NETWORK DIMENSIONING IN RANDOMLY DEPLOYED WIRELESS SENSOR NETWORKS

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ABSTRACT

NETWORK DIMENSIONING IN RANDOMLY DEPLOYED WIRELESS SENSOR NETWORKS

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In this study, we considered a heterogeneous, clustered WSN, which consists of two types of nodes (clusterheads and sensor nodes) deployed randomly over a sensing field. We investigated two cases based on how clusterheads can reach the sink: direct and multi-hop communication cases. Network dimensioning problems in randomly deployed WSNs are among the most challenging ones as the attributes of these networks are mostly non-deterministic. We focused on a number of network dimensioning problems based on the connected coverage concept, which is the degree of coverage achieved by only the connected devices. To evaluate connected coverage, we introduced the term cluster size, which is the expected value of the area covered by a clusterhead together with sensor nodes connected to it. We derived formulas for the cluster size and validated them by computer simulations. By using the cluster size formulas, we proposed a method to dimension a WSN for given targeted connected coverage.

Furthermore, we formulated cost optimization problems for direct and multi-hop communication cases. These formulations utilize not only cluster size formulas but also the well-connectivity concept. We suggested some search heuristics to solve these optimization problems. Additionally, we justified that, in practical cases, node heterogeneity can provide lower cost solutions. We also investigated the lifetime of WSNs and for-

mulated a cost optimization problem with connected coverage and lifetime constraints. By solving this optimization problem, one can determine the number of nodes of each type and the initial energies of each type of node that leads to lowest cost solution while satisfying the minimum connected coverage and minimum lifetime requirements.

Keywords: Wireless Sensor Networks, connected coverage, node heterogeneity, cluster size, network dimensioning

ÖZ

RASTGELE ATILMIŞ KABLOSUZ ALGILAYICI AĞLARINDA BOYUTLANDIRMA

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Bu çalışmada, rastgele atılmış kümebaşı ve algılayıcı olmak üzere iki farklı tipte düğümden oluşan ayrışık ve kümelendirilmiş kablosuz algılayıcı ağlarını (KAA) ele aldık. Küme başlarının genel alıcıya nasıl ulaştığına göre doğrudan ve çok zıplamalı olmak üzere iki ayrı durumu inceledik. Rastgele atılmış KAA'da, ağ boyutlandırma problemleri belirli olmayan niteliklerinden dolayı, en zorlayıyıcı boyutlandırma problemleri arasında yer alır. Bağlı cihazlar tarafından sağlanan kapsamanın seviyesi olan bağlı kapsama kavramını temel alan ağ boyutlandırma problemleri üzerine odaklandık. Bağlı kapsamayı elde edebilmek için küme başı ve ona bağlı algılayıcıların kapsadığı alanın beklenen değerine karşılık gelen küme büyüklüğü terimini önerdik. Küme büyüklüğü için formüller türettik ve bunları bilgisayar benzetimleri ile doğruladık. Bu formülleri kullanarak verilen bir hedef bağlı kapsama gereksinimine göre bir KAA'nı boyutlandırmak için bir yöntem önerdik.

Ayrıca, doğrudan ve çok zıplamalı durumlar için bir maliyet eniyileme problemi tertip ettik. Bu tertipler küme büyüklüğü formülleri ve iyi-bağlanmışlık kavramını kullanmaktadır. Bu eniyileme problemlerini çözmek için bir takım buluşsal arama yöntemleri önerdik. Pratik durumlarda düğüm ayrışıklığının ucuz çözümler sağlayabileceğini

doğruladık. Ayrıca, KAA'nın ömrünü inceledik ve bağlı kapsama ve ömür kısıtları ile bir maliyet eniyileme problemi tertip ettik. Bir kişi, bu eniyileme problemlerini çözerek en düşük bağlı kapsama ve ağ ömrü gereksinimlerini karşılayan en ucuz çözüme götüren her bir tipteki düğüm sayısını ve her tip düğüm için başlangıç enerjisini bulabilir.

Anahtar Kelimeler: Kablosuz Algılayıcı Ağlar, bağlı kapsama, düğüm ayrışıklığı, küme büyüklüğü, ağ boyutlandırma

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To my family...

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LIST OF ABBREVIATIONS

ADV ADVertisement type of message

CCC Constrained Coverage with Connectivity

CSMA Carrier Sense Multiple Access

DSSS Direct-Sequence Spread Spectrum

EAPC Energy Aware Partial-Coverage Protocol

FSC Free Space Channel

IP Internet Protocol

JOIN-REQ Join-REQuest type of message

LEACH Low-Energy Adaptive Clustering Hierarchy

LEACH-C Low-Energy Adaptive Clustering Hierarchy - Centralized

LP Linear Programming

MAC Medium Access Control

MINP Mixed Integer Non-Linear Programming

MP Multipath

NP-hard Nondeterministic Polynomial-time Hard

PCA Probabilistic Coverage Algorithm

PLL Phase-Locked Loop

PPP Poisson Point Process

RSSI Received Signal Strength Indicator

SCHE Schedule notification type of message

SYNC Synchronization type of message

TDMA Time Division Multiple Access

VCO Voltage-Controlled Oscillator

WSN Wireless Sensor Network

LIST OF SYMBOLS

pJ	pico joule
nJ	nano joule
Φ	Poisson Point Process

CHAPTER 1

INTRODUCTION

Mankind has always been assigning troublesome, hazardous, and jeopardous tasks to tools, instruments, appliances, machines, and sometimes to the systems. Recent technological advances in wireless communication, computation, and microsensor devices made it possible to exploit Wireless Sensor Networks (WSNs) in such tasks. Numerous applications that had not been conceived before the launch of WSNs can now be easily realized. WSNs have numerous exciting applications in virtually all fields of science and engineering, including health care, industry, military, security, environmental science, geology, and agriculture. Over the last few years, WSNs have attracted significant attention by many researchers and practitioners for their promising potential use in a variety of applications including environmental monitoring [1],[2],[3],[4],[5],[6] habitat monitoring [7],[8],[9],[10], seismic data-gathering [11], military applications [12],[13],[14],[15], agriculture [16],[17] etc.

1.1 What is a Wireless Sensor Network?

The main motivation for using WSNs is their ability to operate unattended in harsh environments in which human-interacted or human-controlled monitoring schemes are risky, inefficient and sometimes infeasible. Due to WSNs' great potential opportunities, the academia and industry have been making a remarkable progress over the last decade. Numerous hardware platforms have been built, many existing operating systems have been modified and new systems have been developed from scratch to be tailored for the specific requirements of diverse applications. A large number of protocols and algorithms for networking, communication, and processing have been proposed and are still being put forward for different needs. Since WSNs are applied in a wide variety of areas, it is not simple and straightforward to give a universally agreed upon definition. In [18], the authors gave a de facto definition of a WSN as "...a large-scale (thousands of nodes, covering large geographical areas), wireless, ad hoc, multi-hop, unpartitioned network of homogeneous, tiny (hardly noticeable), mostly immobile (after deployment) sensor nodes that would be randomly deployed in the area of interest...". Although this definition seems to be a generic one, it still conforms to only a specific class of WSN applications because there are a number of studies employing heterogeneous nodes and/or assuming single-hop communication.

In this thesis, we opt to give a definition for the typical WSN as "the network consisting of some number of sensor nodes with wireless communication, moderate storage, and on-board processing capability". Each sensor node is responsible for sensing or monitoring physical phenomena of interest around its vicinity. These sensing devices work collaboratively (See Fig. 1.1) to pass the sensed data to the sink (a.k.a., base station or communication center) in an ad hoc fashion wherever a fixed backbone infrastructure is not viable. Fig. 1.1 illustrates a typical WSN consisting of numerous sensor nodes deployed over the sensing field and a sink node connected to some of these sensor nodes.

A typical sensor node is a small, (Fig. 1.2 depicts a real-life sensor node) a battery-operated device and is equipped with a limited amount of storage, and have processing capabilities. Due to their size limitation, sensor nodes are severely energy constrained.

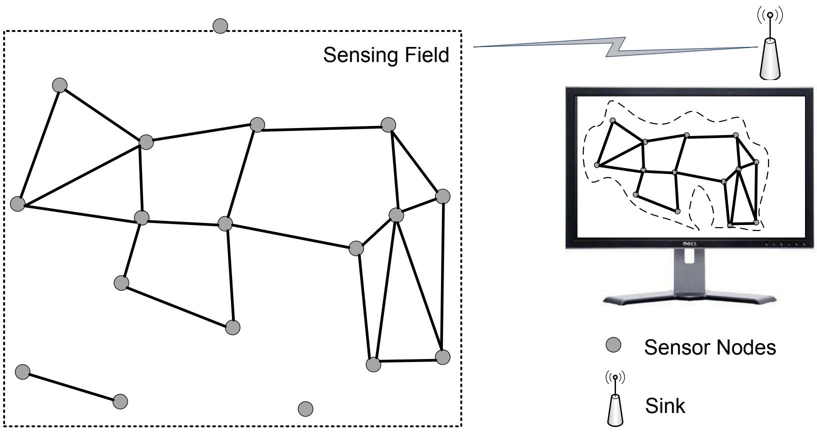

Figure 1.1: Wireless Sensor Network Example

However, these definitions provided are not enough to describe all classes of WSN applications with all their aspects or characteristics. To specify a certain WSN application, one should mention the attributes characterizing the application in hand. In [18], Römer and Friedemann coined the concept "the design spaces for a WSN" for these attributes. Depending on the special requirements and constraints, each application could be identified by using the design spaces listed below:

- **Deployment** - one-time, incremental or as random activity. In one-time case, no replenishment is anticipated. In the incremental deployment, additional nodes are needed to be deployed after the initial deployment to satisfy some specific requirement such as fault tolerance.

- **Mobility** - No mobility (stationary nodes). All nodes or selected set of nodes may have the ability to move within the sensing field either occasionally or continuously.

- **Monetary cost, size, and resources** - WSNs are usually designed based on an anticipated budget and some certain limited system resources such as energy, storage capacity, etc.

- **Heterogeneity** - a single type of node or diverse sets of nodes with varying properties and hierarchies.

- **Communication modality** - Other than radio frequency, some applications may also use optical, acoustic, inductive and capacitive coupled communication.

- **Infrastructure** - Some classes of applications may permit or require the use of fixed infrastructure.

- **Network topology** - single-hop, star, multi-hop, mesh and/or multi-tier.

- **Coverage** - Depending on the specific requirements of the application, full-coverage, partial-coverage, and redundant coverage can be assumed.

- **Connectivity** - Nodes need to satisfy targeted level of connectivity continuously or occasionally.

- **Network size** - Number of deployed nodes may be in the order of tens to thousands.

- **Lifetime** - Lifetime of an application is another important design space since it may range from a few hours to several months or even to many years.

- **Quality of service related and other requirements**- real-time constraints [19] (There may be specific requirements which enforce strict bandwidth and delay bounds, and sometimes some specialized Medium Access Control (MAC) and routing protocols), special requirements for a hardware device that is extremely difficult to reverse engineer or extract information (i.e., tamper-resistance), a hardware device that should not be easily noticed (i.e., unobtrusiveness), and many others.

Figure 1.2: A real sensor node example, MicaZ [20] with dimensions $58mm \times 32mm \times 7mm$ excluding the battery pack

1.2 WSN Design Issues

Due to the large variety of specific requirements (such as degree of required coverage and connectivity, and delay characteristics, etc) and tight constraints (such as limited initial energy), the design of a WSN application is not trivial. These complex systems essentially consist of subcomponents both in hardware and in software domain. While selecting the appropriate subcomponents, the designers should rigorously understand and consider each and every design space given in Section 1.1. Since every design space has a direct impact on the other design space(s), more importantly, it affects the overall network performance. In the following, we focus on how each design space may influence the other design space(s).

- **Deployment** - The deployment method along with the given coverage and connectivity requirements determine the required number of sensor nodes and thus it influences the monetary cost of the network application.

- **Mobility** - If deployed sensor nodes are mobile, the communication scheme maybe handled more easily or less number of sensor nodes maybe needed. Mobility may further simplify the required transmission and reception techniques.

- **Monetary cost, size, and resources** - If a WSN application has an anticipated budget, the monetary cost of each device becomes very critical. And a stringent resource such as initial energy has a direct impact on the selection of appropriate MAC layer and routing protocols.

- **Heterogeneity** - Heterogeneity is exploited to tackle the scalability problems in such large networks along with classical and novel clustering techniques. Heterogeneity can also be employed to have the optimal distribution of the limited resources available.

- **Network topology** - Network topology along with the coverage requirement and the deployment method affect the required number of sensor nodes. Communication schemes are also dependent on the selected network topology. Communication schemes further determine energy dissipation and thus WSN lifetime. Communication schemes further determine energy dissipation and thus WSN lifetime.

- **Coverage** - Coverage is a function of node density (i.e., number of nodes required) and sensing range. Node density and sensing range further specify monetary cost.

- **Connectivity** - Network connectivity is another important issue because it is crucial for most applications where the network should not be partitioned into disjoint parts. Like coverage, connectivity also depends on node density, transmission range, and topology of the sensing field. Targeted level of connectivity determines the choice of MAC and routing protocols.

- **Network size** - As the number of nodes in a network grows, the scalability challenge comes in. Scalability problems can be mitigated by employing the appropriate network topology and protocols. Network size also determines the monetary cost of the WSN.

- **Lifetime** - Lifetime is yet another extremely critical aspect for gaining maximum benefit from a WSN application. To prolong lifetime, one could increase the number of nodes deployed and/or equip the nodes with high capacity batteries where both of which further increase the WSN's monetary cost. Lifetime of a WSN is bounded by power consumption of devices in the network. Thus, it is limited to the initial energies of sensor nodes.

1.3 Clustering

A WSN usually consists of thousands of nodes, therefore, scalability becomes a critical issue and it should be addressed by WSN designers in order to avoid performance degradation as the network size (or node density) increases. One sensible solution to the scalability problem is the clustering. Sensor nodes could be grouped into disjoint and mostly non-overlapping clusters based on their proximity, energy levels, etc. Clustering usually necessitates that only clusterheads perform long-haul communication to the sink or to other clusterheads. This makes the network more scalable and energy-efficient.

Within a cluster, a clusterhead could be selected after the deployment through some selection phase or be predetermined before the deployment. Clusterheads are generally used to perform data aggregation and long-range communication. Effective data aggregation techniques can be utilized at the clusterheads to fuse the correlated data signals from the cluster members into one smaller frame and thus save additional energy.

Although clustering schemes seem to be the most "classical and straightforward solution" to scalability and power saving, these schemes may impose a communication burden on the operation of WSN application such as the clusterhead selection and the inter-cluster communication.

1.4 Node Heterogeneity

A typical WSN is a collection of a large number of sensor nodes that self-organize themselves to perform sensing, computation, and data delivery. The nodes in a WSN can collaborate with each other by making use of a flat or a tiered architecture. In the flat architecture, all nodes are peers (i.e., homogeneous / identical) from the structural and functional point of view. In the tiered architecture, on the other hand, nodes use some clustering scheme to form a hierarchy in which a node at a given level performs a specific set of tasks on behalf of the nodes underneath. Nodes in the lower layer are usually responsible for relatively simpler tasks.

In WSN applications, the flat architectures are usually not favorable, as some of the sensor nodes which are closer to the sink (i.e., single sink case) are mostly required to route more traffic than the sensor nodes farther away from the sink. Such sensor nodes are referred as critical nodes. As the load on the sensor nodes are not evenly balanced, these critical sensor nodes tend to die early, leaving some of the region uncovered and thus cause partitions. In this respect, it is not always meaningful to assign equal loads to critical nodes with non-critical nodes. Thus, node heterogeneity can be used.

Due to the fact that some of the nodes have superior capability and/or capacity, designers prefer to organize the applications using tiered architectures. In a tiered network, the functions of sensing, computation, and data delivery could be divided unequally among nodes. Functional decomposition of a sensor network can reflect physical characteristics of nodes, or it can simply be a logical distinction. For instance, a subset of nodes with a long-range communication capability may form a physically hierarchical overlay network topology. On the other hand, a subset of nodes in the network might be logically distinct in that they perform a service on behalf of the other nodes. Such services might include data aggregation, communication, or route aggregation on behalf of a set of nodes. As mentioned in [21], there are three characteristics to help determine whether a WSN is an appropriate candidate for a tiered hierarchy. These characteristics are given as:

- **Cost-Effectiveness:** The monetary cost of a WSN is an important performance parameter for a WSN application as it determines whether the application is feasible or not. That is, within a specified time period, the monetary benefit provided by the WSN application must be cost-justifiable to purchase and set-up the network. Tiered architectures can reduce the cost of a sensor network by dividing the labor where they can be most effectively utilized. For example, sensing task typically requires a large number of nodes but relatively few resources at each node. The nodes responsible for sensing do not need to have high processing, communication, and storage capability. Therefore, we can separate the tasks of WSNs among differently capable sensor nodes. As also mentioned in [21], we can reduce the monetary cost of a WSN by employing node heterogeneity.

- **Longevity:** Without explicit analytical findings, [22] claimed that using node heterogeneity (i.e., energy and link heterogeneity), the lifetime of a WSN can significantly be extended and the average data delivery rate can extensively be increased.

- **Scalability:** Like all ad hoc networks, WSNs also suffer from bandwidth degradation problem due to their large size. In [31], the authors have derived analytically that per-node throughput in a randomly deployed ad hoc network of N nodes is given as $\Theta(B/\sqrt{N.logN})$,where B is the bandwidth of the shared channel. Thus, as the size of the network increases, per-node throughput decreases toward 0. There are various promising analytical and simulation-based studies of tiered architectures which show that tiered architectures offer effective solutions to scalability problem.

Despite the advantages of tiered architectures, the communication overhead incurred by hierarchical architectures is one of the most typical drawbacks.

1.5 Thesis Scope and Contributions

In this thesis, we consider randomly deployed heterogeneous WSNs with two-layers of cluster hierarchy. In this heterogeneous and "statically clustered" WSN model, there are two types of devices: clusterheads and sensor nodes. Capacities and capabilities of these devices may vary while their roles are pre-assigned before the deployment and remain unchanged over the course of network lifetime. We work with this network model for the two cases below, based on how clusterheads can reach the sink:

1. Direct Communication Case

2. Multi-Hop Communication Case

For these two cases of our network model, the connected coverage problems are investigated and optimal network dimensioning solutions are proposed. In this respect, throughout this thesis, we will consider connected coverage. Connected coverage which is the degree of coverage achieved by the "connected devices", can be considered as "effective coverage" provided by a WSN application.

- We first start with formulating connected coverage by introducing the cluster size as the expected value of the area covered by a single clusterhead and a number of sensor nodes connected to it. We investigated the cluster size and found out analytical solutions for it by using Boolean Coverage Disc Model. Analytical solutions are validated by computer simulations. From a set of sample scenario, it is revealed that these cluster size equations are good measures for determining the area covered by a single cluster. By using cluster size equations derived, one can find the expected area covered by given numbers of deployed sensor nodes and clusterheads, the sensing field and sensing and transmission ranges. Similarly, one can also dimension the network for given targeted coverage requirement, the sensing field and sensing and transmission ranges.

- We focus on minimum cost network dimensioning problem by employing node heterogeneity. We initially formulate the monetary cost of the WSN considering our network model and a linear relationship between cost of a clusterhead and a sensor node. Then, we formulate an optimization problem to find minimum cost solution that provides the targeted connected coverage. A heuristic algorithm is proposed to solve this optimization problem. We demonstrate that by making use of optimization problem and our heuristic algorithm, one can find the solution for a set of parameters of a sample scenario. In addition to these, we also compare the monetary cost of the homogeneous network and the heterogeneous network for direct communication case. These results can be used to justify the cost-effectiveness of node heterogeneity. For the multi-hop communication case, to find the minimum cost network configurations, we again exploit cluster size equations derived and assume well-connected clusterheads. After tackling with the connected coverage problem with cluster size equations and well-connectivity originated from percolation theory, we also justify the cost-effectiveness of node heterogeneity for the multi-hop communication case through sample scenarios.

- We also investigate the lifetime of WSNs and formulate a cost optimization problem with connected coverage and lifetime constraints. By solving this optimization problem one can determine the number of nodes of each type and the initial energies of these devices that lead to lowest monetary cost while satisfying the minimum connected overage and minimum lifetime requirements. By using the cluster size equations and given targeted connected coverage, monetary costs of the hardware component and the battery cell, and the minimum lifetime, we formulate a joint cost-lifetime optimization problem to achieve minimum cost WSNs. To solve this problem, we propose a cost model for a WSN application assuming that cost differentiation of different types of nodes is due to the equipped number of cells. After modeling the monetary cost, we formulate monetary cost optimization problem for a given lifetime and connected coverage constraints. We show that by making use of optimization problem and a proposed heuristic algorithm, one can find the number of nodes of each type and the initial energies of these devices that lead to lowest cost while satisfying the minimum connected coverage and minimum lifetime requirements.

1.6 Thesis Organization

The remainder of the thesis is organized as follows: Chapter 2 includes the literature survey on the related work and gives the required definitions about coverage and connectivity. The issues related to coverage and connectivity such as connected coverage are also presented in Chapter 2. We also provide the taxonomy of deployment in WSNs. We discuss the mathematical model followed in this study to analyze coverage and connectivity. Chapter 2 summarizes the points regarding clustering and lifetime issues in WSN domain.

Chapter 3 presents the network model considered. It states the assumptions, the necessary notation used, the general architecture, and provides a detailed look at two different cases investigated on this network model.

In chapter 4, we define the cluster size with its geometric and probabilistic interpretation. We introduce an analytical solution for the cluster size by using following Boolean Coverage Disc Model. Then, we validate the analytical solutions through computer simulations. Chapter 4 also contains heuristic search methods to solve the network dimensioning problems.

In Chapter 5, we propose a monetary cost model. Chapter 5 contains analytical solutions for the network dimensioning problem resulting in a minimum monetary cost for a randomly deployed heterogeneous WSN. It also provides a justification of cost-effectiveness of node heterogeneity.

In Chapter 6, the network dimensioning problem to have minimum monetary cost discussed in Chapter 5 is complemented with lifetime requirements. A sample solution for the monetary cost-lifetime joint optimization problem is also given in this chapter.

Chapter 7 outlines the summary and the contributions of the thesis. Potential future research topics are projected in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

Recently, a lot of research studies have been carried out on WSNs, including coverage, connectivity, deployment methods, routing protocols, media access control schemes, clustering techniques, power consumption, and, sensing models, etc. This chapter basically provides a review of the related literature and is divided into five sections. Section 2.1 is a literature survey concerning coverage and connectivity issues in the field of WSNs. In Section 2.3, we provide the taxonomy of the different attributes of deployment in WSNs. Section 2.2 presents the mathematical model used in this thesis to analyze connectivity and coverage issues for the subsequent discussions. Section 2.4 is devoted to clustering techniques in WSNs. Section 2.5 focuses on definitions of WSN lifetime from the previous studies, moreover it provides a brief review on the common techniques to prolong WSN lifetime.

2.1 Coverage and Connectivity in WSNs

In section 2.1.1 and 2.1.2, we first define the terms coverage and connectivity, and go through the related work on these concepts, and focus on the connected coverage which is one of the main theme of this thesis. Then, we investigate on the relationship between coverage and connectivity.

2.1.1 Coverage in WSNs

In the context of WSNs, coverage basically quantifies "how well a field of interest is monitored by a certain deployment scenario". It is the primary performance metric and the dominating factor to achieve the optimal use of the scarce resources. Thus, an important research issue in WSNs is the coverage problem. We believe that the main reason of existence of a WSN is that it should firstly monitor some phenomenon as required. That's why many researchers like Meguerdichian et. al. in [78] and Chen and Koutsoukos in [30] regarded the coverage as the measure of quality of service of a given WSN scenario.

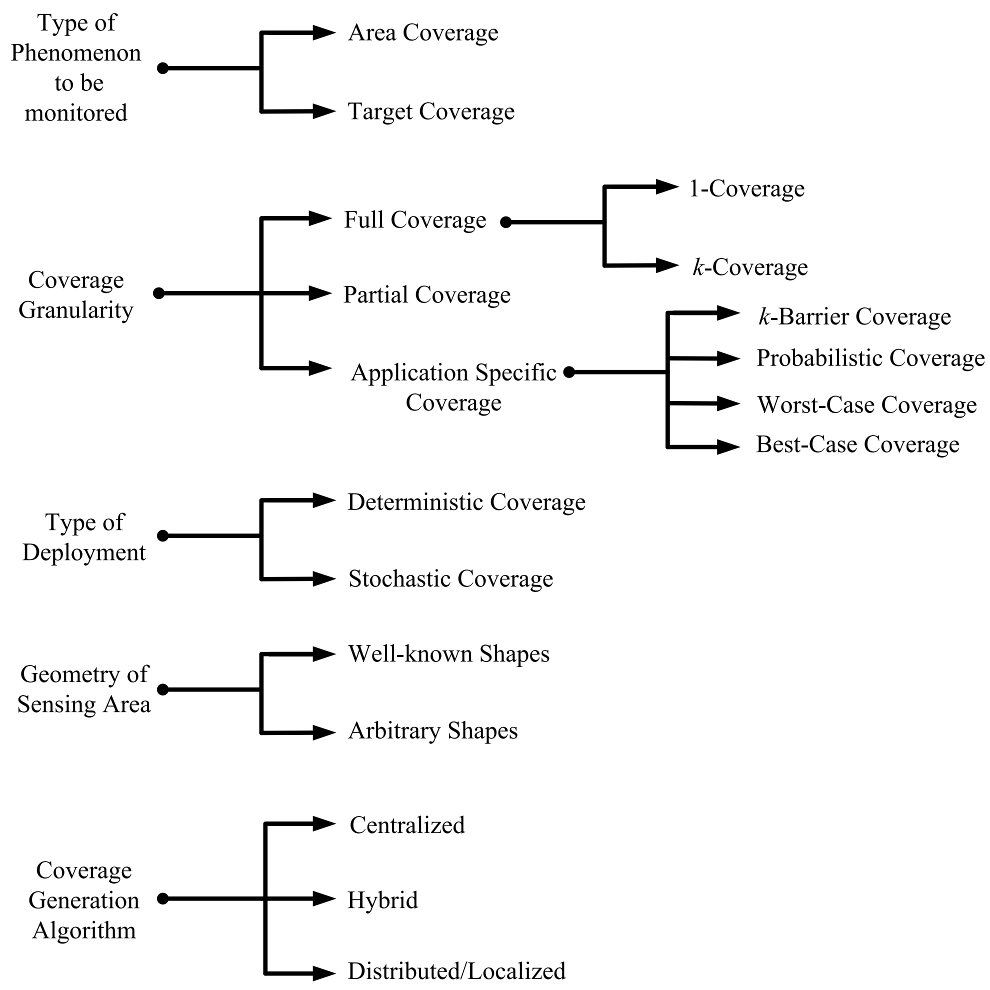

Figure 2.1: Taxonomy of the different attributes of coverage in WSNs

In this section, we categorize and differentiate coverage categories in the literature for WSNs based on set of attributes given in Fig. 2.1 which summarizes the presented taxonomy of these attributes.

Type of the Phenomenon to be Monitored:

As seen from Fig. 2.1, this categorization was made based on the type of the phenomenon to be monitored. As proposed in [83], these coverage types are:

1. Area Coverage

2. Target Coverage (i.e., Point Coverage)

Area and Target Coverage: In area coverage, the emphasis is on monitoring the entire or some fraction of the sensing field. Whereas in target coverage, the objective is to monitor solely a set of targets. As the name reflects, target coverage could be the best candidate in target tracking applications. In target coverage, a target can be considered as a point. Actually, target coverage can be regarded as the special case of the area coverage. Thus, area coverage problem can essentially be transformed to the target coverage problem [67].

Vast majority of the applications in the literature assume area coverage. However, there are a few examples related to target coverage. For example, in [81], Cardei and Du address the target coverage problem in which a limited number of points (targets) need to be monitored. In [81], the locations of the targets are known. A number of sensor nodes are deployed randomly in the vicinity of the targets and send the sensed data to the sink node. The objective of the study in [81] is that every target must be monitored at all times by at least one sensor node, assuming that every sensor node is able to monitor all targets within its sensing range. The authors modeled this target coverage problem as maximum disjoint set covers problem to prolong the WSN lifetime.

Coverage Granularity

Another categorization of coverage can be made based on the coverage granularity (See Fig. 2.1). The coverage categories can be given as:

1. Full (Area) Coverage

2. Partial (Area) Coverage

3. Application Specific Coverage

Now, we start with discussing full (area) coverage:

Full (Area) Coverage:

Consider a sensor field to be monitored by some number of sensor nodes. If every point is covered by at least one sensor node, then the sensor field, D, is said to be fully covered. [80], [36], [81], [82] are some of the applications employing full area coverage. Based on the above definition of full (area) coverage, we can further categorize full-coverage as:

1. 1-Coverage
2. k-Coverage

1-Coverage:

Again, consider a sensor field to be monitored by numerous sensor nodes. If every point is covered by at least k sensor nodes, then the sensor field D is said to be k-covered. If $k = 1$, then this type of coverage is referred as "1-coverage".

Philips et al. [90] considered the condition that a certain sensing field D is 1-covered with a high probability by randomly deployed nodes whose sensing range is r_s. Their analysis was done under the assumption of Poisson Point Process, with a fixed density of nodes λ. Philips et al. proved that, for any $\epsilon > 0$, if

$$r_s = \sqrt{\frac{(1+\epsilon)\ln D}{\pi\lambda}} \tag{2.1}$$

then $\lim_{D\to\infty} P(1-covered) = 1$. However, this approach neglects the border effect due to the infinity assumption. Border effect is an issue for the finite-sized fields. Because, if a sensor node is located to the border of the sensing field, it will cover less area than sensor nodes located within the field (since not all its sensing region will be within the deployment field).

k-Coverage:

Generally, the number of sensor nodes deployed is higher than the required depending on requirements of the application. Hence, the existence of these redundant sensor nodes results in higher degree of coverage (i.e., $k > 1$). If the application in hand necessitates only 1-coverage, this over abundance of sensor nodes makes the WSN more robust to failures and more fault tolerant. Many applications in the literature anticipate k-coverage for their studies [79], [86], [37], [45], [49].

In [45], Huang and Tseng investigated k-coverage for the conditions when the sensing ranges of sensor nodes are both unit disks and non-unit disks.

In [49], by employing node redundancy and exploiting k-coverage, the authors considered the fundamental problem of determining the sufficient number of sensor nodes that achieve k-coverage of a sensing field when a set of sensor nodes are allowed to turn to sleep mode to extend the WSN lifetime. They derived critical conditions for this class of applications. They also showed that the conditions for deterministic deployment are similar to the conditions for random deployments. In [49], the authors considered three deployment scenarios on a unit square $\sqrt{N}\times\sqrt{N}$ grid, random uniform (for all N points), and Poisson distribution with density N. The authors claim that the critical value of the function $Np\pi r_s^2/\ log(Np)$ is 1 for the event of k-coverage of every point where p is the probability of a sensor node being active.

In [91], Yen et. al have analyzed the expected k-coverage provided by randomly deployed sensor nodes based on their 1-coverage while considering the border effects. They found that, although many combinations of the number of sensor nodes, N, and sensing range, r_s, can be set for a particular expected 1-coverage ratio, the expected number of links per node has a upper bound that depends only on the desired expected 1-coverage ratio, not on any specific values of N and r_s.

Partial (Area) Coverage:

While in some WSN applications the goal is to achieve full-coverage, for many others, partial-coverage is more realistic and feasible since full-coverage in randomly deployed WSNs reveals asymptotic behavior. The reason for this behavior is when the number of sensor nodes deployed or the sensing range are increased beyond a certain threshold value, the coverage as well as connectivity increases only marginally.

In [28], Ghosh and Das argued that the degree/level of coverage (i.e., granularity) is determined by the requirements of the application. For example, an application for military surveillance purposes would enforce full-coverage since any failure in the monitoring, the security of the field is not compromised. While, environmental monitoring applications, such as habitat monitoring or indoor temperature monitoring possibly necessitate a low degree of coverage due to its relatively looser requirements.

With respect to the above discussion on full-coverage, partial-coverage is defined as "If not all the points in the sensing field are covered by all sensor nodes deployed, then the sensor field D is said to be partially covered".

As mentioned, one of the reasons for considering partial-coverage is the fact that the "full area coverage" exhibits asymptotic behavior. That is, even if the number of sensor nodes deployed is increased beyond some threshold value, the coverage improves only limited in extent. This behavior makes the WSN applications exploiting partial-coverage operationally and economically more feasible. Thus, there are many studies in the literature that use the partial-coverage due to its above mentioned advantageous feature.

In [87], the authors proposed a protocol called *pCover* and showed that sacrificing coverage slightly can significantly increase the lifetime of the application, when compared to protocols considering full-coverage.

In [88], Mao et. al. proposed an Energy Aware Partial-Coverage Protocol (EAPC) whose objective is to select a set of sensor nodes to be active among the randomly deployed sensor nodes to fulfill the desired level of coverage based on the sensor nodes' residual energy.

Application Specific Coverage:

This category of coverage incorporates coverage with different categories and heuristic or application dependent coverage scenarios. In this respect, we can give some of the application specific types of coverage as:

1. k-barrier Coverage
2. Probabilistic Coverage
3. Worst-Case Coverage
4. Best-Case Coverage

k-Barrier Coverage:

In [71], Kumar et al. extended the k-coverage problem to a k-barrier coverage problem in which sensor nodes in an application is deployed as a belt so as to ensure that all routes crossing the belt are k-covered by the network. Using a probabilistic approach, an efficient algorithm was proposed and several interesting results, such as the optimal number of sensor nodes required to achieve k-barrier coverage, were provided.

Probabilistic Coverage:

In [92], Ahmed et. at. provided a different perspective on looking at coverage that uses probabilistic approach to address the irregularities (e.g. topology, obstacles, decaying signals etc.) of the environment in which WSNs operate. Most of the applications assume that the sensing coverage of a node is isotropic (i.e., uniform in all directions) and application follows the binary detection model, rather than considering environmental factors in real deployment scenarios. The authors assumed that the signal propagation from a point to a sensor node follows a certain probabilistic model. This assumption is only valid for certain kind of sensor nodes e.g. radio, acoustic, seismic etc. where the signal strength decays with the distance from the source. The authors specifically follow the path loss log normal shadowing model. They also proposed a distributed Probabilistic Coverage Algorithm (PCA) to evaluate the degree of confidence in detection probability provided for a randomly deployed WSN. The authors claimed that their approach can be extended to incorporate different signal decay models.

Worst-Case Coverage:

In the worst-case coverage, the problem is formulated aiming to find a path through the sensing field such that, a moving target along that a certain path has the least observability by the sensor nodes, and thus, the probability of detecting that moving target is minimum. Finding such a worst-case path is important because additional sensor nodes could be deployed along that path to improve the degree of coverage, thus, increasing observability. The two well-known approaches to the worst-case coverage problem are the Minimal Exposure Path [59] and the Maximal Breach Path [78] and [60].

Best-Case Coverage:

In the best-case coverage problem, the objective is to find a path that has the highest observability, and therefore, a target moving along such a path will be covered with a high probability. The two suggested solutions to resolve the best-case coverage problem are the Maximal Exposure Path introduced by [61] and the Maximal Support Path presented by [78].

Type of Deployment:

We can also classify the coverage based on how the sensor nodes in WSNs are deployed (See Fig. 2.1). These categories are:

1. Deterministic Coverage
2. Stochastic Coverage

Deterministic Coverage:

Deterministic coverage can be defined as the degree of coverage achieved when nodes are placed at "predetermined locations". Deterministic coverage problem is actually very similar to a well-known problem called the "Classical Art Gallery Problem" [97].

Stochastic Coverage:

Stochastic coverage is defined in [28] as the degree of coverage achieved when sensor nodes are deployed randomly or according to some statistical distribution, such as uniform, Gaussian, Poisson, etc. To propose a solution to the stochastic coverage problems in WSN domain, the researchers uses several concepts from computational geometry while others from stochastic processes and probability theory. Voronoi diagrams and Delaunay triangulation are the frequently used tools for computational geometry. On the other hand, a random graph is a graph generated by some random process. The theory of random graphs lies at the intersection between graph theory and stochastic processes. Here, in this thesis, we make use of Boolean Poisson Model which is discussed in Section 2.2.

Geometry of Sensing Areas

Another category of coverage is the one based on geometry of the sensing regions of sensor nodes. In coverage with well-known shapes, each node typically monitors a region whose shape is a well-known "convex" region such as a perfect disc. Vast majority of the previous works in the literature use the perfect disc model due to its analytical features. However, there are also some studies such as [74] and [86] that pursue coverage with some arbitrary shapes. The use of arbitrary shapes certainly makes a coverage model more generic.

In [74], Lazos and Poovendran consider a generic network model where sensor nodes are deployed according to some statistical distribution; sensing areas can be any arbitrary shape rather than following the perfect disk model. Sensors are not also required to have identical sensing capability (i.e., node heterogeneity).

In [86], Fan and Jin also propose an approach that allows evaluating the degree of coverage of the intersection points where each sensor may have any arbitrary sensing shape.

Miorandi and Altman [69] describe another coverage problem where channel randomness exists in a WSN. With the sensor nodes are distributed according to Poisson Point Process, they formulated the node isolation probability which is closely related to coverage probability. They define random variable R, which is defined as a cumulative distribution function that incorporates fading and shadowing effects, instead of considering a perfect disc for communication and monitoring. This function essentially changes the geometry of the sensing and communication range. In [69], the authors analyze the impact of shadowing and Rayleigh fading phenomenon on coverage and connectivity.

Coverage Generation Algorithms:

We can also categorize coverage based on how the algorithms provide coverage. The coverage algorithms proposed are either centralized (LEACH-Centralized, LEACH-C [75]) or distributed/localized (LEACH [93]). In distributed algorithms, the decision process is decentralized. The objective of these algorithms is to organize the sensor nodes into a number of subsets such that each subset can completely or partially cover the sensing field. By distributed and localized algorithms, we refer to a distributed decision process at each node that makes use of only neighborhood information, within a constant number of hops. Because the WSNs have a dynamic topology and needs to accommodate a large number of sensor nodes, the algorithms and protocols designed should be distributed and localized, in order to better accommodate a scalable architecture. These algorithms are not always used to only generate coverage. They usually incorporate connectivity, longevity, energy-efficiency, etc.

2.1.2 Connectivity in WSNs:

Connectivity has always been important performance metric in the context of packet switched radio networks. In particular, multi-hop connectivity has gained renewed attention recently due to the promising advances in ad-hoc and WSN applications.

In order to gain maximum benefit from a WSN application, we should design the network in such a way that all nodes are fully-connected. However, due to the limitation of resources such as limited transmission radio range or limited output power for transmission, it is not always possible to employ devices with the required radio ranges or powerful batteries. Fortunately, we can improve the degree of connectivity by increasing node density at the expense of monetary cost for given transmission ranges and initial energy. Therefore, the level of connectivity directly impacts the monetary cost of the WSN. Therefore, there has been great interest in exploring the minimum number of sensor nodes that is required to achieve a targeted connectivity within a given sensing field.

Beside its direct impact on the monetary cost, connectivity is also an important factor that should be considered as it affects the robustness and the achievable throughput of the communication.

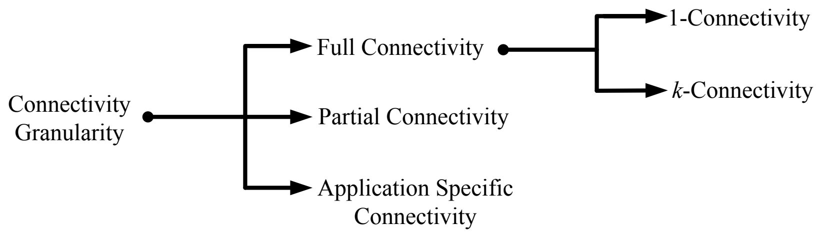

Figure 2.2: Taxonomy of the different attributes of connectivity in WSNs

Herein, we can categorize the connectivity based on the granularity shown in Fig. 2.2 as:

1. Full-Connectivity
2. Partial-Connectivity
3. Application Specific Connectivity

Full-Connectivity:

Connectivity problem deals with determining if it is possible to establish at least one active communication link between any two nodes. This type of connectivity is referred as full-connectivity.

1-Connectivity:

Actually 1-Connectivity is very similar to 1-coverage. In 1-coverage, every point in sensing field should be covered by at least 1 sensor node. On the other hand, in 1-connectivity, every node should be reachable by the all nodes in the network by using at least 1 route.

k-Connectivity:

In some applications, 1-connectivity is the sufficient condition for the operation whereas for some other applications more strict forms of connectivity is required for improving lifetime, fault tolerance, and robustness. If every sensor node in a WSN has at least k different routes, this type of connectivity is called k-connectivity. In Fig. 2.3, various degrees of connectivities are shown. In Fig. 2.3 (a), there are 4 sensor nodes. Each sensor node has only one route/link to reach any node in the network. In Fig. 2.3 (b) each of these 4 nodes has at least 2 disjoint routes/links to reach rest of the network. On the other hand, in Fig. 2.3 (c), there are 5 sensor nodes all of which are connected with each other using a meshed topology. In this figure, we can see that, the network is 4-connected. Indeed, k-connectivity is worth some comments. A k-connected network has the property that removing any $k-1$ sensor nodes will still maintain the network connectivity.

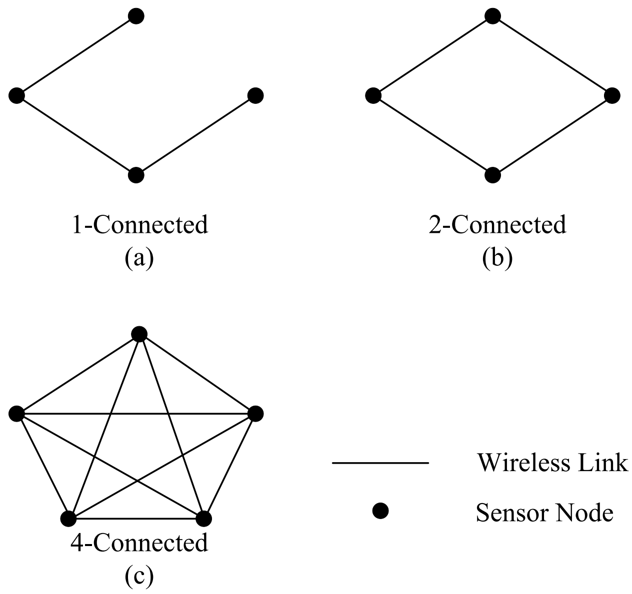

Figure 2.3: Various Degrees of Connectivities

Partial-Connectivity:

Partial-connectivity can be defined as "if not all the sensor nodes are connected, then the WSN is said to be partially connected". However, the fraction of the connected sensor nodes is of importance in partial-connectivity. Generally, in WSN applications, the vast majority of sensor nodes are expected to be connected. That is, there is giant set of nodes to be connected and a few set of isolated/partitioned nodes are acceptable.

In [73], the authors show the benefits of replacing k-connectivity (full-connectivity) requirement by that of a partial, η-connectivity, where only a given fraction $\eta < 1$ of the sensor nodes needs to be connected to the network. They made a case study to investigate the partial-connectivity using Boolean Model and information theoretic models.

2.1.3 Connected Coverage

Up to this point, the concepts of coverage and connectivity have been described separately. However, we should only take into account the extent of monitoring achieved by the connected sensor nodes (i.e., effective nodes). Thus, we need to define connected coverage as the degree of coverage achieved by simply the connected sensor nodes for a certain deployment scenario. Here, what is meant by "connected sensor nodes" is that these connected devices should have at least one route to the sink. As the name implies, to be able to achieve the targeted connected coverage, we need to satisfy coverage and connectivity simultaneously. Although, there is a strong correlation between the coverage and connectivity, satisfying one does not necessarily guarantee to have the other one.

For example, let's assume that we have 9 identical sensor nodes placed at a predefined location within a sensing field as seen in Fig. 2.4. Here, sensor nodes with transmission radius of r_{ts} and sensing radius of r_s. And, as seen from this figure, $r_{ts} = r_s$. We further assume that these nodes satisfy some partial area coverage requirement, say %75 of the sensing field (See Fig. 2.5).

Consider now that, these 9 identical sensor nodes are now deployed randomly over the sensing field as seen in Fig. 2.6. From this figure, we can see that these nodes satisfy the "full-connectivity" requirement. That is, each node can reach rest of the sensor nodes in the network. However, this time, the partial-coverage requirement of %75 is not satisfied as seen from Fig. 2.7. This example reveals that a WSN satisfying the "full-connectivity" may fail to fulfill the coverage requirement and thus may fall short of connected coverage.

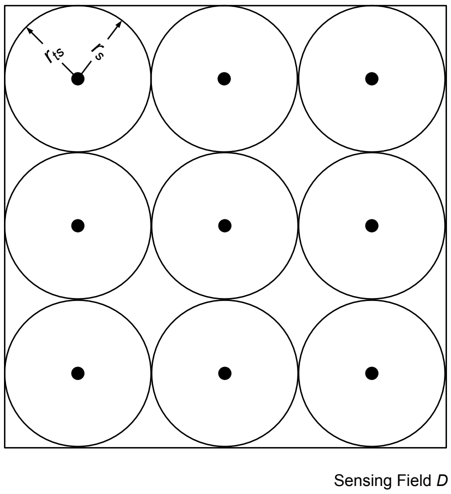

Figure 2.4: 9 sensor nodes with transmission radius, r_{ts}, and sensing radius, r_s

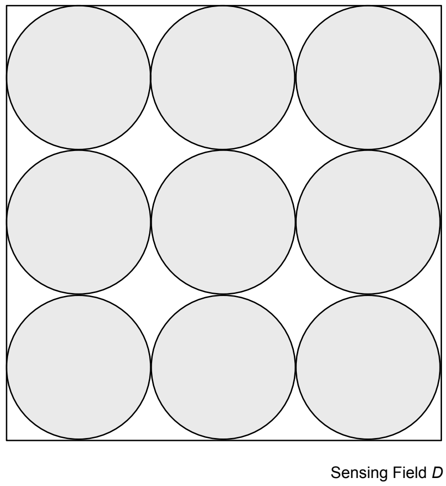

Figure 2.5: 9 unconnected sensor nodes covering some fraction of the sensing field

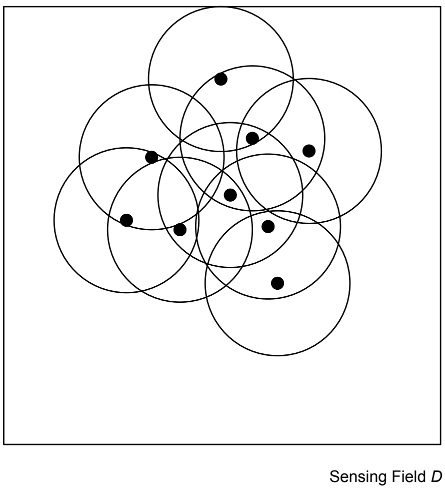

Figure 2.6: Randomly deployed 9 sensor nodes

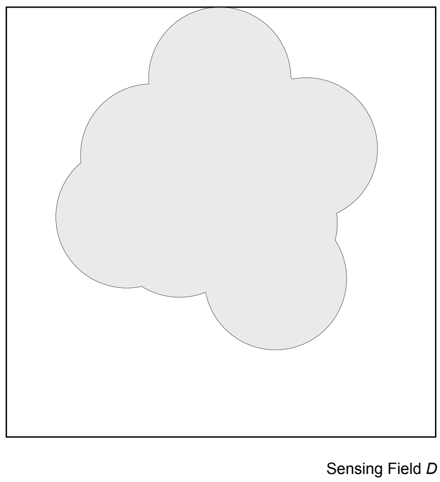

Figure 2.7: 9 connected sensor nodes with their sensing region

Full-Connected Coverage:

[70] presents the results of a study on the connected coverage problem when deterministic node placement is employed. In [70] it is assumed that the sensing and transmission radii of sensor nodes are equal and that homogeneous nodes are devised. The authors propose a simple disk placement pattern which covers the entire field and achieves connectivity at the same time. It is shown that this pattern provides solutions that are within a small factor of the optimum solution.

[72] introduces a new coverage-preserving scheme that guarantees initial coverage even after eligible sensor nodes have been turned off. The solution extends the Center Angles Calculation Method and proposes a new Decision Algorithm that is used to determine status. A smart wake-up strategy that optimizes the wake-up phase in the given solution is also described.

Carle and Simplot [82] propose a mechanism for energy-efficient connected area coverage for the case when all sensor nodes have the identical sensing range and the transmission range equals the sensing range. The goal of the algorithm is to select an area-dominating set of sensor nodes of minimum cardinality, such that the selected set covers the given field.

Partial-Connected Coverage:

In [68], Liu and Liang emphasize the importance of partial-coverage and relationship between coverage and connectivity for randomly deployed WSNs. The study criticizes that full-coverage is sometimes impossible and unnecessary. Hence, the authors discuss partial-coverage with connectivity which they refer to as "partial-connected coverage problem". The partial-connected coverage problem is also shown to be a NP-hard problem. Hence, a heuristic is proposed not only to find a subset of sensors for partial-coverage with a given coverage guarantee but also ensuring that the connectivity graph induced by the chosen sensor nodes is connected.

Constrained Coverage:

In [32], the authors study coverage with connectivity for three classes of applications: 1) full-coverage with connectivity, 2) partial-coverage with connectivity, and 3) They also introduce a new class, named constrained coverage with connectivity (CCC). In CCC, the maximum size of an area that an event can occur without being reported to the sink node, is bounded and constrained. CCC concept can be used in an application of WSN that is deployed to monitor forest wildfire. CCC means that it is required that a wildfire must be detected and reported before it propagates to a field of a certain size.

2.1.4 Relationship between Coverage and Connectivity

Recently, some research has been carried out to describe the relationship between coverage and connectivity. Most of the studies state the necessary condition(s) for achieving connectivity when full-coverage is guaranteed. That is, the relationship between coverage and connectivity is generally expressed in terms of the relation between the transmission ranges and sensing ranges when full-coverage has already been provided.

In [36] and [37], it is independently proven that "transmission range at least twice the sensing range" is the sufficient condition for connectivity as long as full-coverage is guaranteed for a convex region. Both of the studies focus on analyzing the condition for a fully covered network to guarantee full-connectivity.

Wang et al. [37] generalized the above mentioned result in [36] by showing that, when the transmission range is at least twice the sensing range, a k-covered network will result in a k-connected network. In particular, the relationship between k-coverage and k-connectivity under various ratio between transmission range and sensing range are also studied in [64] and [65].

There are also other publications studying the relation between coverage and connectivity under various ratios other than the ratio stating that transmission range is at least twice that of the sensing range. For example, the authors in [62] focus on the case when transmission range/sensing range = 1. They develop a necessary condition on the spatial density of sensor nodes required for an optimal topology that provides connected coverage in a sensing field. It is shown that the node density required by the optimal topology is given by:

$$d_{opt} = \frac{0.522}{r^2} \tag{2.2}$$

2.2 Mathematical Model: Connectivity and Coverage

2.2.1 Mathematical Model: Connectivity

As stated in [96] , stochastic geometry and random graphs have emerged as essential tools to analyze and design of wireless networks. In the context of WSNs, coverage and connectivity are the issues mainly investigated by using these tools. In this thesis, we assume that devices are deployed randomly over a planar sensing field D. We further assume that the transmission region of devices is a perfect disc with diameter r_t. To model the connectivity of this network, we use the basic random graph or disk graph given in [96] $B(\lambda, r_t)$ with the devices as vertices and the wireless communication link between a pair of these devices as an edge. This simple model relies on two assumptions:

1. Devices' locations follow 2D Poisson Point Process (PPP)

2. Each device can communicate directly with any other device within a transmission range

Actually, $B(\lambda, r_t)$ graph is called a Poisson Boolean Model because it incorporates Poisson Point Process and Boolean Model. We can explain Poisson Boolean Model by describing the Poisson Point Process and Boolean Model separately.

Let's start with discussing Poisson Point Process briefly. Poisson Point Process [85] is usually represented as Φ. It can be interpreted as points "uniformly distributed" over the whole plane with average density λ. PPP can be characterized by the following two features:

1. The number of points of Φ in a bounded set D has a Poisson distribution of mean $\lambda|D|$ for some constant λ.

2. The numbers of points of Φ in s disjoint sets form s independent random variables, for arbitrary s.

On the other hand Boolean Model is the simple model that describes the connectivity between devices. This model assumes the condition that for any two nodes is directly connected if only if they are within each other's transmission ranges. Hence the connectivity only depends on these nodes [85]. To summarize, PPP is related to the distribution of the devices and Boolean Model is related to the connectivity of the devices.

In this thesis, we essentially adopted the partial-connectivity (later which we will refer to it as "well-connectivity") since partial-connectivity results in low cost network configurations. A randomly deployed WSN considering partial-connectivity requires fewer number of devices than the WSN considering full-connectivity for given transmission range and node density.

To have a targeted level of partial-connectivity, we make use of a result from percolation theory. Actually, percolation theory deals with the cases where the sensing field is infinite. In such a sensing field, the fraction of connected nodes can be found deterministically and is a function of transmission range and node density. As far as the real-world WSN applications are concerned, infinite sensing field assumption may not feasible. However, Penrose and Pisztora [98] demonstrated that for a huge but finite sensing field, the fraction of connected nodes is close to that deterministic function. This finding enables us to use the percolation theory by approximating infinite field with relatively very large but finite field.

Without explicit proof, the theorem of percolation for Poisson Boolean model in [44] can be stated as follows:

Consider a Poisson Boolean model $B(\lambda, r_t)$ in R^2. There exists a critical density λ_c > 0 such that

- in the sub-critical case, defined by $\lambda < \lambda_c$, all clusters are bounded almost surely (a.s.)
- in the super-critical case, defined by $\lambda > \lambda_c$, there exists a unique unbounded cluster $\mathcal{U}$ a.s.

In the randomly deployed WSN context, this means that the sub-critical case, where the network is partitioned in an infinite number of bounded clusters. In the super-critical case however, the result is much more related to achieving a high degree of connectivity, because of the existence of an unbounded cluster.

To provide a targeted partial-connectivity, we adopt the super-critical phase of the theorem. Because in the super-critical phase, the nodes are divided into two categories: those belonging to the unbounded cluster $\mathcal{U}$, and the others. The nodes in the first category can communicate with nodes located arbitrarily far away, whereas the others are restricted to a finite area. Thus, the quality of the connectivity is related to the fraction η of nodes belonging to the unbounded cluster. η can be defined as the probability of an arbitrary node to belong to the unbounded cluster, and is called percolation probability.

As claimed in [43], there is no explicit expression for η and λ_c. However, there are numerous studies that have obtained the bounds on λ_c. On the contrary, η can only be evaluated through simulation.

Here in this thesis, we determine the degree of partial-connectivity as a function of average number of neighbors, θ, for each node.

2.2.2 Mathematical Model: Coverage

A similar Boolean Model is used to study coverage, by assuming that each sensor node covers a region of perfect disk with radius r_s. In this coverage model, we assume that a point p is covered by a sensor node if their Euclidian distance is less than or equal to the radius r_s. This model is also used by [35], which Koskinen named it as "Boolean Coverage Disk Model".

2.3 Deployment of Devices in WSNs

One of the important concerns related to WSNs is the deployment method due to its direct impact on the degree of coverage and connectivity. Therefore, in this section, we categorize deployment methods for WSNs based on set of attributes given in Fig. 2.8.

We refer the reader to a comprehensive survey [29] to have a detailed perspective on the placement of devices in WSN applications.

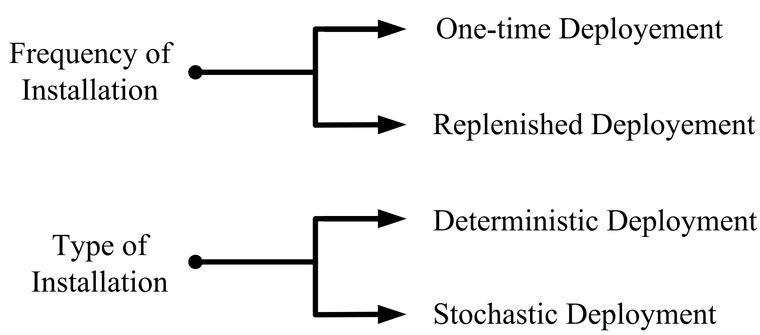

Figure 2.8: Taxonomy of the different attributes of deployment in WSNs

2.3.1 Type of Installation

Considering the type of installation of devices, there are essentially two deployment methods, namely deterministic and random deployment. If the sensor nodes are "positioned" in a location in such a way that satisfies the conditions of the application, then this deployment method is said to be deterministic. Unfortunately, in many applications such as WSN in hostile, inaccessible, and harsh physical environments, deterministic deployment is neither feasible nor practical. Thus, this type of deployment [95], [70] is relatively rare.

If the locations of the sensor nodes are not known a priori, then the deployment method is called stochastic deployment. Consider a scenario where there is a WSN composed of large number of sensor nodes which are dropped from an aircraft on a sensing field. In this scenario, the deployment method is assumed to be stochastic with some distribution scheme such as uniform, Gaussian, Poisson.

In general, random deployment method has a larger potential usage than deterministic deployment. However, the applications that utilize random deployment method require self-organizing, self-maintaining communication mechanisms which increase the burden on communication protocols, and the overall cost of the application.

2.3.2 Frequency of Installation

Another category for the deployment of the devices is the one based on frequency of installation. In one-time deployment, devices are allowed to be deployed only once. On the other hand, in replenished deployment, the network is designed in such a way that insertion of new sensor nodes is possible. In this deployment scenario, it is usually aimed to prolong the WSN lifetime , to increase the degree of coverage and connectivity, and to improve observability, etc.

2.4 Clustering in WSNs

In this section, we will solely provide some key points regarding clustering in WSN applications.

In a typical WSN, hundreds to several thousands of nodes are deployed over a sensing field. To make such highly populated networks more scalable, a lot of research efforts in cluster networking have been pursued recently. A notable work in [26] gives a taxonomy and general classification of published clustering schemes in WSN domain. Authors survey different clustering algorithms for WSNs; categorizing these algorithms according to cluster properties, clusterhead capabilities, and clustering process. We give their taxonomy of the different attributes of clustering in Fig. 2.9. The reader is encouraged to refer to this survey for a detailed view of clustering algorithms.

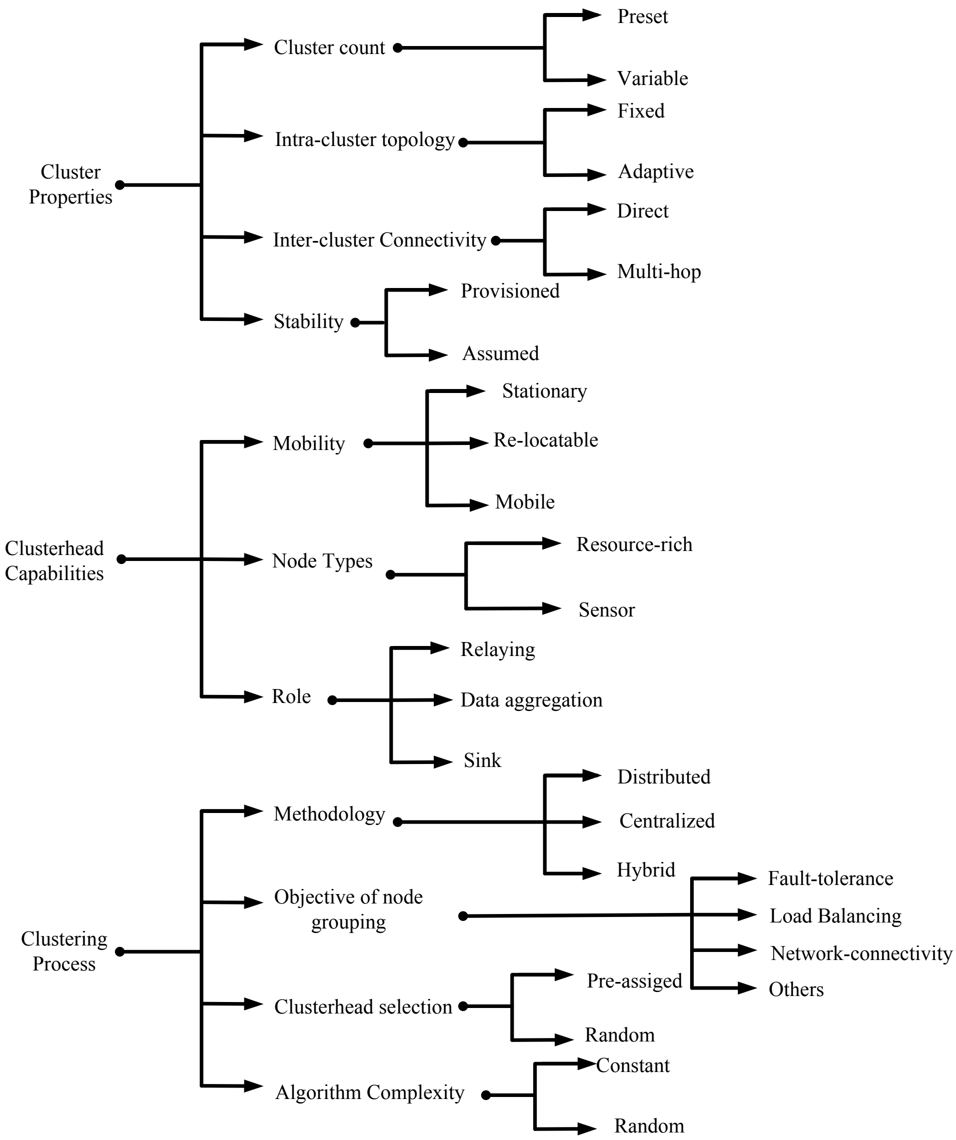

Figure 2.9: Taxonomy of the different attributes of clustering in WSNs [26]

Clustering of sensor nodes in a WSN has been widely recognized as the most promising approach in dealing with the scalability problem. Lack of scalability becomes heavily apparent during the energy consumption. Thus, generally clustering has been proposed as a means to divide large networks into groups of suitably smaller sizes. As seen from Fig. 2.9, objective of clustering can be based on to improve fault-tolerance, to balance the load evenly among sensor nodes, or to achieve network connectivity. Network connectivity is assured using routing protocols. However, IP-based routing is not a scalable alternative. Thus, cluster-based hierarchical routing protocols are proposed. A cluster-based hierarchical routing protocol groups sensor nodes to efficiently relay sensed data to the sink. They are designed to reduce the energy consumption by localizing data communication within a cluster and aggregating data to decrease the transmissions to sink node.

2.5 Lifetime definitions in the Literature

The WSN applications, in particular, randomly deployed networks typically suffer a lot from energy limitation since the energy drainage rates of the nodes are usually not uniform. Considering that there is a sink node in the sensing field and a number of sensor nodes scattered over this field, some of the sensor nodes closer to the sink node are usually required to route/forward more traffic than the sensor nodes farther from the sink node. Such sensor nodes are referred as critical nodes. Therefore, these critical sensor nodes tend to die early, leaving some of the region uncovered and thus cause partitions in the network. Therefore, for a WSN application, the network designers should lessen partitioning to reach the targeted coverage while maximizing the collected information over the course of network lifetime.

Recently, a lot of research on various classes of applications has been carried out on the lifetime issues in WSN domain. There are several possible definitions of the lifetime of a WSN for different applications. Table 2.1 summarizes these different definitions of lifetime with the corresponding reference(s).

Table 2.1: Classification of Lifetime Definitions in WSNs

Reference	Definitions
[50]	Since there is an inverse correlation between the energy dissipation and the WSN lifetime, in [50], the lifetime is defined as the reciprocal of the maximum energy consumption, e_{max}, (i.e., lifetime=$1/e_{max}$) where e_{max} is the maximum energy dissipated for delivering one packet from each sensor node to the sink node. The authors considered that there are three elements of energy dissipation. These are radio transmission, radio reception, and data aggregation.
[51], [54], [94]	Depending on the requirements of an application, the death of a single node may be critical. Thus, in some applications [51], [54], the network lifetime is defined as the time until the first node runs out of energy. While some other applications estimate the lifetime as the time until the last node runs out of energy. Moreover, [94] showed the performance of their algorithm both for the first node death and the last node death cases.
[75]	Yet another approach, looking at the WSN lifetime from another perspective is that the fraction of surviving (alive) [75] or equivalently dead nodes in the network.
[89]	In [89], authors proposed another general-purpose definition which elegantly avoids the ambiguity in WSN lifetime definition by deriving a general formula which holds independently of the underlying network model including network architecture and protocol, data collection initiation, channel fading characteristics, and energy consumption model. Network lifetime is the time span from the deployment to the instant when the network is considered nonfunctional. When a network should be considered nonfunctional is, however, application-specific. Thus authors derive a general formula for lifetime just considering two key parameters at the physical layer that affect the network lifetime: the channel state and the residual energy of sensors. This approach makes the lifetime definition independent of MAC, routing protocols, and other parameters.

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Reference	**Definitions**
[52]	The mean expiration time of all nodes.
[53]	Instead of analyzing the lifetime of all nodes, focusing on the lifetime of critical nodes may be sensible. As the lifetime of relaying nodes is the main determinant of the entire WSN. Hence, if these critical nodes lose their functionalities, the network will become partitioned. Therefore, the authors in [53] defines lifetime as the time until one relay node ceases its functionality.
[55]	Another approach to analyze lifetime is the functional lifetime. Functional lifetime is defined as for given a quantity of data and an energy budget at each sensor node, it is the maximum number of rounds the task of delivering "all the data" to the sink can be repeated before some node depletes its energy.
[56]	The time period from the instant when the WSN starts functioning to the instant when no bits can be transferred to the sink. (due to the partitioning!!)
[57]	The lifetime is defined as the time until when a task is successfully performed by at least one node. Actually, this definition is the variant of the first death node definition described above.
[58]	Authors propose a normalized network lifetime $\tilde{L}$, which measures how many total bits can be transported on the network per unit energy.
[63]	This lifetime definition is based on certain coverage requirement. Network lifetime is defined as the period from the time of network setup to the time that the coverage ratio is less than a threshold.

2.5.1 Common Techniques to prolong WSN lifetime

In this section, we review some of the performance metrics that affect WSN lifetime. Most of these performance metrics are essentially related to energy consumption. To name few:

- Modes of Communication

  - Direct Communication with the sink
  - Multi-Hop Communication with the sink

- Routing and MAC Protocols
- Sleep/Wake-Up Schedules
- Node Redundancy
- Deployment: Type of Installation
- Data Length Reduction (i.e., data aggregation and data fusion)
- Load Balancing
- Network Architecture
  - Flat architecture
  - Tiered architecture

We list below some of the strategies/methods/techniques to prolong the WSN lifetime. Some of approaches in this list are generic techniques while others are highly application specific.

- **Multi-Hop and/or Direct Communication:** In radio environments, the received power typically falls off as the 2^{nd}-4^{th} power of distance as cited in [46]. In this respect, to reduce the energy consumption for communication, the multi-hop communication mode is more favorable than that the single-hop communication. However, depending on the routing and MAC protocols employed, multi-hop communication may introduce significant overhead for topology management and relaying.

- **Energy-Efficient and Energy-Aware Routing and MAC Protocols:** In WSNs, selecting the appropriate the routes is greatly influenced by energy considerations.These energy-efficient schemes typically aim to find the minimum energy path to optimize energy usage at each sensor node. Energy awareness is a very important design consideration for protocols and algorithms in WSNs. Energy management in WSNs involves not only reducing the energy consumption of a single sensor node but also maximizing the lifetime of the entire network. Furthermore, energy awareness should be incorporated into every stage of a WSN design and operation with the goal of making dynamic tradeoffs between energy consumption and system performance. MAC protocols should also selected appropriately to extend the lifetime. As noted in [27], the WSN MAC protocol design should have the following attributes: energy-efficiency, scalability, frame synchronization, fairness, bandwidth utilization, flow control, and error control for data communication. Hence, these attributes could have a substantial effect on the lifetime of a WSN.

- **Tiered architectures and Clustering:** Clustering along with tiered architectures is one of the most frequently used approaches in WSN applications to conserve energy and extend not only sensor node lifetime but also WSN lifetime. These strategies avoid all nodes in WSN to deliver its own data to the sink.

- **Redundant node deployment:** In this method, the WSN is initially deployed with redundant number of nodes and a scheduling mechanism is devised to turn off some or all of the redundant sensors. After a certain period of time, some of the sensor nodes die out due to energy depletion, and the sleeping sensor nodes wake up and take the duties of the dead nodes to prolong the network lifetime.

- **Data Aggregation:** In WSNs, data related to a certain phenomenon such as the temperature and humidity, collected by nearby sensor nodes is normally spatially and/or temporally correlated. Therefore, this correlated data collected by these sensor nodes often carries redundant information. Even if the data is uncorrelated combining multiple packets in a single packet reduces the MAC and routing overhead. Data aggregation is an effective way to remove the redundant information and reduce the potential traffic thereby reducing the energy consumption. The rationale behind this strategy is that most of energy in WSNs is consumed for communication. The energy consumption for processing is substantially low compared to that consumed for communication

- **Load Balancing:** Load balancing is a technique used to dissipate energy uniformly among the sensor nodes in a WSN application. Abrupt energy depletion of the critical nodes can be avoided significantly by load balancing strategies.

This even distribution of energy consumption enables WSN designers to improve lifetime.

CHAPTER 3

NETWORK MODEL

In this chapter, the network models considered in this thesis are presented. The main intent in choosing these models is to tackle the challenges in randomly deployed WSNs by employing "node heterogeneity" and "static clustering" with two-layers of cluster hierarchy. We consider randomly deployed WSNs, which consist of two types of nodes namely, clusterheads and sensor nodes, with varying communication and processing capability, initial energy capacity, and thus monetary cost. The general view of the network model employed in this work is illustrated in Fig. 3.1. In this heterogeneous network, there are N_S sensor nodes and N_H clusterheads deployed randomly over a sensing field, D. Our network model follows Poisson Boolean Model, where the locations of the nodes are distributed according to a Poisson Point Process of constant, finite node density λ. The required number of sensor nodes and/or clusterheads is usually determined according to the requirements of the application.

Each sensor node and clusterhead in the sensing field monitors its vicinity and generates data periodically to be transmitted to the sink node. It is assumed that each sensor node (in the 1^{st} layer shown in the Fig. 3.1) generates one data packet per unit time (or round) to be transmitted to its associated clusterhead (in the 2^{nd} layer shown in the Fig. 3.1). And each clusterhead provides the connectivity between its members and the sink node. In other words, 1^{st} layer can be considered as the plane that is basically used for providing coverage and the second plane is essentially responsible for the connectivity.

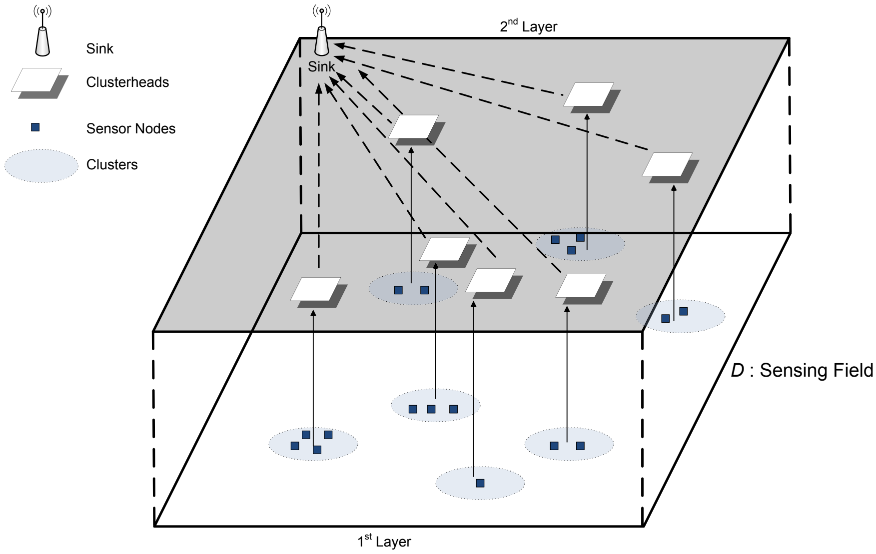

Figure 3.1: Proposed WSN model

3.1 Network Model and Node Heterogeneity

This model essentially relies on the node heterogeneity and employs two types of nodes. Clusterheads are resource rich nodes usually having better processing capabilities, often having higher transmission powers (or equivalently larger transmission ranges) and generally equipped with more battery cells (or equivalently have higher capacity batteries). Higher processing capabilities of clusterheads enable them to aggregate the correlated data received from their cluster members. This aggregation leads to fewer number of bits to be transmitted to the sink node and thus, to energy savings.

Clusterheads' hardware properties and/or energy resources differ from the sensor nodes. This distinction is used to identify the roles within the application and we also use this distinction to justify the cost differentiation between the different types of nodes.

In this respect, we expect that the number of sensor nodes deployed in the sensing field is large. However, such a dense deployment is usually not necessary and feasible for clusterheads, since clusterheads are expected to be more expensive than sensor nodes.

3.2 Network Model and Static Clustering

A clusterhead is the principal device that forms and organizes a cluster. A cluster is assumed to be formed by a clusterhead node and a number of sensor nodes connected to it. In our network model, members of a cluster do not change over the course of network lifetime. This scheme is known as static clustering. One fundamental difference between the cluster formation scheme studied in this thesis and the traditional cluster formation schemes is that in the latter, every node may switch to "clusterhead role" for a certain period of time. This is called "dynamic clustering". However, in this work, the clusterheads are assumed to be "pre-configured" before the deployment and play the role of clusterhead till the end of the WSN's operation.

Static clustering has both advantages and disadvantages. Its main advantage is that static clustering does not require to rerun cluster formation phase in each round. Because, in static clustering, the setup phase occurs only once just after the deployment. That is, nodes in the network need to consume energy to complete this phase just once. This attribute of static clustering makes it superior against dynamic clustering in terms of energy-efficiency. An obvious disadvantage is that the WSN lifetime highly depends on the initial energy of clusterheads. For example, in static clustering, when a clusterhead is dead due to the depletion of energy, all of its cluster members (i.e., connected sensor nodes) become disconnected.

Association between sensor nodes and clusterheads is determined with a "nearest reachable clusterhead (i.e., Euclidean Distance)" approach, and at any given time, each sensor node is a member of a disjoint cluster.

3.3 Network Model and Communication

A sensor node can communicate with a clusterhead if it is within the transmitting range, r_{ts}, of the sensor node. We assumed that r_{ts} is fixed and r_{ts} is the maximal radius allowed by power constraints. In our model, a sensor node can only transmit its sensing data to its associated clusterhead and the clusterhead further transmit sensed data to sink. In other words, communication among sensor nodes is not allowed.

Similar to the communication between a sensor node and its associated clusterhead, a clusterhead can communicate with the sink if it is within the transmitting range, r_{th}, of that clusterhead. Again note that, if a clusterhead loses its connectivity between the sink for some reasons such as energy depletion, then the entire cluster become disconnected.

We assume that the environment, in which our network model is working, enables nodes to have symmetric connectivity. That is to say, for example, if Node A is connected to Node B through some communication link, then Node B is also assumed to be connected to Node A.

3.4 Network Model and Coverage

Both sensor nodes and clusterheads have identical sensing capabilities and their sensing range is r_s. The area sensed by each type of device is assumed to be a perfect disk with an area equal to πr_s^2. It is also assumed that their sensing ability is the same in all directions. For the area coverage, Boolean Coverage Disc Model [35] is used. And also note that, coverage in the presence of obstacles is a challenging problem and has not been addressed in this study.

3.5 Assumptions

Both sensor nodes and clusterheads are assumed to be stationary and unattended. Each type of device is aware of neither network topology nor their location. We assume that both types of devices are capable of measuring Received Signal Strength Indication (RSSI) during the reception of packets to determine the clusterhead to associate with. For the energy dissipation, we primarily consider the wireless communication and data aggregation power consumption and ignore data processing and sensing power consumption.

No replenishment and recharging are anticipated. The sink node is also assumed to have unlimited energy and thus there is no energy constraint at the sink.

We ignore temporal correlation by assuming that sensor readings in different time slots are independent. We ignore capacity and traffic related effects. All devices operate without fault or error. Hence, our formulations do not include any reliability concerns.

3.6 Clusterhead - Sink Communication

There are mainly two models based on how the clusterheads have connectivity with the sink:

1. Direct Communication Case

2. Multi-Hop Communication Case

The network model considering direct communication (i.e., Single-hop) is presented with the assumptions in Section 3.6.1. Section 3.6.2 is devoted for the network model considering multi-hop communication.

3.6.1 Direct Communication Case:

In this case, sensor nodes can only transmit their sensing data to the associated clusterhead and clusterheads transmit this sensed data to sink "directly" (shown with the solid lines on the 2^{nd} layer in Fig. 3.2). In the direct communication case, we strictly assume that all clusterheads have enough power necessary to transmit the data to the sink within one hop. Communication among clusterheads is not allowed.

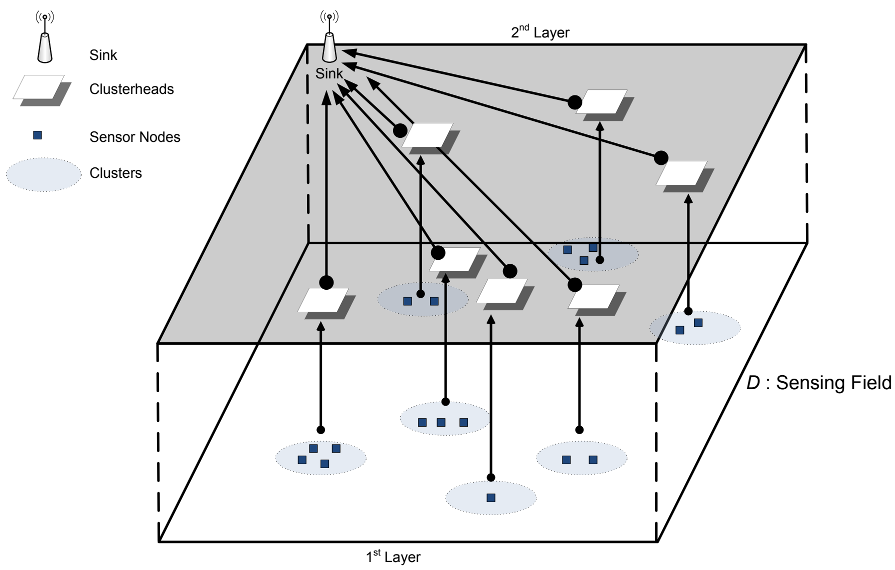

Figure 3.2: Proposed WSN model: The Direct Communication Case

3.6.2 Multi-Hop Communication Case:

Depending on the given specific requirements of a WSN application, the direct communication scheme may be perceived as rather a strong assumption and hence this type of communication may not reflect the characteristics of some classes of WSNs. For example, if the power consumption is a critical issue for an application, then multi-hop communication will be preferred. Because, in radio environments, it is known (e.g. [33]) that the received power typically falls off as the $2^{nd} - 4^{th}$ power of distance. Therefore, connectivity using multi-hop communication is more favorable than that of single-hop for energy stringent applications.

For the multi-hop communication case, we essentially used the same model as the direct communication case except the way the communication is performed between clusterheads and the sink. For the direct communication case, all clusterheads are guaranteed to reach the sink in a single-hop, whereas for the multi-hop communication case, clusterheads have the ability to send the sensed data either to other clusterheads for relaying towards to the sink or directly to reach the sink (shown with the solid lines on the 2^{nd} layer in Fig. 3.3). Due to the dependence on the relaying clusterheads, connectivity in this type of communication differs from the direct communication case and thus is more complex.

In order for a clusterhead node to communicate with another clusterhead or with the sink, the neighboring clusterhead or the sink should be within the transmitting range, r_{th}, of the first clusterhead. We consider the simple case where r_{th} is fixed and r_{th} is the maximal radius allowed by power constraints.

Furthermore, as far as the Multi-Hop Communication Case is concerned, MAC and routing protocols are beyond the scope of this thesis study. We essentially assume that the MAC and routing protocols provide us at least one route/link from a given clusterhead to the sink.

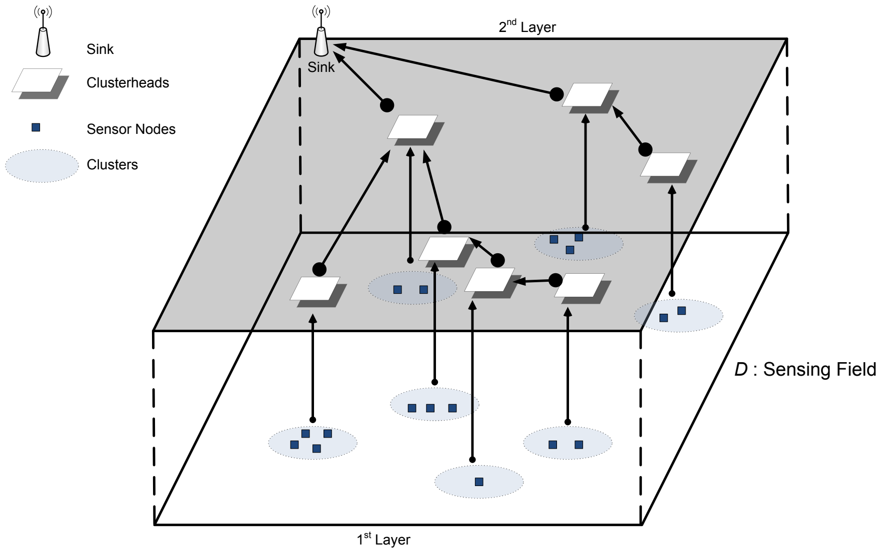

Figure 3.3: Proposed WSN model: The Multi-Hop Communication Case

3.7 Notation

Table 3.1. lists the necessary notation used throughout the thesis to formulate the proposed models.

Table 3.1: Summary of Variables

Symbol	Description
	Network Related
D	Sensing field (or field of interest)
N_S	The number of sensor nodes deployed randomly over D
N_H	The number of clusterheads deployed randomly over D
λ_S	Average number of sensor nodes per unit area
λ_H	Average number of clusterheads per unit area
	Coverage Related
P_{cov}	Targeted level of area coverage of the WSN
r_s	Sensing radius (range) of each sensor node and each clusterhead
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Symbol	**Description**
$S_{cluster}$	The expected value of area covered by each clusterhead together with the sensor nodes connected to it
	Connectivity Related
r_{ts}	Transmission radius (range) of a sensor node
r_{th}	Transmission radius (range) of a clusterhead
n_s	Average number of sensor nodes connected to a single clusterhead
θ	Average number of clusterheads connected to a single clusterhead
θ_c	The super-criticality condition of θ in percolation theory
	Monetary Cost Related
C_S	Monetary cost of a sensor node.
C_{hw}	Monetary cost of the hardware component of a sensor node
C_{bt}	Monetary cost of the battery pack of a sensor node
C_H	Monetary cost of a clusterhead
C_{HW}	Monetary cost of the hardware component of a clusterhead.
C_{BT}	Monetary cost of the battery pack of a clusterhead
C_{cell}	Monetary cost of the a single cell in a battery pack
C_{WSN}	Monetary cost of the entire WSN
	Energy Consumption Related
e_0	Non-rechargeable initial energy of a sensor node
E_0	Non-rechargeable initial energy of a clusterhead
E_M^t	The energy dissipated by a clusterhead to transmit M bits of frame
e_M^t	The energy dissipated by a sensor node to transmit M bits of frame
E_M^r	The energy dissipated by a clusterhead to receive M bits of frame
e_M^r	The energy dissipated by a sensor node to receive M bits of frame
E_{AGG}	The energy dissipated by a clusterhead to aggregate 1 bit of data from the received signal
m	Path loss exponent
α	Energy dissipated in the transmitted circuit (i.e., Phase-Locked Loop (PLL), Voltage-Controlled Oscillator (VCO), etc) depending on the digital coding, modulation, etc.

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Symbol	**Description**
β_{fs}	The coefficient for the radiated power necessary to transmit in free space channel (FSC) model over a distance d
β_{mp}	The coefficient for the radiated power necessary to transmit in multipath (MP) fading channel model over a distance d
ρ	The power consumption coefficient for receiving data
	Lifetime Related
R	Lifetime of the WSN application considering our network model. Lifetime is the time period from the instant when the WSN starts operations related to monitoring to the instant when the level of actual connected coverage is reduced to that of targeted coverage at the sink

CHAPTER 4

CONNECTED COVERAGE IN WSNS: DIRECT COMMUNICATION AND MULTI-HOP COMMUNICATION CASES

Due to WSNs' potential usage in hostile and inaccessible fields, in most deployment scenarios, deterministic deployment of sensor nodes may not be possible. Therefore, the sensor nodes are deployed in such a fashion that it will result in a WSN with random topology. In randomly deployed WSNs, if the goal of a WSN application is to cover the entire field, then full-coverage would require infinitely many sensor nodes [32]. However, due to the budget constraints, it is not always feasible to deploy such a huge number of nodes. Therefore, the designers could sacrifice a predetermined degree of coverage for substantial cost savings. Understanding this trade-off between coverage and monetary cost is one of the key issues in WSN design and it essentially provides the basis for network dimensioning problem.

In this thesis, we study the network dimensioning problem for randomly deployed heterogeneous WSNs. Even with the simplest randomly deployed WSN application, the network dimensioning problem and the other system aspects can be much more complex than initially anticipated because the network dimensioning problem depends on many parameters namely, sensing radius, transmission radius, size and geometry of the sensing field, etc.

In this chapter, we focus on the determining the number of clusterheads and sensor nodes to satisfy the required level of connected coverage. To solve this problem, we propose the cluster size concept. Cluster size, which is the area covered by a clusterhead together with the sensor nodes connected to it, is derived analytically and is validated through computer simulations. Herein, network dimensioning problem is discussed for both direct communication and multi-hop communication cases. In direct communication case, we directly use the cluster size formulas derived to determine the level of connected coverage. On the other hand, for multi-hop communication case, we use not only the cluster size formulas derived but also the "well-connectivity" concept originated from percolation theory.

4.1 Coverage and Connectivity

Coverage is one of the fundamental issues in WSNs. Coverage of a sensor node is meaningful only when the sensor node is able to transmit its data to the sink(s). In other words, coverage of a sensor node alone is not enough when designing an application, because the node should also be connected to the sink for proper operation of the network. Therefore, coverage and connectivity need to be analyzed jointly.

4.1.1 Coverage

We begin by discussing the coverage problem in a randomly deployed WSN when its topology is modeled using the "Boolean Model". Boolean models are mostly used for the connectivity analyses. However, these models can also be used to study coverage in WSNs, by assuming that each sensor node covers some sensing region.

Suppose a large planar area, D, is to be covered by N_S identical sensor nodes which are scattered randomly over this area according to a Poisson Point Process. Suppose the area sensed by each sensor node is a perfect disk with radius r_s and $\lambda_S = N_S/D$ is the average number of sensor nodes per unit area. With all these are given, the probability of a point in D being covered, P_{cov}, can be found by using the Boolean Coverage Disc model [35] as follows.

Assume that there is only one sensor node in D. The probability of a point p to be covered by this single node is $\frac{\pi r_s^2}{D}$ as shown in Fig. 4.1. And, $(1 - \frac{\pi r_s^2}{D})$ is simply the probability of a point p is "not" covered by this node. Since, we have N_S sensor nodes scattered over the field D, the probability of a point p not to be covered by N_S nodes, P_{p-nc}, will be:

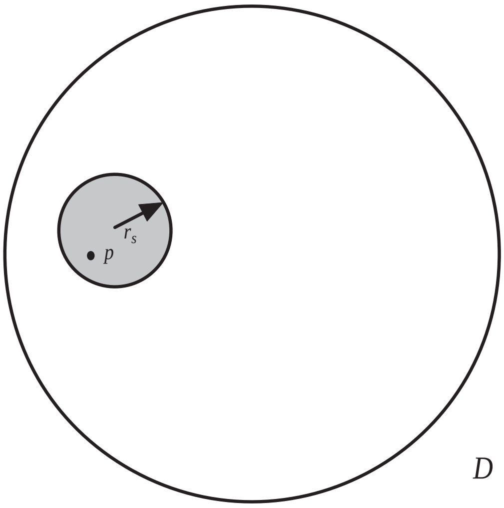

Figure 4.1: A single sensor node with sensing radius, r_s, deployed randomly over field D covering the point p

$$P_{p-nc} = \left(1 - \frac{\pi r_s^2}{D}\right)^{N_S} \tag{4.1}$$

By substituting $N_S = \lambda_S.D$, we have:

$$P_{p-nc} = \left(1 - \frac{\pi r_s^2}{D}\right)^{\lambda_S.D} \tag{4.2}$$

As D goes to infinity[1]:

$$P_{p-nc} = \lim_{D\to\infty} \left(1 - \frac{\pi r_s^2}{D}\right)^{\lambda_S.D} = e^{-\lambda_S \pi r_s^2} \tag{4.3}$$

Therefore, P_{cov} can be found as:

$$P_{cov} = 1 - e^{-\lambda_S \pi r_s^2} \tag{4.4}$$

Therefore, the average area covered by randomly deployed N_S sensor nodes can be found [35] as:

$$A_{cov} = P_{cov}.D = (1 - e^{-\lambda \pi r_s^2}).D \tag{4.5}$$

Note that A_{cov} is the expected value of the area covered for a very large sensing field.

[1]From [77] $\lim_{\phi\to\infty}\left(1 - \frac{\kappa}{\phi}\right)^{\phi} = e^{-\kappa}$

An interesting interpretation of Eqn. 4.4 is that, P_{cov} expression is independent of the geometry of the region sensed by sensor nodes. Therefore, if the sensing region covered by any sensor node is A_S, the coverage probability could be found by replacing πr_s^2 with A_S as:

$$P_{cov} = 1 - e^{-\lambda\ A_S} \tag{4.6}$$

Yet another practical result of Eqn. 4.4 is that it can also be used for WSN applications employing hierarchical topologies. For example, assume that there exists a WSN consisting of N_H clusterheads and N_S sensor nodes, and both sensors nodes and clusterheads have identical sensing capability, and their sensing area is a perfect disk with radius r_s. Therefore, we have $N = N_H + N_S$ sensing devices scattered randomly over the field D, and, without considering connectivity, the coverage probability can be found as:

$$P_{cov} = 1 - e^{-\frac{(N_H + N_S)\pi r_s^2}{D}} \tag{4.7}$$

4.1.2 Connectivity

Like coverage, connectivity is another indispensable requirement in a WSN since the reason of WSN's existence is to monitor some phenomenon and transfer the data effectively to the sink. For the upcoming discussion, we proceed with direct (i.e., single-hop) connectivity of a sensor node to a clusterhead.

Direct Connectivity of a sensor node to a clusterhead

Let there be N_H clusterheads and N_S sensor nodes which are deployed randomly over D. To model the connectivity of these devices, we again use Boolean Disc Model. If a clusterhead is within sensor node's communication range, this sensor node is said to be connected to the clusterhead. By using an approach similar to the one employed in P_{cov} derivation, the probability that a sensor node is within the communication range of at least one of N_H clusterheads, P_{con}, could be derived as:

$$P_{con} = 1 - e^{-\frac{N_H \pi r_{ts}^2}{D}} \tag{4.8}$$

Eqn. 4.8 is very similar to Eqn. 4.4. The differences are 1) sensing radius, r_s, is replaced with transmission radius, r_{ts}, of the sensor nodes. 2) the density of sensor nodes is replaced with that of clusterheads. Actually, this similarity is the essence of Boolean Disc Model. To be able to use Eqn. 4.8, we should assume that each clusterhead is guaranteed to reach the sink. And, Eqn. 4.8 does not consider the connectivity between clusterheads with the sink and connectivity among clusterheads.

Eqn. 4.8 considers only the connectivity between a certain sensor node and at least one of the clusterhead. If we deploy N_S sensor nodes in D, from Eqn. 4.8, we can find the average number of sensor nodes connected to at least one of N_H clusterheads as:

$$\overline{N_S} = N_S \left(1 - e^{-\frac{N_H \pi r_{ts}^2}{D}}\right) \tag{4.9}$$

Similarly, average number of sensor nodes in a cluster, n_s, can be found as:

$$n_s = \frac{N_S}{N_H} \left(1 - e^{-\frac{N_H \pi r_{ts}^2}{D}}\right) \tag{4.10}$$

Here, we should note that, in reality, due to the random deployment of devices, it cannot be guaranteed that every clusterhead has the same number of cluster members, and that n_s is simply an average value.

4.2 Cluster Size - Expected Value of the Area Covered By a Cluster

Up to this point, the concepts of connectivity and coverage have been analyzed separately. However, we should take into account connected coverage, that is, the fraction of the sensing field effectively covered by connected devices. As our network has a mixture of N_H clusterheads and N_S sensor nodes, we need to find the area covered by the "clusters" that effectively forward the sensed data to the sink. We first need to discover the expected value of area covered by a clusterhead together with the sensor nodes connected to it, which we referred it as "cluster size" and denoted it by $S_{cluster}$.

For a set of devices to become a cluster, there first needs to be a clusterhead and other sensor nodes connected to it. Fig. 4.2 (a) shows a single clusterhead (shown with the gray disc in Fig. 4.2 (a) and (b)) in the center and four connected sensor nodes (shown with the solid lines) which are in the r_{ts} range of the clusterhead. In addition, in Fig. 4.2 (a), there are also two isolated sensor nodes (shown with the dashed lines) that are outside the r_{ts} range of the clusterhead. In Fig. 4.2 (b), on the other hand, we can see a cluster composed of a clusterhead and four connected sensor nodes with their sensing range, r_s. Fig. 4.2 (c) illustrates an abstract area which is the average area covered by a cluster, $S_{cluster}$. $S_{cluster}$ is basically the area covered by a single

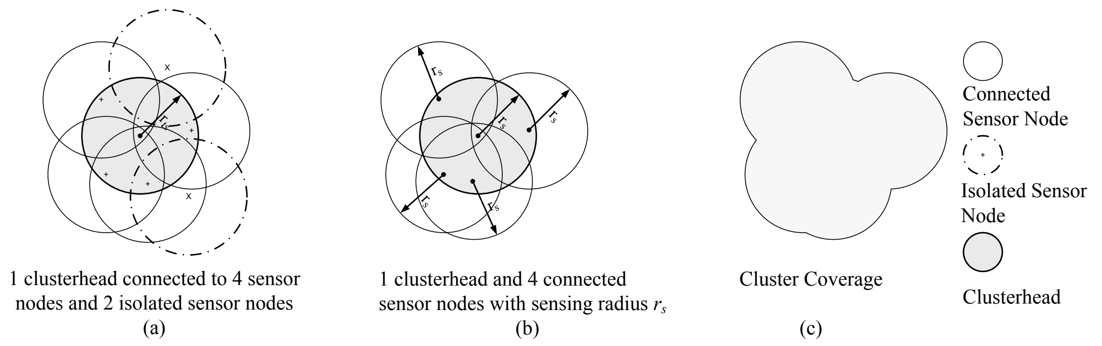

Figure 4.2: A Cluster and its Coverage

clusterhead and n_S sensor nodes. Actually, the geometry of this area is not important, however, as it will be shown, its value is a concept of paramount importance for solving the network dimensioning problems.

To derive $S_{cluster}$, let's consider first a single clusterhead and a set of sensor nodes scattered over a field D (See Fig. 4.3). For the sake of simplicity, we consider a clusterhead located in the center (point H in Fig. 4.3) which is able to communicate with any sensor node within a disc-shaped region with area πr_{ts}^2. Now suppose that a point p, within the outer disc is to be covered by the sensor nodes connected to the clusterhead or the clusterhead itself. The radial distance between the clusterhead and the point p is x. Transmission range of the sensor nodes is denoted by r_{ts}.

In Fig. 4.3, any point within distance r_s from the center is assured to be covered by the clusterhead at the center. And, any point outside the inner circle can only be covered by the sensor nodes connected to the clusterhead. Therefore if the point p is within the inner disc having the radius of r_s, it is definitely covered by the clusterhead and the coverage probability for it will be one. To find the probability of a point p outside the inner disc to be covered, there should be one or more "connected sensor nodes" both sensing the point p and connected to the clusterhead at the center. That is, there should be one or more sensor nodes in region $I(x)$, which is the shaded region in Fig. 4.3.

$I(x)$ is the region formed by the intersection of two discs, and its area is a function of x, the radial distance between the centers of these two discs with radii r_{ts} and r_s. We can examine two different cases to find the area of the shaded region.

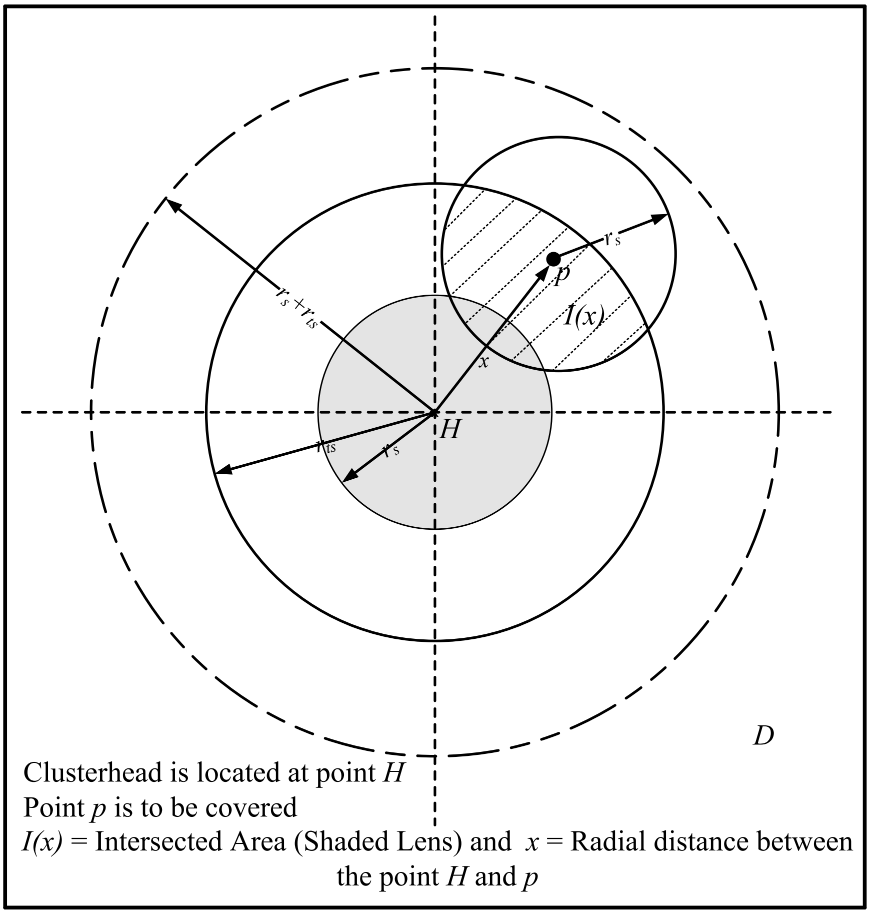

Figure 4.3: A sensing region for a single clusterhead and a set of sensor nodes

Case 1: When r_{ts}-r_s<x≤r_{ts}+r_s the area $I(x)$ can be found as [38]:

$$I(x) = r_s^2 \cos^{-1}\left(\frac{x^2 + r_s^2 - r_{ts}^2}{2xr_s}\right) + r_{ts}^2 \cos^{-1}\left(\frac{x^2 + r_{ts}^2 - r_s^2}{2xr_{ts}}\right) - \frac{1}{2}\sqrt{(r_s + r_{ts} - x)(x + r_s - r_{ts})(x - r_s + r_{ts})(x + r_s + r_{ts})} \tag{4.11}$$

Case 2: When x≤r_{ts}-r_s,

$$I(x) = \pi r_s^2 \tag{4.12}$$

Let $P_{p1}(x)$ be the probability that a point p is not sensed by any sensor node connected to the clusterhead at the center. In order for a point p not to be sensed, no sensor node should be in the intersected area $I(x)$. Let the average number of sensor nodes connected to a clusterhead be n_s (See Eqn. 4.10). The number of connected sensor nodes in the entire sensing field, C_s, can be found as:

$$\frac{n_s}{C_s} = \frac{\pi r_{ts}^2}{D} \Longleftrightarrow D = \frac{C_s}{n_s/\pi r_{ts}^2} \Longleftrightarrow C_s = \frac{D n_s}{\pi r_{ts}^2} \tag{4.13}$$

Probability of no sensor node in $I(x)$ can be found as:

$$P_{p1}(x) = \left(1 - \frac{I(x)}{D}\right) \tag{4.14}$$

From Eqn. 4.13, we have C_s sensor nodes in region D. Therefore, the probability of having no sensor node in the shaded area $I(x)$ is:

$$P_{p-nc}(x) = \left(1 - \frac{I(x)}{D}\right)^{C_s} \tag{4.15}$$

As C_s goes to infinity, we have:

$$P_{p-nc}(x) = \lim_{C_s \to \infty} \left(1 - \frac{\frac{I(x) n_s}{\pi r_{ts}^2}}{C_s}\right)^{C_s} = e^{-\frac{I(x) n_s}{\pi r_{ts}^2}} \tag{4.16}$$

Therefore, the probability that a point p which is x units away from the clusterhead is sensed by "at least one sensor node" connected to the clusterhead can be found as:

$$P_{pc}(x) = 1 - e^{-\frac{I(x) n_s}{\pi r_{ts}^2}} \tag{4.17}$$

We now know the probability of a point p being covered by at least one of the sensor nodes connected to the clusterhead or the clusterhead itself. Therefore we can find the average value of the area covered by a cluster by using a simple expectation. From Fig. 4.4, it can be seen that there are two concentric discs. For the grey inner disc with radius r_s, the probability of coverage, P_{inner}, is one since inner disc is assured to "be covered" by the clusterhead at point H (See Fig. 4.4).

Suppose that the probability of coverage in the ring-shaped segment (starting from r_s to $r_s + r_{ts}$) is P_{pc}. Thus, $S_{cluster}$ can be found by integration in cylindrical coordinates as:

$$S_{cluster} = \int_{x=0}^{r_s} \int_{\phi=0}^{2\pi} P_{inner} x \, d\phi \, dx + \int_{x=r_s}^{r_s + r_{ts}} \int_{\phi=0}^{2\pi} P_{pc} x \, d\phi \, dx \tag{4.18}$$

Since $p_{inner} = 1$, the Eqn. 4.18 can rewritten as:

$$S_{cluster} = \pi r_s^2 + \int_{x=r_s}^{r_s + r_{ts}} \int_{\phi=0}^{2\pi} P_{pc} x \, d\phi \, dx \tag{4.19}$$

By using the Eqn. 4.17 for p_{pc}:

$$S_{cluster} = \pi r_s^2 + \int_{x=r_s}^{r_s + r_{ts}} \int_{\phi=0}^{2\pi} x(1 - e^{-\frac{I(x) n_s}{\pi r_{ts}^2}}) \, d\phi \, dx \tag{4.20}$$

Therefore:

$$S_{cluster} = \pi r_s^2 + 2\pi \int_{x=r_s}^{r_s + r_{ts}} x(1 - e^{-\frac{I(x) n_s}{\pi r_{ts}^2}}) \, dx \tag{4.21}$$

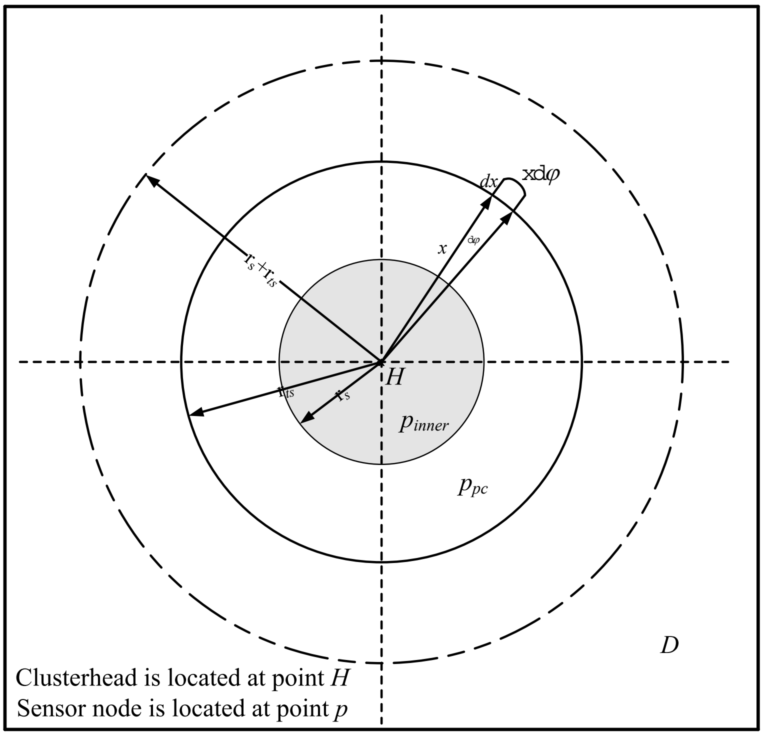

Figure 4.4: Derivation of $S_{cluster}$

4.2.1 Linear Approximation for Area of Intersection

To find $S_{cluster}$, the complex integral in Eqn. 4.21 should be taken. We plotted $I(x)$ $vs.$ x in Eqn. 4.21 for some sample parameters. By investigating similar plots, we found that it can be approximated by a line segment. So as to simplify the integration, $I(x)$ can be approximated by a line segment (see Fig. 4.5) whose equation is:

$$I(x) = -(\pi r_s/2)x + (\pi r_s/2)(r_s + r_{ts}) \tag{4.22}$$

4.2.2 Derivation of Cluster Size

In this section, we derive a compact formula for $S_{cluster}$ by using a linear approximation given in Eqn. 4.22 and the integration in Eqn. 4.21.

If $r_{ts} \leq 2r_s$ the $P_{pc}(x)$ remains unchanged between the upper and lower boundaries of the definite integral. However, for $r_{ts} > 2r_s$ case, we should further split the $P_{pc}(x)$ in two intervals. In the first interval $P_{pc}(x)$ is $1 - e^{-\frac{I(x)n_s}{\pi r_{ts}^2}}$ whereas in the second interval

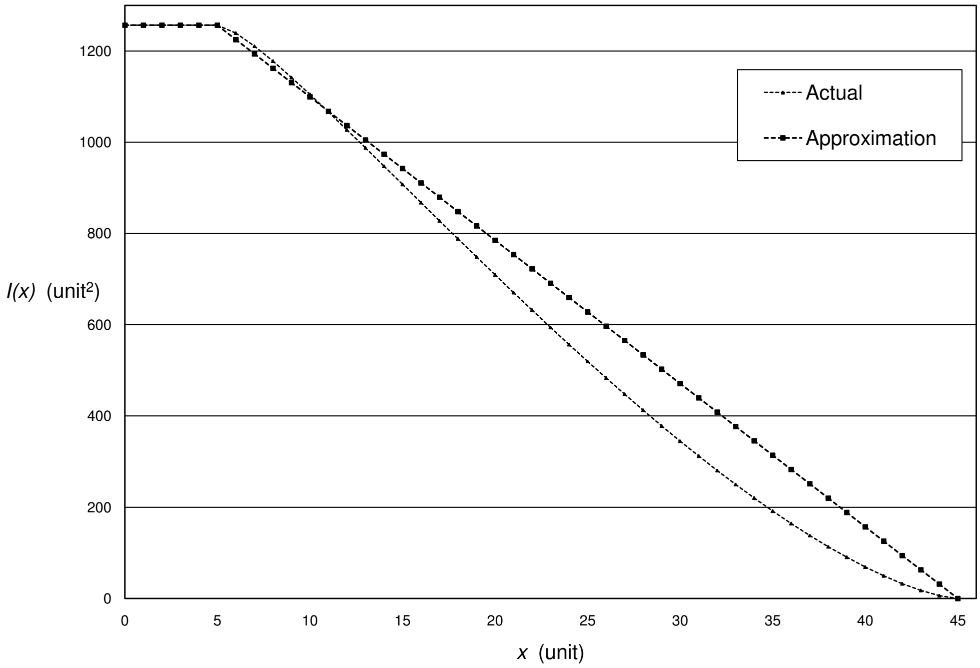

Figure 4.5: $I(x)$ $vs.$ x (x is the radial distance between the centers of the two intersecting discs) where $r_{ts} = 25\ units$ and $r_s = 20\ units$

$P_{pc}(x)$ is either $1 - e^{-\frac{\pi r_s^2 n_s}{\pi r_{ts}^2}}$ or $1 - e^{-\frac{I(x) n_s}{\pi r_{ts}^2}}$. Hence, for these two cases, $S_{cluster}$ can be derived as follows.

Case 1: If $r_{ts} \leq 2r_s$ then the area covered by a clusterhead and sensor nodes connected to it can be found as:

$$S_{cluster} = \pi r_s^2 + 2\pi \int_{x=r_s}^{r_s+r_{ts}} x(1 - e^{-\frac{[-(\frac{\pi r_s}{2})x + (\frac{\pi r_s}{2})(r_s+r_{ts})]n_s}{\pi r_{ts}^2}})dx \tag{4.23}$$

By substituting,

$$\alpha = \frac{n_s r_s}{2r_{ts}^2} \tag{4.24}$$

$S_{cluster}$ can be rewritten as:

$$S_{cluster} = \pi r_s^2 + 2\pi \int_{x=r_s}^{r_s+r_{ts}} x(1 - e^{-[-\alpha x + \alpha(r_s+r_{ts})]})dx \tag{4.25}$$

By rearranging the terms

$$S_{cluster} = \pi r_s^2 + 2\pi \int_{x=r_s}^{r_s+r_{ts}} xdx - 2\pi \int_{x=r_s}^{r_s+r_{ts}} xe^{-[-\alpha x + \alpha(r_s+r_{ts})]}dx \tag{4.26}$$

$$S_{cluster} = \pi r_s^2 + 2\pi \left[\frac{x^2}{2} \Bigg|_{x=r_s}^{r_s+r_{ts}} - \int_{x=r_s}^{r_s+r_{ts}} x e^{-[-\alpha x + \alpha(r_s+r_{ts}]})dx \right] \quad (4.27)$$

$$S_{cluster} = \pi r_s^2 + 2\pi \left[\left(\frac{(r_s+r_{ts})^2}{2} - (\frac{r_s^2}{2}) \right) - \int_{x=r_s}^{r_s+r_{ts}} x e^{-[-\alpha x + \alpha(r_s+r_{ts})]} dx \right] \quad (4.28)$$

$$S_{cluster} = \pi r_s^2 + 2\pi \left[\left(\frac{(r_s+r_{ts})^2}{2} - (\frac{r_s^2}{2}) \right) - e^{-\alpha(r_s+r_{ts})} \int_{x=r_s}^{r_s+r_{ts}} x e^{\alpha x} dx \right] \quad (4.29)$$

By integration by parts [77], we can find that:

$$\int x e^x dx = x e^x - e^x + Constant \quad (4.30)$$

Using the Eqn. 4.30 in Eqn. 4.29

$$S_{cluster} = \pi(r_s+r_{ts})^2 + 2\pi \left[-e^{-\alpha(r_s+r_{ts})} \left((\frac{x e^{\alpha x}}{\alpha}) - (\frac{e^{\alpha x}}{\alpha^2}) \right) \Bigg|_{x=r_s}^{r_s+r_{ts}} \right] \quad (4.31)$$

Now let's consider only the last term:

$$C = \left[\left((\frac{x e^{\alpha x}}{\alpha}) - (\frac{e^{\alpha x}}{\alpha^2}) \right) \Bigg|_{x=r_s}^{r_s+r_{ts}} \right] \quad (4.32)$$

Therefore:

$$C = \left[\left((\frac{(r_s+r_{ts})e^{\alpha(r_s+r_{ts})}}{\alpha}) - (\frac{e^{\alpha(r_s+r_{ts})}}{\alpha^2}) \right) - \left((\frac{r_s e^{\alpha r_s}}{\alpha}) - (\frac{e^{\alpha r_s}}{\alpha^2}) \right) \right] \quad (4.33)$$

By substituting H and G into C

$$\alpha(r_s+r_{ts}) = H \qquad \alpha r_s = G \quad (4.34)$$

Using the Eqn. 4.33 and Eqn. 4.34

$$C = \frac{1}{\alpha^2} \left(e^H(H-1) - e^G(G-1) \right) \quad (4.35)$$

Rearrange the following term in Eqn. 4.31 and Eqn. 4.35

$$B = e^{-\alpha(r_s+r_{ts})} \qquad B = e^{-H} \quad (4.36)$$

where BC is the expression inside the square brackets in Eqn. 4.31

$$BC = \frac{e^{-H}}{\alpha^2} \left(e^H(H-1) - e^G(G-1) \right) \quad (4.37)$$

$$BC = \frac{1}{\alpha^2} \left((H-1) - e^{-H} e^G (G-1) \right) \quad (4.38)$$

$$BC = \frac{1}{\alpha^2}\left[\alpha(r_s + r_{ts}) - 1 - e^{-\alpha r_{ts}}(\alpha r_s - 1)\right] \tag{4.39}$$

Rearrange the following term in Eqn. 4.31 and Eqn. 4.39

$$S_{cluster} = \pi(r_s + r_{ts})^2 - 2\pi BC \tag{4.40}$$

Replacing the Eqn. 4.39 into Eqn. 4.40, $S_{cluster}$ is:

$$S_{cluster} = \pi(r_s + r_{ts})^2 - \frac{2\pi}{\alpha^2}\left[\alpha(r_s + r_{ts}) - 1 - e^{-\alpha r_{ts}}(\alpha r_s - 1)\right] \tag{4.41}$$

$$S_{cluster} = \pi(r_s + r_{ts})^2 - \frac{2\pi}{\alpha}\left[(r_s + r_{ts}) - \frac{1}{\alpha} - \frac{e^{-\alpha r_{ts}}}{\alpha}(\alpha r_s - 1)\right] \tag{4.42}$$

Finally by rearranging the terms, we find:

$$S_{cluster} = \pi(r_s + r_{ts})^2 + \frac{2\pi}{\alpha}\left[(\frac{1}{\alpha} - r_s)(1 - e^{-\alpha r_{ts}}) - r_{ts}\right] \tag{4.43}$$

Case 2: If $r_{ts}>2r_s$ then the area covered by a clusterhead and sensor nodes connected to it can be found as:

$$S_{cluster} = \pi r_s^2 + 2\pi\int_{x=r_s}^{r_{ts}-r_s} x(1 - e^{-\frac{\pi r_s^2 n_s}{\pi r_{ts}^2}})dx +$$
$$2\pi\int_{x=r_{ts}-r_s}^{r_s+r_{ts}} x(1 - e^{-\frac{[-(\frac{\pi r_s}{2})x + (\frac{\pi r_s}{2})(r_s+r_{ts})]n_s}{\pi r_{ts}^2}}))dx \tag{4.44}$$

By substituting the $\alpha = \frac{n_s r_s}{2r_{ts}^2}$, we have;

$$S_{cluster} = \pi r_s^2 + 2\pi\int_{x=r_s}^{r_{ts}-r_s} x(1 - e^{-2\alpha r_s})dx + 2\pi e^{-\alpha(r_s+r_{ts})}\int_{x=r_{ts}-r_s}^{r_s+r_{ts}} xe^{\alpha x}dx \tag{4.45}$$

$$S_{cluster} = \pi r_s^2 + 2\pi\left[\frac{x^2}{2}(1 - e^{-2\alpha r_s})\Big|_{x=r_s}^{r_{ts}-r_s}\right] + 2\pi e^{-\alpha(r_s+r_{ts})}\int_{x=r_{ts}-r_s}^{r_s+r_{ts}} xe^{\alpha x}dx \tag{4.46}$$

If we substitute T in $S_{cluster}$ expression;

$$T = 2\pi e^{-\alpha(r_s+r_{ts})}\int_{x=r_{ts}-r_s}^{r_s+r_{ts}} xe^{\alpha x}dx \tag{4.47}$$

We have

$$S_{cluster} = \pi r_s^2 + 2\pi\left[\left(\frac{(r_{ts} - r_s)^2}{2} - (\frac{r_s^2}{2})\right)(1 - e^{-2\alpha r_s})\right] + T \tag{4.48}$$

By using Eqn. 4.30, T can be found as:

$$T = 2\pi\left[\left(\frac{(r_s + r_{ts})^2}{2} - (\frac{(r_{ts} - r_s)^2}{2})\right) - B'C'\right] \tag{4.49}$$

where B' is

$$B' = e^{-\alpha(r_s + r_{ts})} \qquad B' = e^{-H'} \tag{4.50}$$

and C' is

$$C' = \frac{1}{\alpha^2}\left(e^{H'}(H'-1) - e^{G'}(G'-1)\right) \tag{4.51}$$

and where H' and G' is

$$H' = \alpha(r_s + r_{ts}) \qquad G' = \alpha(r_{ts} - r_s) \tag{4.52}$$

$$T = \left[\pi(r_s + r_{ts})^2 - \pi(r_{ts} - r_s)^2 - 2\pi B'C'\right] \tag{4.53}$$

Using the Eqn. 4.48

$$S_{cluster} = \pi r_s^2 + \left[\left(\pi(r_{ts} - r_s)^2 - \pi(r_s)^2\right) - \left(\frac{(r_{ts} - r_s)^2}{2} - (\frac{r_s^2}{2})\right) 2\pi e^{-2\alpha r_s}\right] + T \tag{4.54}$$

Replace T in Eqn. 4.53

$$S_{cluster} = \pi(r_{ts} + r_s)^2 - \left[\left(\frac{(r_{ts} - r_s)^2}{2} - (\frac{r_s^2}{2})\right) 2\pi e^{-2\alpha r_s}\right] - 2\pi B'C' \tag{4.55}$$

$$S_{cluster} = \pi(r_{ts} + r_s)^2 - \left[\left((r_{ts} - r_s)^2 - (r_s^2)\right) \pi e^{-2\alpha r_s}\right] - 2\pi B'C' \tag{4.56}$$

$$S_{cluster} = \pi(r_{ts} + r_s)^2 - \pi r_{ts}(r_{ts} - 2r_s)e^{-2\alpha r_s} - 2\pi B'C' \tag{4.57}$$

where using the similar approach in Eqn. 4.38

$$B'C' = \frac{1}{\alpha^2}\left((H'-1) - e^{-H'}e^{G'}(G'-1)\right) \tag{4.58}$$

$$B'C' = \frac{1}{\alpha^2}\left((\alpha(r_{ts} + r_s) - 1) - e^{-\alpha r_s}(\alpha(r_{ts} - r_s) - 1)\right) \tag{4.59}$$

By rearranging the terms

$$B'C' = \frac{1}{\alpha^2}\left((\alpha(r_{ts} + r_s) - 1 - 2\alpha r_s) - e^{-\alpha r_s}(\alpha(r_{ts} - r_s) - 1) + 2\alpha r_s\right) \tag{4.60}$$

$$B'C' = \frac{1}{\alpha^2}\left((\alpha(r_{ts} - r_s) - 1) - e^{-\alpha r_s}(\alpha(r_{ts} - r_s) - 1) + 2\alpha r_s\right) \tag{4.61}$$

$$B'C' = \frac{1}{\alpha^2}\left[(\alpha(r_{ts} - r_s) - 1)(1 - e^{-\alpha r_s}) + 2\alpha r_s\right] \tag{4.62}$$

Finally,

$$S_{cluster} = \pi(r_{ts} + r_s)^2 - \pi r_{ts}(r_{ts} - 2r_s)e^{-2\alpha r_s} - \frac{2\pi}{\alpha^2}\left[(\alpha(r_{ts} - r_s) - 1)(1 - e^{-\alpha r_s}) + 2\alpha r_s\right] \tag{4.63}$$

Thus, we end up with two equations for $S_{cluster}$ for two different cases. It may also be useful to comment on the boundary values for $S_{cluster}$ for both of these cases. When there are no sensor nodes deployed in the sensing field, only the clusterheads cover some region. Therefore $S_{cluster}$ takes its minimum value, πr_s^2, with no sensor nodes. Conversely, when there are infinitely many sensor nodes scattered over the sensing field, the entire region inside the outer most disc in Fig. 4.4 will be covered. Therefore, $S_{cluster}$ reaches its maximum value, $\pi(r_{ts} + r_s)^2$, with infinitely many sensor nodes.

4.2.3 Validation of Cluster Size Equations by Simulations

In order to validate the cluster size equations we performed computer simulations by using a custom developed simulator written in Java programming language. The simulator generates a WSN by randomly deploying N_H clusterheads and N_S sensor nodes over a given sensing field. The locations of these nodes are determined through a uniformly distributed random number generator. Each point in the sensing field was abstracted as an element of an array of Boolean type. If a point is covered by a clusterhead or a connected sensor node, then this point is marked as "covered". At the end of each experiment the marked elements in the array, in other words the connected points, are counted. The sum of the connected points gives us the connected coverage value for that given experiment.

The simulation results given in this section are obtained by averaging results of multiple simulations and the number of simulations is determined according to a confidence interval of $\pm 5\%$ with 0.95 probability.

In Fig. 4.6, a WSN with 100 clusterheads within a 1000×1000 $unit^2$ sensing field is considered. We plot the $S_{cluster}$ $vs.$ r_{ts} graph for $N_S = 100$, $N_S = 200$, $N_S = 300$, and $N_S = 400$ values. For each set, we compare the cluster size derived analytically with the values obtained from simulations. Fig. 4.6 shows that there is at most 2% discrepancy between simulation results and the analytical findings. There are two causes of this discrepancy. The first cause is the errors originating from the approximation made in deriving the cluster size equations. The second source of the discrepancy is due to the

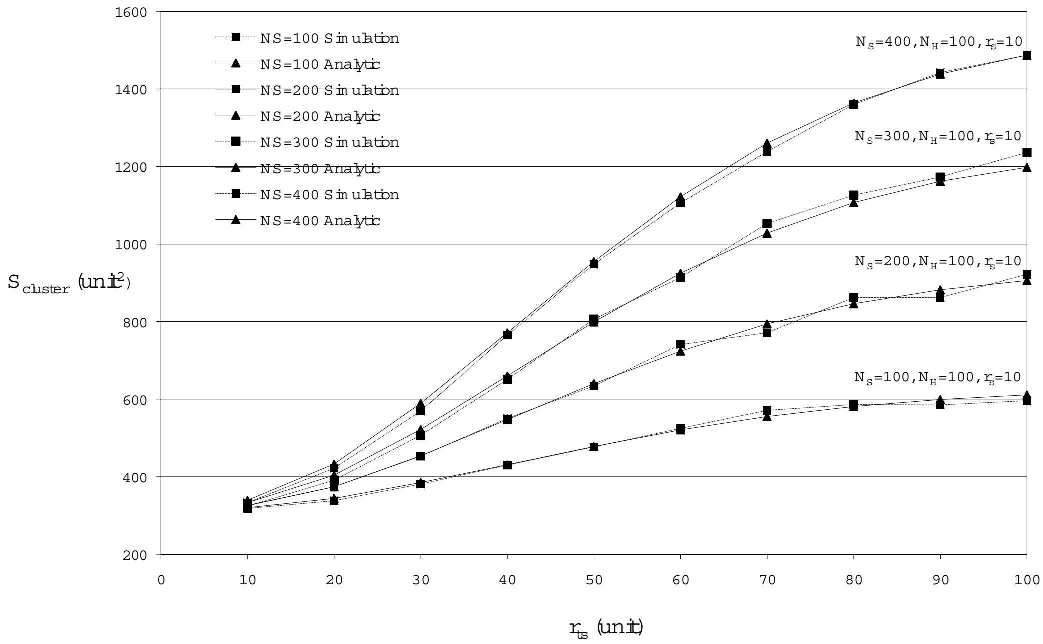

Figure 4.6: $S_{cluster}$ *vs.* r_{ts} where $D = 1000 \times 1000\ unit^2$, $r_s = 10\ units$, and $N_H = 100$

border effect because Fig. 4.6 demonstrates that for smaller values of r_{ts}, analytical and simulation values do not deviate significantly. However, as the r_{ts} values get larger, the error increases.

In Fig. 4.7, the number of sensor nodes is fixed at 400 and $S_{cluster}$ is obtained for $N_H = 50$, $N_H = 100$, $N_H = 150$, and $N_H = 200$. This second figure also demonstrates a similar outcome to that of Fig. 4.6. Therefore, we can say that cluster size equations derived in this chapter are good measures for the area covered by a clusterhead together with the sensor nodes connected to it.

4.3 Connected Coverage: Direct Communication Case

Recall that, we have considered a randomly deployed WSN consisting of N_S sensor nodes and N_H clusterheads. These sensor nodes are setting up clusters with the nearby clusterheads statically. For the direct communication case, we assumed that clusterheads are able to reach the sink directly (i.e., in one-hop). That is, we consider the first case described in Section 3.6.1. In this network configuration, neither the sensor nodes

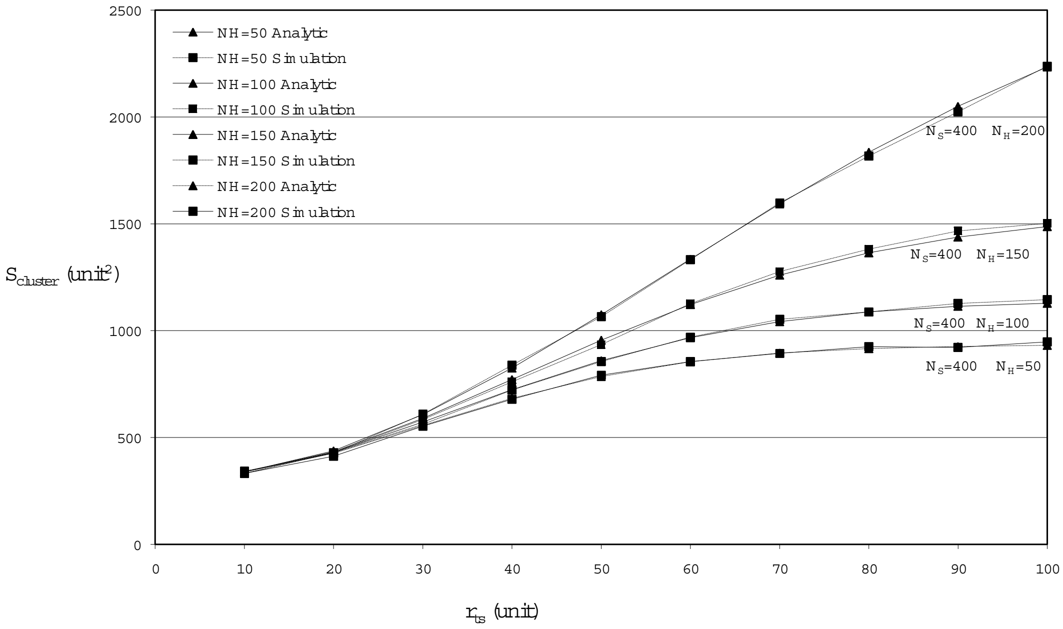

Figure 4.7: $S_{cluster}$ *vs.* r_{ts} where $D = 1000 \times 1000\ unit^2$, $r_s = 10units$, and $N_S = 400$

nor the clusterheads are able to communicate with the devices which are the same type. Therefore, for the direct communication case, we can find the connected coverage by using Eqn. 4.6 as:

$$P_{cov} = 1 - e^{-\frac{N_H S_{cluster}}{D}} \tag{4.64}$$

where $S_{cluster}$ for different r_{ts} and r_s values can be found using Eqn. 4.43 and Eqn. 4.63.

However, if we tackle the problem the other way around. That is, for given r_{ts}, r_s, P_{cov}, and D, one can find N_H and N_S "implicitly" by using the following expression derived from Eqn. 4.64.

$$N_H.S_{cluster} = Dln\left(\frac{1}{1 - P_{cov}}\right) \tag{4.65}$$

where $S_{cluster}$ is a function of N_H and N_S

Eqn. 4.65 is essentially the key formula for the network dimensioning problem for the direct communication case. This finding is one of the important contributions of this dissertation.

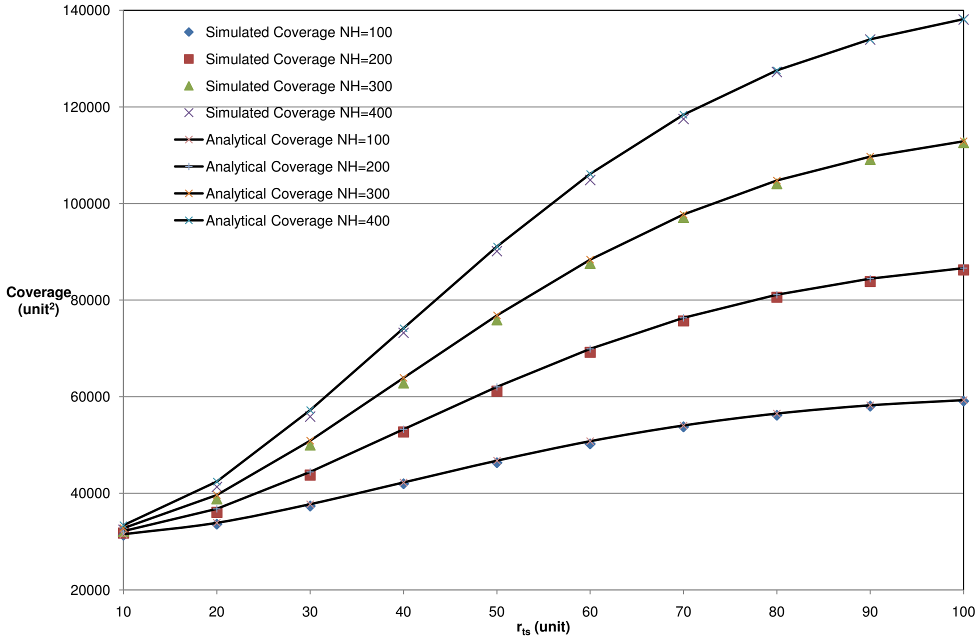

Figure 4.8: Coverage $vs.$ r_{ts} where $D = 1000 \times 1000\ unit^2$, $r_s = 10units$, and $N_H = 100$

In the previous section, we showed through computer simulations that the expected value, $S_{cluster}$, can be used as measures for the area covered by a cluster. We also performed simulations to compare the coverage derived analytically (i.e., $=P_{cov}.D$ where P_{cov} is given in Eqn. 4.64) with the average values of coverage obtained from simulations. To validate these analytical findings, we exploited the same sample parameters used in Fig.4.6. We plot the Coverage $vs.$ r_{ts} graph for $N_S = 100$, $N_S = 200$, $N_S = 300$, and $N_S = 400$ values. Fig. 4.8 shows that there is at most 3% discrepancy between simulation results and the analytical findings.

In Fig. 4.9, we also plot the same curves in Fig. 4.8 by adding the minimum and maximum values of coverage obtained from simulations. Herein, the variation between the average of the coverage which is actually obtained from a number of experiments and the extreme values of coverage are illustrated. As demonstrated in Fig. 4.9, in practice, one can use our coverage formulations when these minimum and maximum values are close to the average values.

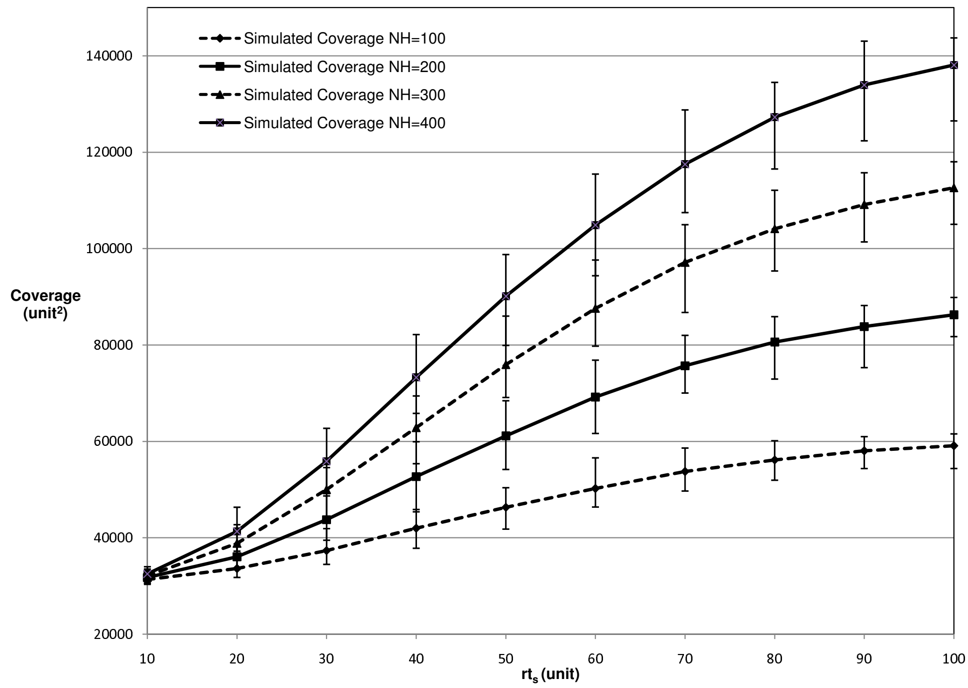

Figure 4.9: Coverage with errors $vs.$ r_{ts} where $D = 1000 \times 1000\ unit^2$, $r_s = 10units$, and $N_H = 100$

4.4 Connected Coverage: Multi-Hop Communication Case

In this section, what is meant by "multi-hop connectivity" is the communication that is between clusterheads and the sink performed in a multi-hop fashion. That is, we consider the second case described in Section 3.6.2. Our aim here is to ensure that the targeted partial-coverage achieved from the sensing field, will be delivered to the sink node. To make this possible it may not be necessary to have all clusterheads connected. Some fraction of clusterheads may remain disconnected although this is normally not a desirable situation. The aim of this section is to find out what are N_S and N_H values to achieve the targeted connected coverage.

The ideal case to achieve connectivity is to have all clusterheads connected to each other and the sink node. However, this full-connectivity case cannot always be achieved properly due to the random deployment of clusterheads and the limited transmission ranges of the clusterheads. That is why, we need to deploy infinitely many clusterheads to reach a fully connected network. This is the essence of the asymptotic behavior in full-connectivity highly similar to full-coverage. However, in real-life applications, it is not feasible to deploy such a dense network. That is why we need to analyze the relationship the required number of clusterheads, N_H, the transmission ranges of clusterheads, r_{th}, and the targeted level of connectivity.

In particular, this section has been inspired by the study of Dousse et. al. [40], who analyzed "well-connectivity" in a multi-hop wireless network by using percolation theory. Percolation theory states that when the sensing field is infinite, if the node density λ_H and the transmission range, r_{th} are such that $\pi r_{th}^2 \lambda_H \geq \theta_c$, for a critical clusterhead density $\theta_c \approx 4.5$, then the network of clusterheads is indeed formed by a giant connected component, plus a multitude of finite components (disconnected clusterheads).

As mentioned in [42], the "exact value for θ_c" at which the network percolates is still an open problem. There are many studies some of which found the bounds of θ_c analytically whereas many others solve this problem numerically.

Here, we propose a heuristic to solve the network dimensioning problem to satisfy a certain level of coverage in randomly deployed heterogeneous WSN considering "well-connectivity" concept and "cluster size" equations.

4.4.1 Heuristic on Connected Coverage Network Dimensioning Problem

Firstly, we begin with determining the value N_H that fulfills the well-connectivity requirement. Because, connectivity of a cluster can solely be provided by its clusterhead. Let the average number of clusterheads connected to a single clusterhead be $\theta = \pi r_{th}^2 \lambda_H$ for a chosen $\theta > \theta_c$.

The required number of clusterheads as a function of θ can be found as:

$$N_H = \frac{\theta.D}{\pi r_{th}^2} \tag{4.66}$$

If the value of θ is selected in such a way that, it is greater than θ_c value, then we denote this N_H by N_H^*. In other words, N_H^* is the value of the number of clusterheads which simply satisfies the well-connectivity requirement.

From Eqn. 4.4, we can find the probability of coverage (sensing range of a clusterhead is r_s) provided by only the "clusterhead nodes", $P_{cov\ head}$, as:

$$P_{cov\ head} = 1 - e^{-\frac{N_H \pi r_s^2}{D}} \tag{4.67}$$

By using Eqn. 4.67 and Eqn. 4.66, we have:

$$P_{cov\ head} = 1 - e^{-\frac{\frac{\theta . D}{\pi r_{th}^2}\pi r_s^2}{D}} \tag{4.68}$$

And, by rearranging the terms, $P_{cov\ head}$ can be rewritten as:

$$P_{cov\ head} = 1 - e^{-\theta \frac{r_s^2}{r_{th}^2}} \tag{4.69}$$

After finding $P_{cov\ head}$, we compare it with the targeted coverage P_{cov}. Because, if $P_{cov\ head}$ is equal to or greater than P_{cov}, no sensor nodes are required due to the fact that WSN composed of only clusterheads already provide sufficient coverage and connectivity simultaneously. Otherwise, we need to answer the following fundamental question: Given the sensor nodes' transmission radius, is it possible to reach the targeted coverage by adding sensor nodes with having identical sensing radius to that of a clusterhead. We know that the minimum value of $S_{cluster}$ is πr_s^2 and similarly the maximum value of $S_{cluster}$ is $\pi(r_{ts} + r_s)^2$. Therefore, given number of clusterheads may require an $S_{cluster}$ value larger than $\pi(r_{ts} + r_s)^2$ which is impossible even if we employ infinitely many sensor nodes. Therefore, we have to consider the following two cases:

Case 1: N_H^* clusterheads is sufficient to reach given P_{cov}:

Then, by using the P_{cov} expression in Eqn. 4.64, transform P_{cov} as a function of $S_{cluster}$ and θ as given in Eqn. 4.70.

$$P_{cov} = 1 - e^{-\frac{\frac{\theta . D}{\pi r_{th}^2}}{D} . S_{cluster}} \tag{4.70}$$

And, we end up with the following expression:

$$S_{cluster} = \left(\frac{\pi r_{th}^2}{\theta}\right) ln \left(\frac{1}{1 - P_{cov}}\right) \tag{4.71}$$

$S_{cluster}$ is an expression of type closed form and is a function of N_S and N_H. Therefore, the minimum number of required sensor nodes N_S and clusterheads N_H can be found by using exhaustive search.

Case 2: More than N_H^* clusterheads is required:

In this case we have to find a proper N_H value to satisfy required level of coverage. Here, in this case, note that we do not need to consider connectivity since it is already guaranteed by having a N_H value greater than N_H^*. From the cluster size and connected coverage formulas, we can find the bounds of N_H as follows:

1) Maximum value of cluster size is achieved when there are too many sensor nodes. Therefore minimum value of N_H is achieved when $S_{cluster} = \pi(r_{ts} + r_s)^2$. That is.

$$P_{cov} \leq 1 - e^{-\frac{N_H \pi (r_{ts}+r_s)^2}{D}} \tag{4.72}$$

Therefore,

$$N_H \geq \left(\frac{D}{\pi(r_s + r_{ts})^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \tag{4.73}$$

Hence, minimum number of clusterheads should be:

$$Min\ N_H = \left\lceil \left(\frac{D}{\pi(r_s + r_{ts})^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \right\rceil \tag{4.74}$$

2) Minimum value of cluster size is achieved when there are no sensor nodes. Therefore, the maximum value of N_H is achieved when $S_{cluster} = \pi r_s^2$. That is.

$$P_{cov} \leq 1 - e^{-\frac{N_H \pi r_s^2}{D}} \tag{4.75}$$

Therefore,

$$N_H \geq \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \tag{4.76}$$

So, maximum number of clusterheads should be:

$$Max\ N_H = \left\lceil \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \right\rceil \tag{4.77}$$

after choosing an N_H value satisfying $Min\ N_H \leq N_H \leq Max\ N_H$ condition, the required cluster size can be found as:

$$S_{cluster} = \left(\frac{D}{N_H}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \tag{4.78}$$

Finally, the required number of sensor nodes can be found using N_H and $S_{cluster}$.

The above explained algorithm to determine the number of clusterheads and sensor nodes is summarized in the flowchart given in Fig. 4.10.

4.4.2 Numerical Results and Validation

In this section, we validate the above discussed analyses by computer simulations and the results are discussed. All simulations are conducted via a custom simulator written in the Java programming language. The simulator generates a WSN by deploying N_H clusterheads and N_S sensor nodes randomly over a 1000×1000 $unit^2$, 2000×2000 $unit^2$, 3000×3000 $unit^2$, 4000×4000 $unit^2$, and 5000×5000 $unit^2$ square-shaped sensing field

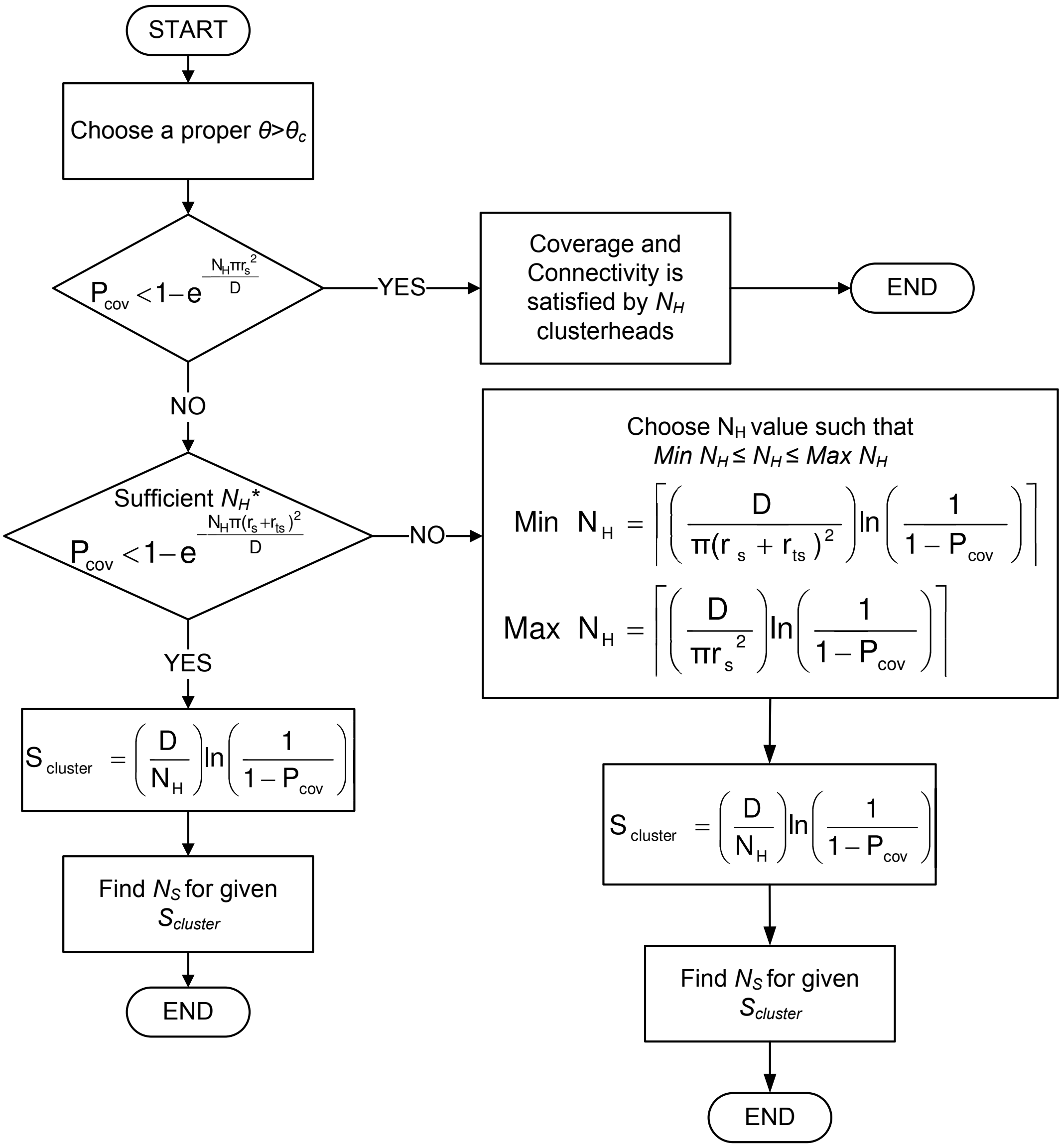

Figure 4.10: Flowchart for Network Dimensioning for Multi-Hop Communication Case

D. N_H and N_S pairs are determined according to the heuristic approach introduced in the previous section. The clusterheads are connected to the sink located in the center of the square sensing field in one or more hops. The simulation results given in this section are obtained by averaging results of multiple simulations and the number of simulations for each achieved actual coverage value is determined according to a confidence interval of $\pm 5\%$ with 0.95 probability.

To analyze the measure of connected coverage with varying degree of connectivity,

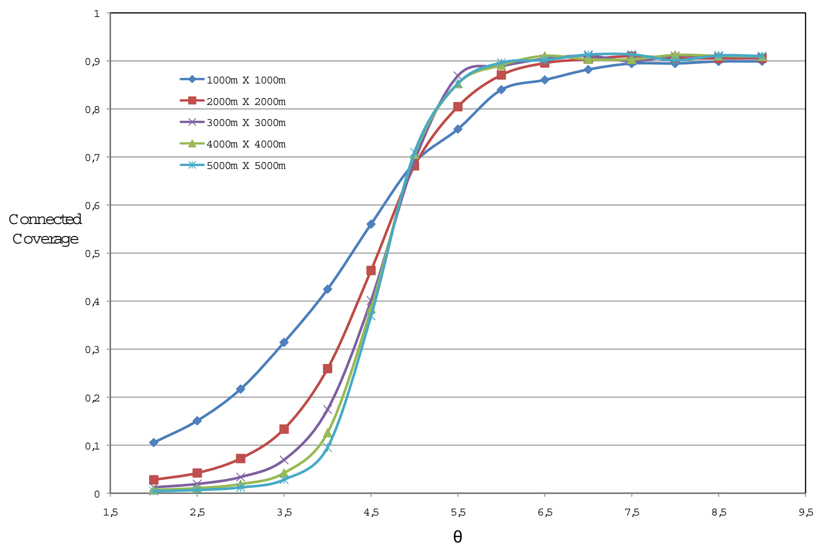

Figure 4.11: Connected Coverage *vs.* θ where $P_{cov} = 0.9$, $r_s = 40$ $units$, $r_{ts} = 100$ $units$, and $r_{th} = 100$ $units$

θ, we plot a connected coverage *vs.* θ graph for P_{cov}=0.9, $r_s = 40$ $units$, $r_{ts} = 100units$, and $r_{th} = 100units$ values, in Fig. 4.11. The results indicate that as the area of the sensing field increase, connected coverage increases more sharply. This is essentially in accordance with percolation theory as it assumes infinite area. As discussed in the previous sections, when $\theta \geq 4.5$ and the sensing field is infinite, there would be a giant component which is composed of connected clusterheads. However, this huge component of WSN does not necessarily assure to cover the field of interest.

From Fig. 4.11, WSNs deployed on sensing fields of different size satisfy the targeted coverage constraint (i.e., 0.9) at different θ values. As it can be seen from the figure, for all scenarios, WSNs fulfill the targeted coverage requirement when θ value larger than the critical value ~ 4.5. These validate our claim that θ and $S_{cluster}$ is a good measure for estimating the number of devices required.

Fig. 4.12 provides connected coverage for 3000×3000 $unit^2$, $P_{cov} = 0.9$, $r_s = 40$ $units$, and $r_{ts} = 100$ $units$ for different values of r_{th} and θ to observe the impact of transmission range of clusterheads on connected coverage. We notice that in Fig. 4.12, when D/r_{th} ratio gets larger, the curve rises more sharply. Another interesting result regarding Fig. 4.12 is that for smaller values of D/r_{th}, our heuristic enforces that the

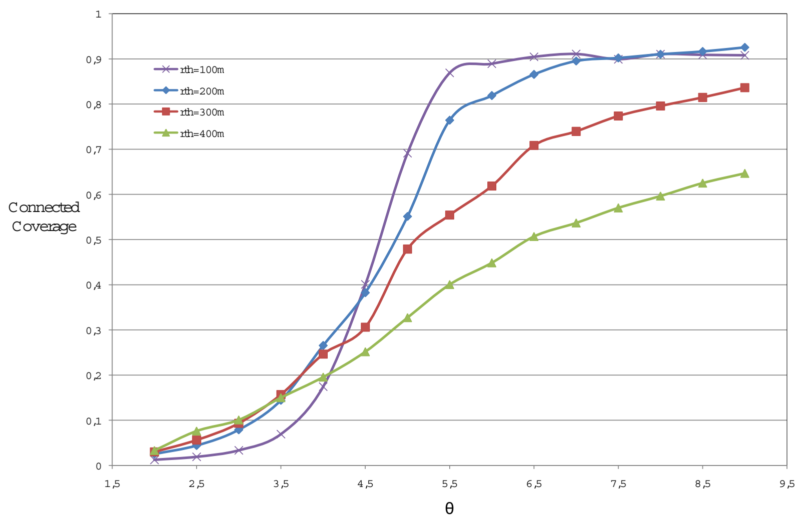

Figure 4.12: Connected Coverage *vs.* θ where $P_{cov} = 0.9$, $r_s = 40$ *units* , $r_{ts} = 100$ *units*, and 3000×3000 $unit^2$

WSN requires less number of clusterheads and the connected coverage becomes more sensitive to loss of clusterheads.

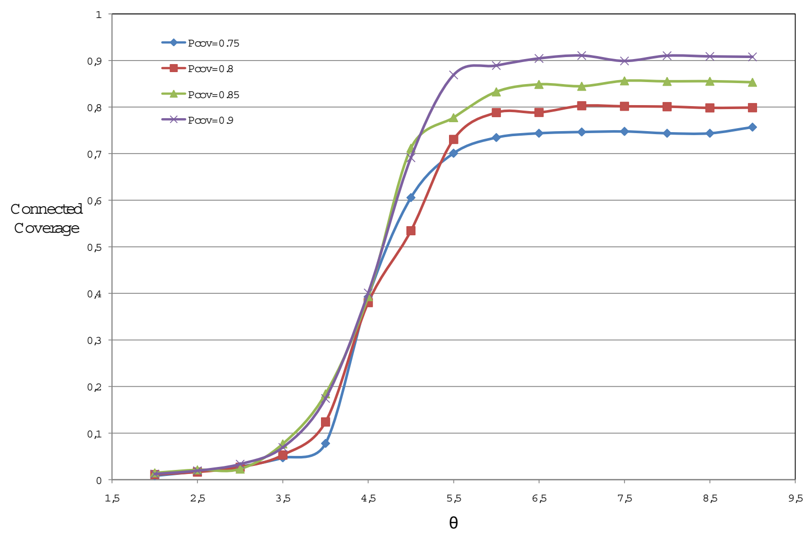

Figure 4.13: Connected Coverage *vs.* θ where $r_s = 40$ *units*, $r_{ts} = 100$ *units*, $r_{th} = 100$ *units*, and 3000×3000 $unit^2$

We use the Fig. 4.13 which illustrates the four connected coverage $vs.$ θ curves for different targeted coverage requirements. This figure again verifies our heuristic which depends on cluster size and well-connectivity, is a good measure for estimating the number of devices required for varying P_{cov} values.

CHAPTER 5

COST MODELS AND OPTIMUM COST HETEROGENEOUS NETWORK DIMENSIONING

Although a lot of progress has been achieved in WSN domain in the last decade, the expected level of maturity has not yet been reached in terms of both hardware and software. This is evident in the fact that the applications which are currently being used remain at an experimental level. These experienced applications are being realized especially in indoor and sheltered environments and the numbers of nodes in these applications are relatively modest. This is mainly caused by the fact that the per node costs are still very high in the market. In this respect, it is essential to have monetary low cost or cost-effective applications. The monetary cost of a WSN is dominantly determined by the number of devices deployed. The requirements, especially coverage and connectivity, have a significant impact on the required number of these devices.

In this chapter, we deal with the network dimensioning problem resulting in a minimum monetary cost for a randomly deployed heterogeneous WSN. While putting forward a solution to this problem, we make use of derived cluster size equations and the "well-connectivity" concept. We propose heuristic for the solution of this problem. These heuristics are based on reducing the solution set by evaluating the boundary values through cluster size equations and the well-connectivity concept. Herein, we also provide examples to show in which cases the heterogeneous networks will yield less costly configurations than the homogeneous networks.

In Section 5.1, the related literature on the monetary cost models is presented. In Section 5.2, we propose a general purpose monetary cost model for WSN applications.

Section 5.3 mainly focuses on the minimum cost network dimensioning problem for given targeted coverage and monetary costs of different types of devices (or equivalently relative monetary costs) in a randomly deployed heterogeneous WSN for direct communication case. In Section 5.4, we adapt the same dimensioning problem formulation from direct communication case for multi hop communication case. In this adapted problem, we also make use of "well-connectivity concept".

5.1 Cost Models in the Literature

To the best of our knowledge, there are two different cost models to estimate the monetary cost of a WSN [47] and [48]. In [47], total monetary cost includes the sum of individual monetary cost of each processor on each sensor node in a single level tree network architecture. The link-processor monetary cost is composed of the cost of communication between the root processor and each child processor and the cost incurred to process the fraction of load. Objective of the study in [47] is to find an optimal sequence for the distribution of the load on each processor that will minimize the monetary cost. This approach is essentially based on the energy consumption of the processors.

On the other hand, in [48], to prolong the system lifetime, the authors divide the sensing field into k concentric ring areas and deploy nodes such that the ones with the highest power resources are placed to the ring where the highest energy is required. They used a simple monetary cost model for a sensor node located in i^{th} ring as $C_i = \alpha+\beta.E_i$, where the constant α is the cost of the hardware, while β is the unit battery cost and E_i is the energy level of each sensor node in ring $i = 1,...,k$. They simply calculate the total cost of the entire network by multiplying the number of nodes located in the i^{th} ring with the cost of each sensor node in the i^{th} ring as C_i.

Other than these two monetary cost models, we can also estimate/judge monetary cost of an application through a market survey on today's well-known WSN component/tool kit manufacturers and WSN applications solution providers. Some of the component manufacturers and the solution providers include but are not limited to the following list:

- Dust Networks URL:http://www.dustnetworks.com/
- Digi International® URL:http://www.digi.com/

- Atmel Corporation URL:http://www.atmel.com/
- Arch Rock URL:http://www.archrock.com/
- Coronis URL:http://www.coronis.com/
- RFM URL:http://www.rfm.com/index.shtml
- Crossbow Technology URL:http://www.xbow.com/
- Daintree Networks URL:http://www.daintree.net/
- Ember URL:http://www.ember.com/
- Libelium URL:http://www.libelium.com/

5.2 Proposed Monetary Cost Model

Herein, we proposed a general-purpose monetary cost model for WSN applications. The primary objective of proposing a general-purpose cost model is that although there are many manufactures in the WSN domain, we still have no insight about the entire cost of an application. Components of the monetary cost of a WSN application over the course of lifetime and related issues are as follows:

- **Deployment Cost:** C_{deploy}
  - Deterministic deployment of nodes (e.g. deploying nodes in the edges on a grid possiblly by using robots)
  - Random deployment of nodes (e.g. dropping the sensor nodes from an aircraft)
- **Hardware cost of nodes:**
  - Node hardware cost = C_{HW}
  - Cost of battery packs = C_{BT}
- **Hardware cost of the sink:**
  - Sink hardware cost = $C_{HW-sink}$
  - Sink maintenance cost = $C_{main-sink}$

- Sink operation cost = $C_{oper-sink}$

- **Labor cost:** C_{labor}
  - Labor cost induced during setting up and running the application

- **Replenishment cost (if required):** C_{replen}
  - Cost associated due to the addition of sensor nodes after deployment, and recharging the batteries.

According to the above mentioned components of cost, we can find the monetary cost of a WSN consisting of N_S sensor node(s) and N_{sink} sink(s) as:

$$C_{WSN} = C_{deploy} + (C_{HW} + C_{BT}).N_S + C_{HW-sink}.N_{sink} + C_{main-sink} + C_{oper-sink} + C_{labor} + C_{replen} \tag{5.1}$$

In this thesis, we will only consider the second term, as we will only concentrate on the pre-deployment cost of an WSN. Hence we limit the discussion here to network dimensioning problem and thus Eqn. 5.1 is reduced to the following equation.

$$C_{WSN} = (C_{HW} + C_{BT}).N_S \tag{5.2}$$

Recall that, we consider heterogeneous WSN consisting of two types of devices: sensor nodes and clusterheads. We assume that sensor nodes and clusterheads have different capabilities and capacities. Therefore, in order to incorporate node heterogeneity, we modify Eqn. 5.2 as:

$$C_{WSN} = N_S(C_{hw} + C_{bt}) + N_H(C_{HW} + C_{BT}) \tag{5.3}$$

where C_{hw} and C_{HW} are the hardware costs of sensor nodes and clusterheads respectively. And, C_{bt} and C_{BT} denote the battery costs of sensor nodes and clusterheads respectively.

If we combine battery and hardware costs into C_S and C_H, the Eqn. 5.3 reduces to:

$$C_{WSN} = N_S.C_S + N_H.C_H \tag{5.4}$$

After providing the monetary cost model, in Section 5.3 and Section 5.4, we will focus on the network dimensioning problem for direct communication case and multi-hop communication case respectively.

5.3 Direct Communication Case

This section will dwell on the network model described in Section 3.6.1. According to this network model, N_H clusterheads and N_S sensor nodes are deployed randomly over a sensing field. And, let the monetary cost of clusterhead be C_H and a sensor node be C_S. We further assume that there is a $C_H = k.C_S$ relationship between C_H and C_S. There are 2 reasons for setting up such a relationship.

1) How to accurately model the monetary cost of a WSN consisting of different types of nodes is currently not known.

2) For given k, it is easier to determine whether the heterogeneous WSN or homogeneous WSN has a lower monetary cost. For example, for given $k > 1$, we can easily find N_H and N_S values to satisfy targeted connected coverage by making use of cluster size equations and/or "well-connectivity" concept. After finding N_H and N_S values, one can easily estimate monetary cost of the heterogeneous WSN, which is denoted by $C_{WSN\ hete}$. Similarly, for the same configuration, it is also possible or even easier to calculate the monetary cost of the homogeneous WSN, $C_{WSN\ homo}$. If we come up $C_{WSN\ hete} < C_{WSN\ homo}$ result, then we can say that "node heterogeneity" is cost-effective. Thus, we found it very sensible to formulate C_{WSN} by using the relative monetary cost.

To focus on the direct communication case, we can rearrange the terms in Eqn. 5.4 by using $C_H = k.C_S$ relationship mentioned above

$$C_{WSN} = C_H.\left(N_H + \frac{N_S}{k}\right) \tag{5.5}$$

To dimension a network with the minimum cost for a given coverage requirement, P_{cov}, we formulate an optimization problem as:

$$\begin{aligned}
\min C_{WSN} \quad &= \quad \min C_H.\left(N_H + \frac{N_S}{k}\right) \;\equiv\; \min\left(N_H + \frac{N_S}{k}\right)\\
& \quad\quad s.t.\\
& \quad\quad P_{cov} \leq 1 - e^{-\frac{N_H S_{cluster}}{D}}\\
given \quad & \quad\quad P_{cov}, r_s, r_{ts}, C_H, k, D > 0\\
& \quad\quad N_H, N_S \in \mathbb{N}
\end{aligned} \tag{5.6}$$

In this formulation, P_{cov}, r_{ts}, r_s, C_H, k, and D, are given and all should be positive real numbers. On the other hand, note also that, the independent variables (i.e., N_H and

N_S) of the optimization problem should be all integers. After all these are considered, one can say that Eqn. 5.6 is an optimization function, of type Mixed Integer Non-Linear Programming (MINP). In this problem, the only constraint in Eqn. 5.6 focuses on the partial-coverage requirement, which uses the cluster size equation. P_{cov} is the minimum threshold value for targeted coverage. Note that, in Eqn. 5.6, there is no constraint related to connectivity of clusterheads. Because this optimization function is formulated for the direct communication case which assumes that connectivity between clusterheads and the sink node is assured. And the connectivity of sensor nodes and the associated clusterhead is already taken into account in the first constraint.

After formulating the network dimensioning problem in Eqn. 5.6, we can analyze it for two cases:

- Homogeneous - Direct Communication Case
- Heterogeneous - Direct Communication Case

5.3.1 Homogeneous - Direct Communication Case

In the homogeneous - direct communication case, since the sensor nodes' transmission ranges are limited they cannot communicate with the sink directly. Therefore, we can only deploy a single type of node, clusterhead. Actually this type of WSN is a network in which every clusterhead senses a disc-shaped region πr_s^2 around its vicinity in D and forwards the sensed data to the sink "directly".

In this case, since the WSN only consists of N_H clusterheads, then $N_S = 0$. Thus, the cost of the WSN is simply given with the Eqn. 5.7.

$$C_{WSN} = C_H . N_H \tag{5.7}$$

For homogeneous case, size of the cluster is reduced to the area covered by a single clusterhead whose value is simply πr_s^2. That is, $S_{cluster} = \pi r_s^2$

For given C_H, finding the $\min C_{WSN}$ is reduced to finding the $\min N_H$ for given targeted coverage P_{cov}, where $P_{cov} \leq 1 - e^{-\frac{N_H S_{cluster}}{D}}$.

Therefore, N_H can be found from:

$$N_H \geq \left(\frac{D}{\pi r_s^2}\right) ln \left(\frac{1}{1 - P_{cov}}\right) \tag{5.8}$$

Thus, the minimum number of clusterheads, $minN_H$, can be found as:

$$minN_H = \left\lceil \left(\frac{D}{\pi r_s^2}\right) ln \left(\frac{1}{1-P_{cov}}\right) \right\rceil \tag{5.9}$$

Then, for homogeneous case, $minC_{WSN}$ can be found by using Eqn. 5.7 and Eqn. 5.9 as:

$$minC_{WSN} = C_H. \left\lceil \left(\frac{D}{\pi r_s^2}\right) ln \left(\frac{1}{1-P_{cov}}\right) \right\rceil \tag{5.10}$$

5.3.2 Heterogeneous - Direct Communication Case

For the heterogeneous case, consider a network with N_H clusterheads and N_S sensor nodes where both $N_H \geq 1$ and $N_S \geq 0$.

To find the optimum N_H and N_S pairs to minimize the monetary cost of the WSN, Eqn. 5.6 could have been solved by using a conventional MINP solver. As there is a single constraint and we have a quite simple objective function, we proposed a beneficial heuristic for exhaustive search.

In this heuristic, to improve the performance of the exhaustive search, we first reduce the solution set of N_H. We define $\min N_H$ for lower bound of N_H and similarly, $\max N_H$ for upper bound for N_H. Both $\min N_H$ and $\max N_H$ values are evaluated by using cluster size, $S_{cluster}$.

To deploy minimum number of clusterheads $\min N_H$, we can use infinitely many sensor nodes. As N_S goes to infinity, N_H will have its minimum value and similarly $S_{cluster}$ takes its maximum value. Thus, $\min N_H$ is achieved when $N_S \to \infty$ giving $\max S_{cluster} = \pi(r_s + r_{ts})^2$.

Therefore,

$$minN_H = \left\lceil \left(\frac{D}{\pi(r_s + r_{ts})^2}\right) ln \left(\frac{1}{1-P_{cov}}\right) \right\rceil \tag{5.11}$$

To deploy maximum number of clusterheads $\max N_H$, it is assumed that no sensor node is deployed. Hence, as N_S goes to 0, N_H will have its maximum value and similarly $S_{cluster}$ takes its minimum value. Thus, $\max N_H$ is achieved when $N_S \to 0$ giving $\min S_{cluster} = \pi r_s^2$. Therefore,

$$maxN_H = \left\lceil \left(\frac{D}{\pi r_s^2}\right) ln \left(\frac{1}{1-P_{cov}}\right) \right\rceil \tag{5.12}$$

After finding $\max N_H$ and $\min N_H$, we are ready to find the optimum N_H and N_S pairs to minimize the WSN cost. In a nutshell, the complete heuristic search procedure is given in Fig. 5.1 to compute the optimum number of sensor nodes deployed N_S and the number of clusterheads deployed N_H that minimizes the monetary cost of the WSN by assuming that the unit cost, 1.

```
optimum_k=0;
optimum_NH=0, optimum_Ns=0;
min_CWSN = infinity;
for (int NH=MIN_NH; NH<=MAX_NH; NH++)
  {
     Scluster = -(D/NH)*(ln(1-Pcov));
     From given NH, D, Pcov, rt, rts find Ns to satisfy Scluster;
     CWSN = NH + Ns/k;
         if (CWSN< min_CWSN)
          {
           min_CWSN= CWSN;
           optimum_k=k;
           optimum_NH=NH;
           optimum_NS=NS;
          }
  }
```

Figure 5.1: Algorithm for Heuristic Search to Dimension The Network

5.3.3 Condition of Cost-Effectiveness - Direct Communication Case

After introducing the approach to solve optimization problem for direct communication case, here, we opt to explore the condition under which node heterogeneity is more cost-effective than employing single type of node. To explore this, we plotted C_{WSN} $vs.$ monetary cost coefficient, k, graphs for given D, P_{cov}, r_{ts}, and r_s values. We executed a computer program to run an exhaustive search and the results are plotted in Fig. 5.2. This exhaustive search demonstrated that for $r_{ts} = 40units$, $r_s = 20units$, and $D = 1000 \times 1000unit^2$ values, k values greater than ~ 1.2 resulted in inexpensive configurations and thus significant cost reductions are achievable when heterogeneity is employed. However, for smaller k values, employing heterogeneity does not lead to considerable cost reductions.

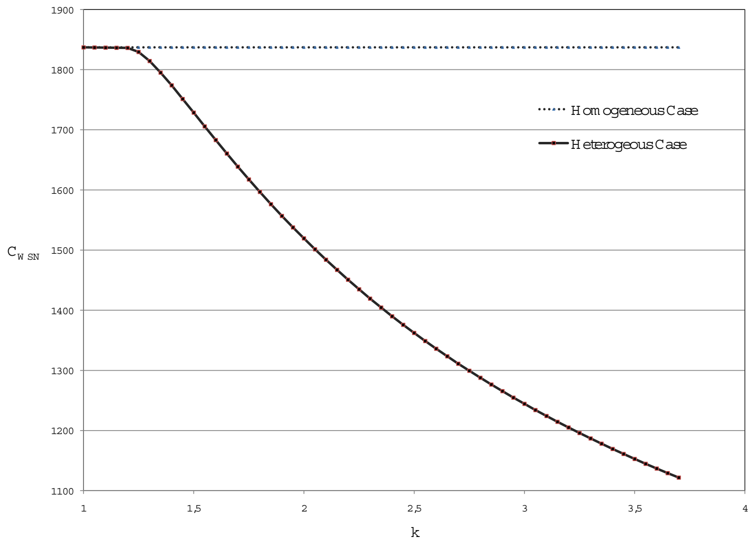

Figure 5.2: C_{WSN} $vs.$ k for $D = 1000 \times 1000unit^2$, $P_{cov} = 0.9$, $r_t = 40units$, and $r_s = 20units$

This result of the search is very influential, since the cost-effectiveness of heterogeneous networks is justified. As it shows, when the cost of nodes with different capabilities slightly differ, lower cost solutions are possible. Depending on the system parameters, there is a critical cost coefficient k_c above which cost reductions starts to occur. And, this can be used by WSN designers to justify the feasibility of heterogeneity. Considering the example above, it is a rather optimistic/rational/reasonable assumption that k_c will be greater than 1.2. This is because the difference between hardware and the battery packs used are the factors that can change cost differentiation.

Yet another result is that, as $k \to \infty$, $\frac{N_S}{k}$ vanishes, therefore we can use as many sensor nodes as possible which leads to:

As $k \to \infty$; $C_{WSN} \to (C_H).(\min N_H)$

5.4 Multi-Hop Communication Case

In the formulation of the optimization problem for multi-hop communication case, there is no difference between the direct communication case in the objective function and is written as $C_{WSN} = C_H.\left(N_H + \frac{N_S}{k}\right)$. However, we should add a constraint to represent multi-hop connectivity of clusterheads and the sink. This constraint is very important since there should be minimum sufficient number of clusterheads to satisfy multi-hop connectivity.

We devised "well-connectivity" to satisfy multi-hop communication. In order for our network to be well-connected, each clusterhead should have more than θ_c clusterheads connected to it. Therefore, to express N_H in terms of θ_c, the following equation derived from Eqn. 4.66 can be used:

$$N_H = \lambda_H D \geq \frac{\theta_c D}{\pi r_{th}^2} \tag{5.13}$$

where θ_c quantifies how many clusterhead neighbors are required for each clusterhead to achieve targeted connectivity. As explained in Section 2.2.1, for infinite sensing area, θ_c should be around 4.5. For relatively smaller regions, it should be chosen much larger than 4.5.

As a result, our optimization problem becomes:

$$\begin{aligned}
\min C_{WSN} \quad &= \quad \min C_H . \left(N_H + \frac{N_S}{k} \right) \; \equiv \; \min \left(N_H + \frac{N_S}{k} \right) \\
& \quad\quad s.t. \\
& \quad\quad P_{cov} \leq 1 - e^{-\frac{N_H S_{cluster}}{D}} \\
& \quad\quad N_H \geq \frac{\theta_c D}{\pi r_{th}^2} \\
given \quad & \quad\quad P_{cov}, r_s, r_{ts}, r_{th}, C_H, k, \theta_c, D > 0 \\
& \quad\quad N_H, N_S \in \mathbb{N}
\end{aligned} \tag{5.14}$$

After formulating the network dimensioning problem in Eqn. 5.14, we can analyze it for two cases:

- Homogeneous - Multi-Hop Communication Case
- Heterogeneous - Multi-Hop Communication Case

5.4.1 Homogeneous - Multi-Hop Communication Case

In the homogeneous - multi-hop communication case, we can only deploy a single type of node, namely clusterhead. Actually, this type of WSN is a network in which every clusterhead senses a disc-shaped region, πr_s^2, around its vicinity in D and forwards the sensed data to the sink either directly or using other "connected clusterheads" as relays.

For the multi-hop communication case, clusterheads are the devices responsible for connectivity as well as coverage. Therefore, for the homogeneous case, we need to find the minimum value of N_H that satisfies both connectivity and coverage. Since, $N_S = 0$, $S_{cluster}$ is reduced to its minimum value πr_s^2.

In order to satisfy the coverage constraint, $N_H \geq \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1-P_{cov}}\right)$ should be satisfied. Moreover, $N_H \geq \frac{\theta_c D}{\pi r_{th}^2}$ (from the well-connectivity concept) condition should also be satisfied due to the connectivity constraint. Therefore, N_H that minimizes C_{WSN} can be found as:

$$N_H \geq \max\left\{\left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1-P_{cov}}\right), \frac{\theta_c D}{\pi r_{th}^2}\right\} \tag{5.15}$$

Therefore, for homogeneous case, $minC_{WSN}$ and $minN_H$ can be found as:

$$\min N_H = \left\lceil \max\left\{\left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1-P_{cov}}\right), \frac{\theta_c D}{\pi r_{th}^2}\right\}\right\rceil \tag{5.16}$$

And,

$$\min C_{WSN} = C_H . \min N_H \tag{5.17}$$

5.4.2 Heterogeneous - Multi-Hop Communication Case

For the heterogeneous case, Eqn. 5.14 could have been solved by using a conventional MINP solver. Similar to the direct communication case, as there are a few constraints and we have a quite simple objective function, we again performed an exhaustive search discussed in Section 5.3.2.

To reduce the solution set of N_H, we again define $\min N_H$ for lower bound of N_H and, $\max N_H$ for upper bound for N_H. Both $\min N_H$ and $\max N_H$ values are found by using $S_{cluster}$ and "well-connectivity" requirement.

To find $\min N_H$ to satisfy the coverage requirement:

As N_S goes to infinity, N_H will have its minimum value and similarly $S_{cluster}$ takes its maximum value. Thus, according to coverage constraints only:

$$\min N_H \; for \; coverage = \left\lceil \left(\frac{D}{\pi(r_s + r_{ts})^2}\right) ln\left(\frac{1}{1-P_{cov}}\right)\right\rceil \tag{5.18}$$

To find $\min N_H$ *for connectivity* to satisfy the connectivity constraint:

$$\min N_H \; for \; connectivity = \left\lceil \frac{\theta_c D}{\pi r_{th}^2} \right\rceil \tag{5.19}$$

Therefore, by combining these two, we have:

$$\min N_H = \lceil \max\{\min N_H \; for \; coverage, \min N_H \; for \; connectivity\}\rceil \tag{5.20}$$

$$\min N_H = \left\lceil \max\left\{ \left(\frac{D}{\pi(r_s + r_{ts})^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right), \frac{\theta_c D}{\pi r_{th}^2} \right\} \right\rceil \tag{5.21}$$

To find $\max N_H$, as N_S goes to 0, N_H will have its maximum value and similarly $S_{cluster}$ takes its minimum value. Thus, according to the coverage constraint:

$$\max N_H for\ coverage = \left\lceil \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right) \right\rceil \tag{5.22}$$

To find $maxN_H forconnectivity$ to satisfy the connectivity requirement:

$$\max N_H for\ connectivity = \left\lceil \frac{\theta_c D}{\pi r_{th}^2} \right\rceil \tag{5.23}$$

Therefore, by combining the above constraints we have:

$$\max N_H = \lceil \max\{\max N_H\ for\ coverage, \max N_H\ for\ connectivity\}\rceil \tag{5.24}$$

That is:

$$\max N_H = \left\lceil \max\left\{ \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1 - P_{cov}}\right), \frac{\theta_c D}{\pi r_{th}^2} \right\} \right\rceil \tag{5.25}$$

5.4.3 Condition of Cost-Effectiveness - Multi-Hop Communication Case

After formulating the optimization problem for multi-hop communication case, we opt to explore the condition under which the node heterogeneity is more cost-effective than homogeneous case and node heterogeneity for direct communication case by using the heuristic search described in Fig. 5.1. We assumed that, each clusterhead should be connected to at least 6 clusterheads in order for the network is considered as well-connected. That is to say, we solve the heuristic search for $\theta = 6$. To explore the cost-effectiveness, we plotted C_{WSN} $vs.$ cost difference coefficient, k, graphs for D, P_{cov}, r_{ts}, r_{th}, and r_s values. We executed a computer program to run an exhaustive search and the results are plotted in Fig. 5.3 for $P_{cov} = 0.9$, $r_{ts} = 40units$, $r_{th} = 40units$, $r_s = 20units$, $D = 1000 \times 1000unit^2$, and $\theta = 6$.

In Fig. 5.3, we can see three lines. The horizontal line showing the cost of a WSN for the homogeneous direct communication case is the most expensive configuration since its value is simply $C_{WSN} = C_H . \min N_H$ where $\min N_H = \left(\frac{D}{\pi r_s^2}\right) ln\left(\frac{1}{1-P_{cov}}\right)$.

There are also 2 more plots for the WSNs exploiting node heterogeneity in Fig. 5.3. One of them is for direct communication case while the other one illustrates the multi-hop case. As anticipated, the cost associated to the multi-hop case is more than the

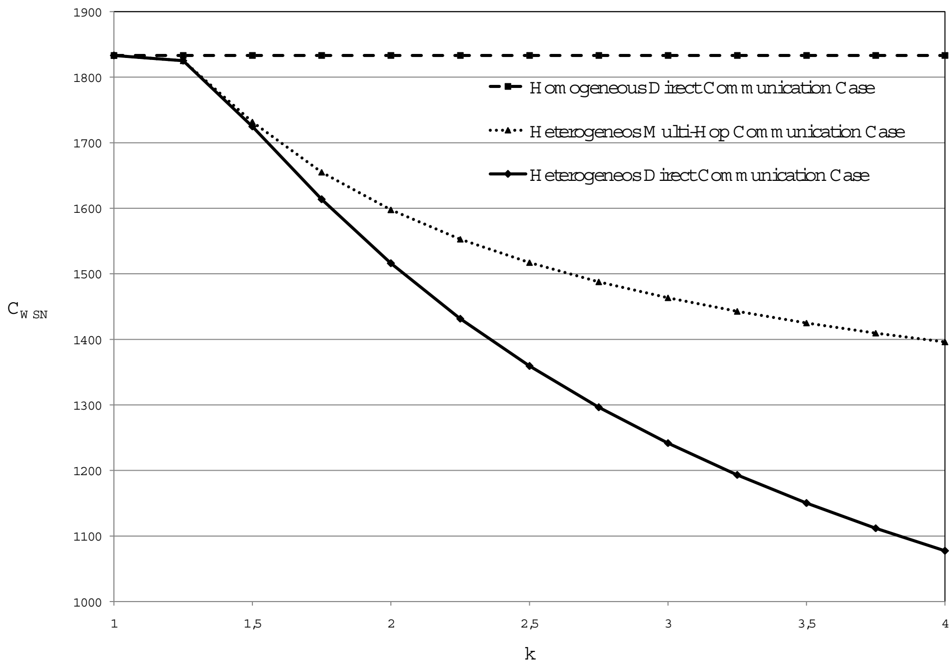

Figure 5.3: C_{WSN} *vs.* k for $P_{cov} = 0.9$, $r_{ts} = 40units$, $r_{th} = 40units$, $r_s = 20units$, $D = 1000 \times 1000unit^2$, and $\theta = 6$

direct communication case. Because, for the former case, the required number of clusterheads are larger than the latter case due to the fact that multi-hop case requires more clusterheads to satisfy the "well-connectivity" requirement as well as the targeted coverage requirement. However, for the direct communication case, the network requires minimum sufficient number of clusterheads and sensor nodes only to satisfy the coverage requirement.

Yet another result is that, as $k \to \infty$, $\frac{N_S}{k}$ vanishes, therefore we can use as many sensor nodes as possible which leads to:

As $k \to \infty$; $C_{WSN} \to (C_H).(\min N_H)$

CHAPTER 6

ENERGY CONSUMPTION MODEL AND COST-LIFETIME OPTIMUM DIMENSIONING

The devices in WSNs typically operate on batteries and usually have scarce energy resources. Therefore, energy dissipation and lifetime are among the most essential performance metrics. Lifetime of a WSN, in spite of promising recent advances and the progress that have been made, is still the primary bottleneck that limits the applicability of the most of the real-life WSN applications. Thus, prolonging network lifetime for nodes in a WSN is a critical issue and is though requiring additional research.

In this chapter, we take into account lifetime constraints in network dimensioning problem for randomly deployed heterogeneous WSNs employing direct communication. In the subsequent sections, we will give the energy consumption model for our formulations. For a given lifetime and partial area coverage constraint we find optimum number of sensor nodes and clusterheads together with the number of battery cells on each type of device that leads to the lowest cost solution.

6.1 Lifetime Definition

The WSN models considered in this thesis study essentially incorporate connected coverage. With respect to the our network model and existing definitions in the literature, we define lifetime as the time period from the instant when the WSN starts functioning (i.e., possibly after a short span of time for the set-up phase) to the instant when the level of "actual connected coverage" is reduced to that of targeted coverage at the sink for given r_s, r_{ts}, r_{th}, D, P_{cov}, and initial energies of the sensor nodes and clusterhead.

6.2 Joint Cost-Lifetime Optimum Dimensioning

In this part of the study, we consider the WSN described in Section 3.6.1. In this heterogeneous network, different types of nodes typically consume different amounts of energy since their functions are different. Due to their different energy consumption behavior, it is important to equip the devices with optimal initial energy such that the targeted lifetime is achieved. On the other hand, equipping the devices with different initial energies implies that each type of device has a different monetary cost. Increasing the initial energy may prolong the WSN lifetime at the expense of more money. Therefore, in order to minimize the cost we can design the network such that leftover energy (i.e., wasted energy) in the devices is minimum at the end of the lifespan of the WSN. Therefore, to have a cost-effective WSN, there is an optimum mixture of different types of devices equipped with optimal battery capacities that satisfy certain partial-coverage and lifetime requirements.

6.3 Cost Model

Typically, a WSN functions for a targeted lifetime at a minimum cost, or operates as long as possible for a given cost budget. In this thesis, we consider the former problem. We analyze the optimum mixture of different types of nodes that leads to minimum cost while satisfying the targeted lifetime and partial-coverage requirements.

By upgrading the battery capacity of devices and by increasing the number of nodes, one can prolong the targeted lifetime. Thus, both of these methods may lead to an increase in lifetime at the expense of more cost. This lifetime-cost trade-off is the driver of this study. As far as our network model is concerned, there are two types of nodes with different functionalities and capabilities. Therefore, the cost associated with clusterheads and sensor nodes are denoted by C_H and C_S, respectively. Each type of device is composed of a hardware component and a battery providing the power for this hardware. A clusterhead may have superior hardware compared to a sensor node or similarly may have more initial energy than a sensor node or both. The cost of a sensor node, C_S, is the sum of the cost of its hardware unit, C_{hw}, and the cost of its battery C_{bt}. Similarly, the cost of a clusterhead, C_H, is the sum of the cost of its hardware unit,

C_{HW}, and its battery C_{BT}. Thus, the monetary cost of a WSN C_{WSN} can be found as:

$$C_{WSN} = N_H.(C_{HW} + C_{BT}) + N_S.(C_{hw} + C_{bt}) \tag{6.1}$$

The cost differentiation between a clusterhead and a sensor node depends on a wide variety of features of the devices, such as transmission and sensing ranges, availability of adaptive power control, processing power, storage capacity, and initial energies etc.

In the related literature, for some WSNs [48], heterogeneity implies that a set of nodes simply has more initial energy than others while the entire network has identical hardware components (i.e., $C_{hw} = C_{HW}$). According to this approach, we assume that each sensor node and clusterhead may probably have different initial energies. If we use identical battery cells with identical energies, each sensor node and clusterhead will have a different number of these battery cells for heterogeneity. Therefore, it is required to determine the number of cells in each type of device for a given network lifetime, R. By using these, the WSN monetary cost, C_{WSN}, can be rewritten as:

$$C_{WSN} = N_H.(C_{HW} + E.C_{cell}) + N_S.(C_{HW} + e.C_{cell}) \tag{6.2}$$

where e and E are the number of cells used by each sensor node and clusterhead respectively and the monetary cost of battery in each type of device can be found as the cost of a single cell C_{cell} multiplied with the number of cells used in that device type.

6.4 Radio Model

The lifetime of a WSN application is determined by the initial energies of the power resources of the nodes. In WSNs, power is a scarce resource due to the size limitations. Hence, one of the most imperative constraints on WSNs is the low power consumption.

In a typical WSN, power consumption can broadly be divided into three domains namely, sensing, communication, and processing. In the following discussion, we simply focus on wireless communication power consumption and will not consider the processing power and sensing consumption due to the argument in [24] that wireless communication energy cost has been considered the prevailing factor in power consumption in WSNs. A radio usually consumes considerable portion of its total power when it is in receive and transmit states. Therefore, in this thesis, we will be considering solely power consumption for transmission and reception.

6.4.1 Transmission Power Model

We pursue the communication power consumption model used in [46]: Assume that each sensor node and clusterhead is equipped with a limited initial energy supply, denoted by, e_0 and E_0 respectively. For a sensor node S to transmit a packet of L bits to the clusterhead C, the transmission energy dissipation E^t at the radio transmitter of that sensor node is:

$$E^t = (\alpha + \beta.d^m).L \tag{6.3}$$

where α and β are two constant terms, d is the Euclidian distance between the nodes C and S, and m is the path loss exponent, with $2 \leq m \leq 4$. Typical value for $\alpha = 50nJ/b$. And, α is the energy dissipated in the transmitter circuit (PLLs, VCOs, etc) which depends on the digital coding, modulation, etc [54].

The value of coefficient β, the radiated power necessary to transmit, is determined by the environment in which the WSN is working. The environment is usually modeled by one of the two models: free space channel (FSC) model and multipath (MP) fading channel model. When MP model is used $\beta_{mp} = 0.0013pJ/b/m^4$ (for $m = 4$) and if FSC model is used, then $\beta_{fs} = 10pJ/b/m^2$ (for $m = 2$)[75].

6.4.2 Reception Power Model

For a clusterhead C to receive an L bit packet from a sensor node S, the energy consumed in the receiver circuit E^r is [46]:

$$E^r = \rho.L \tag{6.4}$$

where, ρ is the power consumption coefficient for receiving data and a typical value for this parameter is 50 nJ/b [75].

6.5 Energy Model

We essentially adopt the energy model and data dissemination technique used in Low-Energy Adaptive Clustering Hierarchy (LEACH) [75]. LEACH is a protocol architecture that integrates the concept of energy-efficient cluster-based routing and medium access to prolong the system lifetime. However, there is a slight difference between LEACH and our model. In LEACH, all sensor nodes in the network are identical and a subset of these sensor nodes [1] switches their role to that of a clusterhead for a certain period of time, whereas in our model, there are essentially two types of "pre-configured" nodes. Types of these nodes are known a priori before the deployment and their roles remain the same throughout the network lifetime.

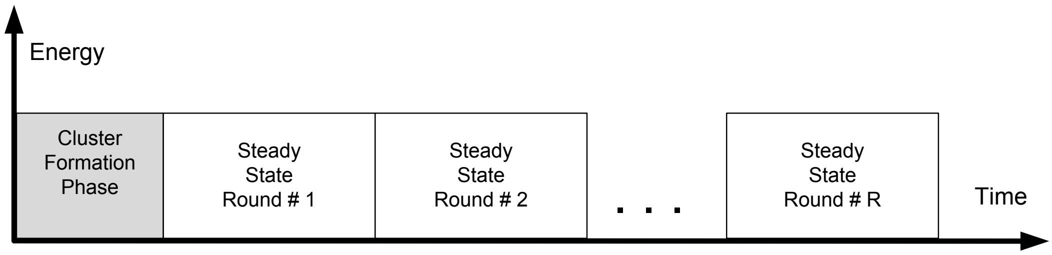

Figure 6.1: Sequence of Operations of the Proposed Model

Similar to LEACH, the operation of our model is divided into rounds (See Fig .6.1). According to our definition, the lifetime of the WSN is the maximum achievable number of rounds until connected coverage reduces to the targeted coverage. The tasks performed by clusterheads and sensor nodes in a round vary. For the sake of simplicity, in our model, we consider the wireless communication and data aggregation power consumption and ignore the power consumption incurred by data processing and sensing. However, incorporating these into our model would not be very difficult.

6.5.1 Cluster Formation Phase

After deploying a number of clusterheads and sensor nodes randomly over a sensing field, the operation of a WSN starts with the cluster formation phase. Cluster formation phase may be initiated by a beacon frame sent by the sink nodes. In the cluster formation phase, clusterhead nodes broadcast an advertisement message frame (ADV) using the non-persistent Carrier Sense Multiple Access (CSMA)[2] protocol. This ADV frame is of crucial importance since cluster formation is achieved based on the strength of ADV

[1] clusterhead selection is based on the randomized rotation of high energy nodes
[2] We neglect the energy consumption by a node while performing carrier-sense

frame signal. The ADV frame consists of fields containing node's ID and the type identifier. Upon receiving this ADV message, sensor nodes determine which cluster to join according to the RSSI of the received ADV message.

Upon making the decision on which cluster to join, each sensor node transmits join-request (JOIN-REQ) frame back to the corresponding clusterhead again using the non-persistent CSMA protocol. The JOIN-REQ frame consists of fields containing node's and clusterhead's IDs.

After receiving the JOIN-REQ frames, the clusterhead performs the required tasks to generate a Time Division Multiple Access (TDMA) schedule which guarantees that there will be no collision during the intra-cluster transmissions. Clusterhead then broadcasts a schedule notification (SCHE) frame to inform the cluster members about the duty-cycle schedule. Sensor nodes within a cluster put themselves in the sleep state when they complete their transmission according to the received schedule. In the sleep state, nodes turn-off their radio entirely which results in considerable amount of reduction in the energy consumption achieved by the idle-listening.

Timeline showing the operations at cluster formation phase both in clusterheads and sensor nodes are illustrated in Fig. 6.2 and Fig. 6.3 respectively.

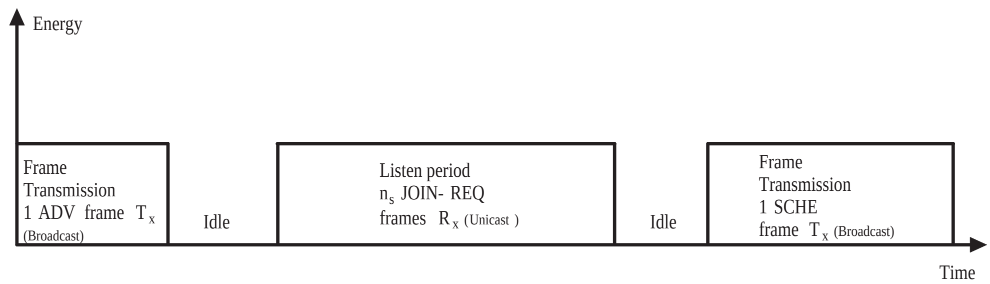

Figure 6.2: Operation of a clusterhead during cluster formation phase

Fig. 6.2 illustrates the sources of energy consumption for a clusterhead during the cluster formation phase. Firstly, a clusterhead broadcasts R_{ADV} bits of advertisement frame and then immediately switches to idle mode. Secondly, it receives $R_{JOIN-REQ}$ bits of join-request frames from each of the nearby sensor nodes to make decision on the selection of cluster members. If there are n_s sensor nodes, the total number of bits received will be $n_s.R_{JOIN-REQ}$. It again turns its radio to the idle mode. Finally, the clusterhead broadcasts R_{SCHE} bits of schedule notification frame to inform the prospective cluster members.

According to Eqn. 6.3, the energy dissipated by a clusterhead to broadcast R_{ADV} bits of advertisement frame can be found as:

$$E^t_{ADV} = (\alpha + \beta_{fs}.r^2_{th}).R_{ADV} \tag{6.5}$$

Note that in this equation, the path loss exponent m is chosen as 2 because for relatively shorter distances between transmitters and receivers (i.e., the distance between a clusterhead and the cluster members), free space channel (FSC) model is used. β_{fs} is the coefficient for the radiated power necessary to transmit in FSC model.

Similarly, the energy dissipated by a clusterhead to broadcast R_{SCHE} bits of schedule notification frame is:

$$E^t_{SCHE} = (\alpha + \beta_{fs}.r^2_{th}).R_{SCHE} \tag{6.6}$$

As given in Eqn. 6.4, the energy dissipated by a clusterhead to receive $n_s.R_{JOIN-REQ}$ bits of join-request frames is:

$$E^r_{JOIN-REQ} = \rho.(R_{JOIN-REQ}.n_s) \tag{6.7}$$

Thus, the energy dissipated by a clusterhead to complete the cluster formation phase is:

$$E_{c-formation} = E^t_{ADV/SCHE} + E^r_{JOIN-REQ} \tag{6.8}$$

As can be seen from the Fig. 6.3, during cluster formation, a sensor node listens to the channel to receive R_{ADV} bits of join-request frame. Upon receiving the message, it immediately switches to idle mode. Based on the received signal strength indicator of the ADV messages, it transmits a unicast $R_{JOIN-REQ}$ bits of join-request frame to the nearest clusterhead. Since there are other nearby sensor nodes, a sensor node may also hear their $R_{JOIN-REQ}$ frames. And finally, the operation of a sensor node during cluster formation phase finishes with the reception of R_{SCHE} bits of TDMA schedule frame from the associated clusterhead. The energy dissipated by a sensor node to complete cluster formation is given from Eqn. 6.9 through Eqn. 6.11.

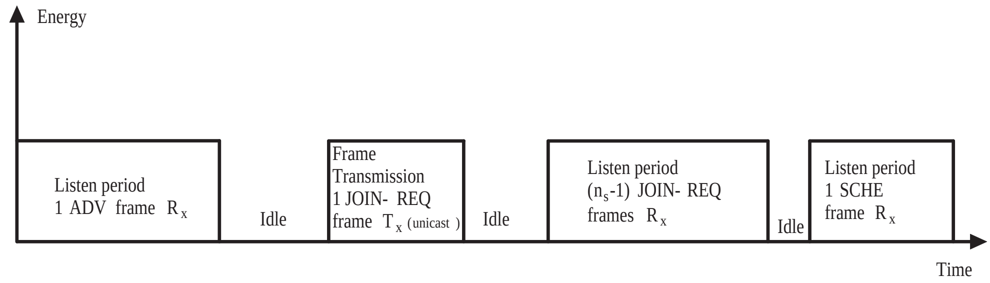

Figure 6.3: Operation of a sensor node during cluster formation phase

The energy dissipated by a sensor node to transmit $R_{JOIN-REQ}$ bits of join-request frame to the clusterhead is

$$e^{t}_{JOIN-REQ} = (\alpha + \beta_{fs}.r_t^2).R_{JOIN-REQ} \tag{6.9}$$

The energy dissipated by a sensor node to receive $(n_s - 1).R_{JOIN-REQ}$ bits of join-request frame, R_{SCHE} bits of TDMA schedule frame, and R_{ADV} bits of advertisement frame is

$$e^{r}_{ADV/SCHE/JOIN-REQ} = \rho.(R_{JOIN-REQ}.(n_s - 1) + R_{SCHE} + R_{ADV}) \tag{6.10}$$

Therefore, the energy dissipated by a sensor node to complete the cluster formation phase is

$$e_{c-formation} = e^{t}_{JOIN-REQ} + e^{r}_{ADV/SCHE/JOIN-REQ} \tag{6.11}$$

6.5.2 Steady State Phase

Cluster formation phase is performed only once to determine which sensor node will be associated with which clusterhead and to decide on the necessary sensor node transmission schedule to be used in the steady state phase. In the steady state phase, the sensed data received from the cluster members are forwarded directly to the sink by clusterheads on regular basis. Every successful operation in the steady state phase is called a "round" (See Fig. 6.4) and is denoted by R. In each round, sensor nodes send the sensed data to the clusterhead in the scheduled TDMA (Time Division Multiple Access) slots, and the clusterhead aggregates this data and sends resultant data to the sink. Using TDMA enables preserving energy consumption by enabling sensor nodes remain in the sleep state, for a relatively long time in their duty cycle. In our model, the number of members within a cluster will not change once a cluster is formed, therefore the TDMA schedule does not need to be changed over the course of WSN lifetime.

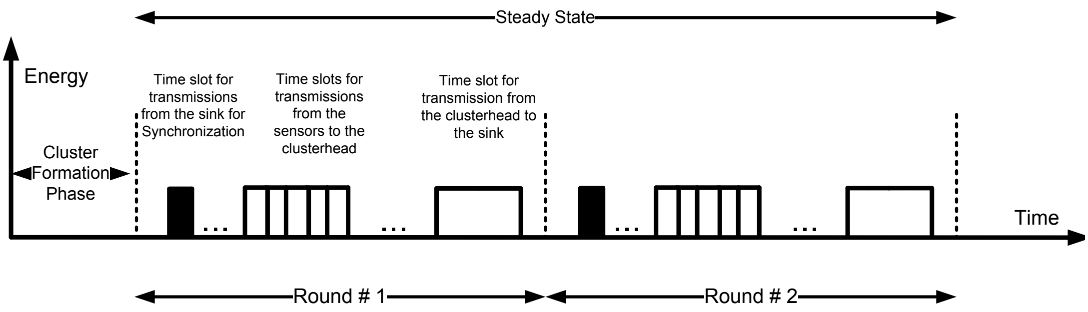

Figure 6.4: Cluster Formation and Steady State Phases in a cluster

In the steady state, both sensor nodes and clusterheads are usually required to synchronize their clocks. Therefore, before the start of each round, synchronization type of message (SYNC) frames are broadcasted by the sink node to prevent timing errors due to long-term clock drift. SYNC frames provide simple clock synchronization for all types of nodes in the WSN.

Throughout the steady state phase, clusterheads should be awake to receive all the sensed data from the scheduled cluster members. As soon as, all sensed data are received, clusterheads aggregate the sensed data and send it to the sink node in a single frame. Aggregated data is sent from the clusterheads to the sink by means of a pre-configured spreading code and CSMA as also assumed in [75]. Since each clusterhead is assumed to communicate with the sink using Direct-Sequence Spread Spectrum (DSSS) and CSMA, each clusterhead is required to use a unique spreading code to avoid interference from both the inter-cluster and intra-cluster transmissions.

By using the same approach used in cluster formation phase, the energy dissipated by a clusterhead and a sensor node to complete steady state phase is given from Eqn. 6.12 through Eqn. 6.18.

The energy dissipated by a clusterhead to transmit R_{AGG} bits of aggregated data to the sink is

$$E^t_{AGG} = (\alpha + \beta_{mp}.r^4_{th}).R_{AGG} \tag{6.12}$$

Note that in Eqn. 6.12, the path loss exponent m is chosen as 4. This is due to the fact that for long distances between transmitters and receivers (i.e., the distance between a distant clusterhead and the sink), multipath (MP) fading channel model is considered. And, β_{mp} is the coefficient for the radiated power necessary to transmit in MP channel model.

Similarly, the energy dissipated by a clusterhead to receive $n_s.R_{DATA}$ bits of data frame is

$$E^r_{DATA} = \rho.(R_{DATA}.n_s) \tag{6.13}$$

Thus, the energy dissipated by a clusterhead in a single round is

$$E_{s-state} = E^t_{AGG} + E^r_{DATA} \tag{6.14}$$

And, the energy dissipated for synchronization by a clusterhead in a single round is

$$E_{SYNC} = E^r_{SYNC} = \rho.R_{SYNC} \tag{6.15}$$

Similarly, the energy dissipated by a sensor node in its operation cycle to transmit R_{DATA} bits of data to the associated clusterhead is

$$e^t_{DATA} = (\alpha + \beta_{fs}.r^2_t).r_{DATA} \tag{6.16}$$

According to Eqn. 6.4, the energy dissipated by a sensor node to receive R_{SYNC} bits of synchronization frame is

$$e_{SYNC} = \rho.(R_{SYNC}) \tag{6.17}$$

Therefore, the energy dissipated by a sensor node within its operation cycle is

$$e_{s-state} = e^t_{DATA} \tag{6.18}$$

6.5.3 Data Aggregation

Within a cluster, the sensed data across the cluster members are often correlated since sensor nodes are likely to be located close to each other in a dense deployment scenario. Thus effective data fusion/aggregation techniques can be utilized at the clusterheads to be processes locally. Clusterheads are expected to fuse the correlated data signals from the cluster members into one smaller frame and thus save energy. Clusterheads also dissipate energy to aggregate the data receiving from the cluster members. The energy dissipated by a clusterhead to aggregate 1 bit of data from a received signal E_{AGG} as given in [75] is $5nJ/b$.

6.6 Cost Optimization

Using the monetary cost of WSN discussed in Eqn. 6.2, the cluster size equations given in Eqn. 4.43 and 4.63, and energy dissipation model given above, we formulated the following optimization problem for the minimization monetary cost of a WSN.

$$\begin{aligned} \min C_{WSN} &= \min N_H.(C_{HW} + E.C_{cell}) + N_S.(C_{HW} + e.C_{cell}) \\ & subject \quad to \\ & 1 - e^{-\frac{N_H S_{cluster}}{D}} \geq P_{cov} \\ & E.e_{cell} - (E_{c-formation} + (E_{SYNC} + E_{s-state} + E_{AGG}).R) \geq 0 \\ & e.e_{cell} - (e_{c-formation} + (E_{SYNC} + e_{s-state}).R) \geq 0 \\ & N_H, N_S, e, E \in \mathbb{Z}^+ \end{aligned} \tag{6.19}$$

In this formulation, we primarily consider the wireless communication and data aggregation power consumption and ignore data processing and sensing power consumptions.

Our objective is to find the optimum values for N_S, N_H, E, and e to minimize the cost for given P_{cov}, R, r_s, r_{ts}, r_{th} , D, e_{cell}, C_{HW}, C_{cell} , ρ, α, β_{fs}, β_{mp}, R_{SYNC}, R_{AGG}, R_{JOIN}, R_{SCHE}, R_{ADV}, R_{DATA}, and E_{AGG}.

The set of constraints in Eqn. 6.19 can be interpreted as follows. The first constraint is for the partial-coverage requirement, where P_{cov}, is the minimum threshold value for coverage. The second and third constraints, which are related to the initial energy at each clusterhead and sensor node, enforce that the energy dissipated for transmissions, receptions, and aggregations should not exceed the initial energy supplies $E.e_{cell}$ and $e.e_{cell}$ respectively. In these constraints, $E_{c-formation}$, E_{SYNC}, $E_{s-state}$, and E_{AGG} are energy dissipation for cluster formation, synchronization, steady state, and aggregation operations respectively. Lastly, the fourth constraint imposes N_H, N_S, E and e to be all positive integers.

Note that, in the above formulation, we tacitly assumed that every cluster has an equal number of sensor nodes, n_s. Definitely, this will not be the case in random deployment. However, this simplifying assumption provides acceptable approximate solutions as it will be demonstrated in the numerical results and validation section.

6.6.1 A Heuristic Solution Method

In Eqn. 6.19, as, there are a few constraints and we have a quite simple objective function, we performed an heuristic search with respect to system parameters: P_{cov}, R, r_s, r_{ts}, r_{th} , D, e_{cell}, C_{HW}, C_{cell} , ρ, α, β_{fs}, β_{mp}, R_{SYNC}, R_{AGG}, R_{JOIN}, R_{SCHE}, R_{ADV}, R_{DATA}, and E_{AGG}.

The complete heuristic search procedure is given in Fig. 6.5. The heuristic can be used to compute the optimum number of sensor nodes deployed N_S, the number of clusterheads deployed N_H, and the number of battery cells used in each type of device (i.e., E and e) that minimizes the cost. While performing this search, we assume that the cost of the hardware component of clusterheads, C_{HW}, is identical to that of sensor nodes. Thus, the main difference between these devices is that clusterheads are more energetic than sensor nodes and this energy differentiation is assumed to have discrete values. The rationale behind this consideration is that devices in WSNs are usually equipped with the "off the shelf" type of batteries, and each device contains a discrete number of battery cells. In Fig. 6.5, $\max N_H$ can be found by setting $N_S = 0$ leads to $S_{cluster} = \pi r_s^2$ in Eqn. 4.43 to Eqn. 4.63. $\min N_H$ can be found by setting $N_S = \infty$; leads to $S_{cluster} = \pi(r_{ts} + r_s)^2$, and the solution for N_H was found accordingly.

```
optimum_e=0, optimum_E=0;
optimum_NH=0, optimum_NS=0;
min_CWSN = infinity;

for (int NH=MIN_NH; NH <=MAXNH; NH++)
{
    find NS using Pcov;
    find ns;
    find E of a clusterhead to achieve R;
    find e of a sensor node to achieve R;
    CWSN = CH.NH + CS.Ns;
        if (CWSN<min_CWSN)
            {
            min_CWSN= CWSN;
            optimum_e=e;
            optimum_E=E;
            optimum_NH=NH;
            optimum_NS=NS;
             }
}
```

Figure 6.5: Algorithm for Heuristic Search

6.6.2 Numerical Results

As a sample case, we used the values given in Table 6.1 to solve the optimization problem. In this sample case, the number of rounds, R, is chosen such that sensor nodes die after approximately R rounds (independent of the clusterheads' lifetime). That is, every sensor node has one battery cell which is sufficient for R rounds.

The solution gives $N_H = 3$, $N_S = 23$, $E = 61$, and $e = 2$. In other words, a WSN consisting of 3 clusterheads and 23 sensor nodes all having a sensing range of 20 *units* will cover a sensing field with the dimensions $100units \times 100units$ with the probability of at least 0.9. Although clusterheads have hardware identical with that of sensor nodes, their battery should contain 30.5 times more cells than the sensors nodes' batteries to satisfy the targeted lifetime requirement. The cost of the WSN *vs.* N_H, N_S pairs satisfying coverage requirement is depicted in Fig. 6.6. From this figure, it is also seen that $N_H = 3$, $N_S = 23$ pair leads to the optimum cost. We also

Table 6.1: Sample Values for Heuristic Search

Parameter	**Value**	**Parameter**	**Value**
Sink(X, Y)	$(50, 175)$	P_{cov}	0.9
R	4500 $rounds$	r_s	20$units$
r_{ts}	60$units$	r_{th}	182$units$
D	100$units$×100$units$	e_{cell}	1 J
C_{HW}	3 unit	C_{cell}	0.3 unit
ρ	50 nJ/b	α	50 nJ/b
β_{fs}	10 $pJ/b/m^2$	β_{mp}	0.0013 $pJ/b/m^4$
R_{SYNC}	50 $byte$	R_{AGG}	1000 $byte$
R_{JOIN}	50 $byte$	R_{SCHE}	100 $byte$
R_{ADV}	50 $byte$	R_{DATA}	500 $byte$
E_{AGG}	5 nJ/b		

performed a computer simulation to validate our formulation and the solution. In the simulations, we used the solutions obtained from the heuristic search and found out the lifetime of the sensor network (i.e., the number of rounds). The simulation results given in this section are obtained by averaging results of multiple simulations and the number of simulations is determined according to a confidence interval of ±5% with 0.95 probability. We found that the average number of achieved rounds is 4375.37, whereas the targeted lifetime in the heuristic search method was 4500. This result reveals that there is at most 2.8% discrepancy between targeted lifetime and simulated lifetime when optimum values are used. We believe that this discrepancy is acceptable because our cost optimization formulation assumes that each clusterhead is connected to equal number of sensor nodes. However, in reality, due to the random deployment of devices, it cannot be guaranteed that every clusterhead has the same number of cluster members. Thus, in the simulation, some clusterheads die earlier.

We also performed extensive simulations to validate our heuristic solution for different coverage requirements. Fig. 6.7 shows the simulated and targeted lifetime values for various partial-coverage values. For the lifetime validation, when the targeted lifetime value is 4500, the 0.75, 0.8, 0.85, 0.9, 0.95, and 0.99 partial-coverage values exhibited

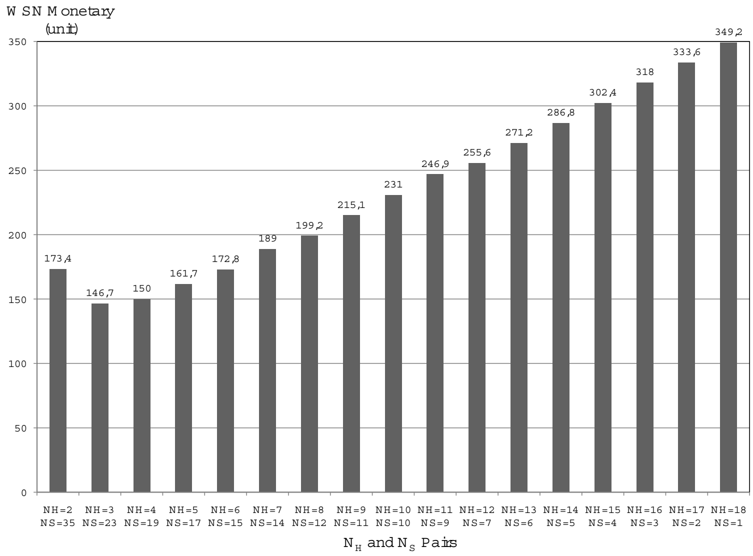

Figure 6.6: Monetary Cost of WSN *vs.* N_H, N_S pairs

1.25%, 2.08%, 2.36%, 2.77%, 4.66%, and 7.49% errors, respectively. The results indicate that the error in the number of rounds increases as the coverage probability increases and as the targeted lifetime increases. This is mainly due to the increase in the number of sensor devices in each cluster to satisfy better coverage. Therefore the probability of having unequal number of sensor nodes across clusterhead will be higher. Thus, our solution performs better under partial-coverage with relatively small coverage probability requirement.

6.6.3 Concluding Remarks

In WSN applications, it is usually common to have scarce resources, and the proper dimensioning of resources is extremely critical. Therefore, there is a need to look from the perspective of optimization as a whole, at a number of issues that have an impact on the WSN's ability to live long, that have cost within the anticipated budget, and that satisfy the coverage and connectivity requirements. In this wider context, we provide a generic framework to optimize these resources in randomly deployed WSNs. We believe that our optimization formulation can be used to aid researchers and practitioners to estimate the total cost of WSN for a given targeted lifetime, required minimum coverage, and other performance parameters.

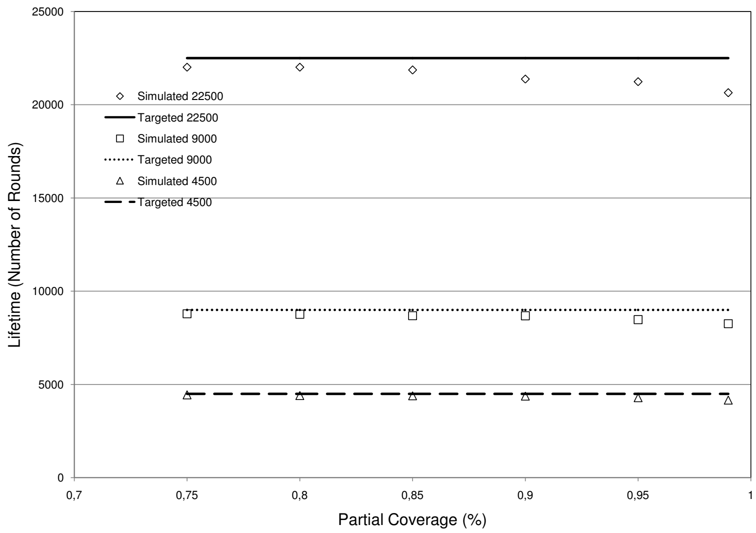

Figure 6.7: Simulated and Targeted Lifetime *vs*. Partial Coverage

CHAPTER 7

CONCLUSION AND FUTURE WORK

With the work presented in this thesis, we contribute towards an approach for the dimensioning of randomly deployed heterogeneous WSNs. The summary of work done and thesis contributions are provided in Section 7.1. This work can be elaborated in many different ways. In Section 7.2, we provide some relevant directions based on the contributions of this thesis.

7.1 Thesis Summary and Contributions

In this dissertation, we have considered randomly deployed WSNs by employing "node heterogeneity" and "static clustering" with two-layers of cluster hierarchy. In our heterogeneous network, there are two types of devices: clusterheads and sensor nodes. Capacities and capabilities of these devices may vary while their roles are pre-assigned before the deployment and remain unchanged over the course of network lifetime. We study this network model for the two cases below, based on how clusterheads can reach the sink:

1. Direct Communication Case: Each clusterhead is assumed to have enough transmission power to reach the sink directly (i.e., single-hop communication).

2. Multi-Hop Communication Case: Depending on the given transmission range, a clusterhead can reach the sink either directly or using other clusterheads as relays.

For two cases we investigate the coverage or connectivity problems and propose optimal network dimensioning solutions for each case.

Most of the previous studies on WSNs consider coverage or connectivity separately. But, here, we consider connected coverage which is the degree of coverage achieved by the "connected devices". Connected coverage can be considered as "effective coverage" provided by a WSN application. That is why the connected coverage is the main emphasis and the theme of this thesis.

We first have defined the cluster size as the expected value of the area covered by a single clusterhead and a number of sensor nodes connected to it. We have investigated the cluster size and have derived an analytical solution for it by using Boolean Coverage Disc Model. The resultant closed-form equations form the basis of our analytical solutions to connected coverage problems. We have validated the analytical solutions by computer simulations. For an example set of parameters, we have observed that there is at most 2% discrepancy between simulation results and the analytical findings. These results revealed that these cluster size equations are good measures for determining the area covered by a clusterhead together with the sensor nodes connected to it. This is one of the important contributions of this thesis.

The importance of the cluster size concept is that it provides a new perspective on looking at the coverage employing clustering. One can use these cluster size equations for the solution of two problems, one of which is essentially the reverse of the other problem. These problems are as follows:

- If we are given a number of deployed sensor nodes and clusterheads, the sensing field, and sensing and transmission ranges, we can find the expected value of the area covered by the connected nodes through these cluster size equations.
- However, if we tackle the problem the other way around. The problem can also be solved by our cluster size equations. That is, we can dimension the network for given targeted coverage requirement, the sensing field, and sensing and transmission ranges. Thus, to dimension the network, one can find the optimum mixture of different type of devices.

We have focused on minimum cost network dimensioning problem by employing node heterogeneity. Due to the distinctions between different types of nodes, different monetary costs are associated for each type of device. To be able to solve the network dimensioning problem resulting to minimum cost WSNs, we used this cost differentiation assumption. We initially formulated the monetary cost of the WSN considering our network model. We assumed that there is a linear relationship between cost of a clusterhead and a sensor node and we formulated an optimization problem to find minimum cost solution that provides the targeted coverage. In order to solve the optimization problem we also propose a heuristic algorithm. Then we have demonstrated that by making use of optimization problem and heuristic algorithm, we found the solution for a set of parameters of a sample scenario. In addition to these, we also compared the monetary cost of the homogeneous network and the heterogeneous network both for direct communication and for multi-hop communication cases. The comparisons have shown that it is possible to have cheaper configurations when node heterogeneity is exploited.

For the monetary cost of a network for direct communication case, we used cluster size equations. For a sample scenario, we justified the cost-effectiveness of node heterogeneity. In this sample network configuration, when the cost differentiation between a clusterhead and a sensor node is greater than ~ 1.2, we obtained cheaper configurations. We also found that significant cost reductions can be achieved depending on the value of some critical relative cost coefficient, k_c. That is, depending on the system parameters of each application, there is a k_c above which cost reductions starts to occur. This result can be used to justify the cost-effectiveness of node heterogeneity.

For the multi-hop communication case, to find the minimum cost network configurations, we again exploit cluster size equations and assume well-connected clusterheads. In order to achieve well-connected clusterheads, each clusterhead should have minimum number of neighboring clusterheads connected to it. This critical value is denoted by θ_c. From the related studies in the literature, it is known that when $\theta_c > 4.5$, clusterheads are said to be well-connected. We extended this finding by adding partial area coverage on top of it to obtain connected coverage. As we investigated the behavior of θ_c for connected coverage adapting our network model, for a number of sample scenarios, we found out that when $\theta_c \geq 4.5$, then WSN achieves the targeted connected coverage. After tackling with the connected coverage problem with cluster size equations and well-connectivity, we also justified the cost-effectiveness of node heterogeneity for the multi-hop communication case through a sample scenario. We further compared the monetary cost of WSNs for multi-hop case with direct communication case. As anticipated, the cost of heterogeneous WSN for multi-hop case is more expensive than the direct communication case. Because, for the former case, the required number of clusterheads are larger than the latter case due to the fact that multi-hop communication case requires more clusterheads to satisfy more strict form of connectivity constraints.

By using the cluster size equations and given targeted connected coverage, monetary costs of the hardware component and the battery cell, and the minimum lifetime, we have formulated a joint cost-lifetime optimization problem to achieve minimum cost WSNs. To solve this problem, we first proposed a cost model for a WSN application based on initial energies of devices. We assumed that clusterheads and sensor nodes have identical hardware component but they are equipped with different numbers of battery cells. Thus, the source of cost differentiation of different types of nodes is due to equipped the number of cells. After modeling cost, we have formulated monetary cost optimization problem for a given lifetime and coverage constraints. We basically adopt the energy dissipation model of LEACH to model the lifetime. Instead of solving this optimization problem using classical Linear Programming (LP) methods, we have proposed heuristic to reduce the solution space significantly. Then, for a sample scenario, we determine the initial energies of different types of nodes and required number of sensor nodes and clusterheads to have the minimum cost WSN by making use of this heuristic search. In the solution for a sample scenario, we have shown by using computer simulations that a mixture of sensor nodes and clusterheads will cover the targeted fraction of the sensing field and operate for almost the targeted lifetime rounds. Although clusterheads have hardware identical with that of sensor nodes, their battery should contain many more cells than the sensors nodes' batteries to satisfy the targeted lifetime requirement. However, in the real-life scenarios, it is not sensible to install too many cells in a clusterhead. Therefore, instead of using identical cells, we can use higher capacity cells in clusterheads and the required number of such cells in the clusterheads can be reduced.

7.2 Future Directions

One of the most important contributions of this thesis is to provide formulations to find the expected value of the area covered by given system parameters. As some classes of WSN applications may be quite critical. Not only the expected value but also boundary values or better yet, confidence intervals may be useful and sensible for these critical types of applications. However, our derivations basically focus on average values. In order for our derivations to be used in practical cases, it is required that a confidence interval should be specified, at least for a minimal number of sample size. In this way, the practitioners can make use of our derivations within some confidence interval. Specifying boundary values and/or a confidence interval are the primary motivating areas of future investigation.

In this thesis, we adopt static clustering approach in which clusters are formed by pre-configured clusterheads. Association between sensor nodes and clusterheads is determined with a "nearest reachable clusterhead" approach, and at any given time, each sensor node is a member of a disjoint cluster. It is evident that static clustering has a poor performance in terms of coverage, lifetime, etc when compared to dynamic clustering algorithms. However, we believe that by employing static clustering, we have obtained many insights and promising results on connected coverage, lifetime analysis, and network dimensioning problems. Thus, studying these problems also for dynamic clustering are among the issues of future research.

In Chapter 6, we incorporate lifetime constraints in the cost optimization problem proposed in Chapter 5. We propose a method to determine the number of sensor nodes and clusterheads and the initial energies to have a minimum cost network while satisfying given coverage and lifetime constraints. A variant of this problem would be to determine the number of devices of each type and their initial energies for given coverage requirement and cost budget such that the lifetime of network is maximized.

Another future work is changing the energy consumption model based on the separation of the nodes within the sensing field. Throughout this work, we assumed that communication ranges are fixed and determined by power constraints. We can modify this assumption to have more energy-efficient schemes. For example, we can consider power adaptive schemes. The benefits of using power adaptive schemes may be quantified.

In the solution approach to solve the joint cost-lifetime optimum dimensioning problem discussed in Section 6.6, we assumed that in clusterheads and in sensor nodes, we used identical but different numbers of cells in each type of device. Therefore, a large number of cells needs to be installed in clusterheads. Instead of using identical cells, we can use higher capacity cells in clusterheads and the required number of such cells in the clusterheads can be reduced. Usually there is a non-linear relationship between the capacity of the cell and its price, hence the cost of such a configuration would be much lower. Issues related to this relation are currently under study.

Our future plan includes a proposal of an energy-efficient MAC and routing protocols to put on top of our network model for multi-hop communication case. Then, we are planning to formulate of cost-lifetime joint optimization problem based on the energy consumption model of the proposed MAC and routing protocols.

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