not less than that of the second deployment because the second deployment just meets the connectivity requirement, while the first one provides better connectivity. The expected number of RNs in B_3 of the first deployment is again not less than that of the second deployment as both deployments provide good connectivity in the first place and $n_{RN}^{l1} > n_{RN}^{l2}$. For a similar reason, the expected number of RNs in the areas A_1 and A_3 of the first deployment is not less than that of the second deployment. Summing the numbers of RNs in all parts, the argument holds.□

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