ABSTRACT

CLUSTERED WIRELESS SENSOR NETWORKS

by
Renita Margaret Machado

The study of topology in randomly deployed wireless sensor networks (WSNs) is important in addressing the fundamental issue of stochastic coverage resulting from randomness in the deployment procedure and power management algorithms. This dissertation defines and studies clustered WSNs, WSNs whose topology due to the deployment procedure and the application requirements results in the phenomenon of clustering or clumping of nodes. The first part of this dissertation analyzes a range of topologies of clustered WSNs and their impact on the primary sensing objectives of coverage and connectivity. By exploiting the inherent advantages of clustered topologies of nodes, this dissertation presents techniques for optimizing the primary performance metrics of power consumption and network capacity. It analyzes clustering in the presence of obstacles, and studies varying levels of redundancy to determine the probability of coverage in the network. The proposed models for clustered WSNs embrace the domain of a wide range of topologies that are prevalent in actual real-world deployment scenarios, and call for clustering-specific protocols to enhance network performance. It has been shown that power management algorithms tailored to various clustering scenarios optimize the level of active coverage and maximize the network lifetime. The second part of this dissertation addresses the problem of edge effects and heavy traffic on queuing in clustered WSNs. In particular, an admission control model called directed ignoring model has been developed that aims to minimize the impact of edge effects in queuing by improving queuing metrics such as packet loss and wait time.

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by
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Now we see but a poor reflection as in a mirror; then we shall see face to face.
Now I know in part; then I shall know fully, even as I am fully known.
-1 Corinthians 13:12

Dedicated to my parents, Thomas and Irene Machado

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I owe my parents, Irene and Thomas Machado a fond and loving acknowledgement for their constant love and care. I thank God for my wonderful parents and their unfailing support through all these years. It is their encouragement that has made a particular contribution to all my efforts, including this dissertation.

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LIST OF SYMBOLS

WSN	Wireless Sensor Network
PCPP	Poisson Clustered Point Process
BS	Base Station
CH	Cluster- head
BC	Broadcast

CHAPTER 1

INTRODUCTION

1.1 Objective

This dissertation addresses the issue of 'naturally clustered' WSNs, a term which we use henceforth in this proposal to define networks of wireless sensor nodes that are randomly distributed throughout the deployment region. To emphasize the concept of clustered topologies in wireless sensor networks, a typical example of a clustered WSN is shown in Figure 1.1a, as opposed to the widely- used measure of a stationary Poisson point process of node distribution in the deployment region (Figure 1.1b). A quick examination of Figure 1.1 reveals the inherent feature of clustered networks: varying coverage in the deployment region. In fact, as we show in the next chapter, clustering has been shown to increase the area of vacancy compared to uniformly distributed nodes, and this preliminary observation signals the need for analysis of clustering properties to design protocols and algorithms that optimize WSN network performance. Although this proposal aims at clustered networks of wireless sensor nodes, it can easily be extended to include a structured analytical model for ad hoc networks of clustered stationary and power constrained nodes.

Clustering is one of the widely prevalent topologies of nodes in random deployments of dense networks. The nature and scale of most WSN applications makes it difficult to arrange the nodes in regular topologies across the deployment region. Despite the impracticability of the widely used assumption of uniform Poisson processes for node distribution, it continues to dominate current literature as the foundation of most

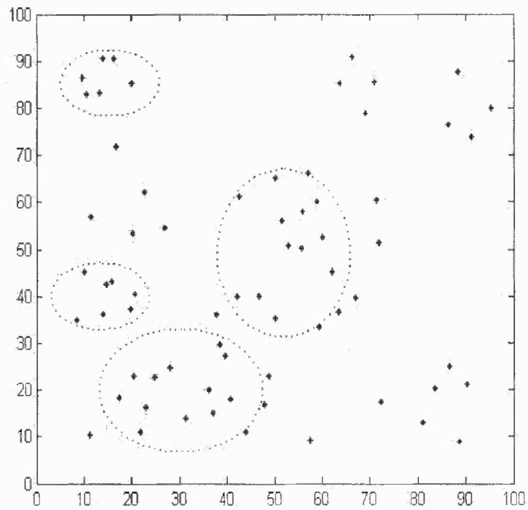


Figure 1.1a.

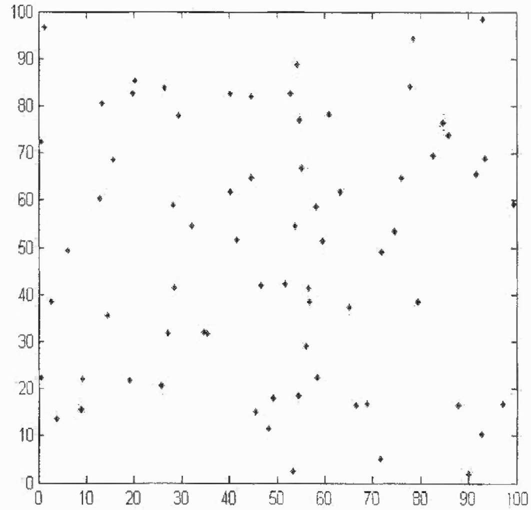


Figure 1.1b

Figure 1.1 (a) shows clustering of nodes in wireless sensor networks and **(b)** shows random distribution of nodes in the network.

algorithms designed to optimize network performance. In this proposal, we identify the phenomenon of clustering in a wide range of topologies and present results for the probabilities of varying degrees of coverage in the deployment region. The knowledge of coverage is essential in developing algorithms for optimizing the tradeoff between coverage and power consumption of densely clustered WSNs. These results are derived from the development of an analytical model of cluster densities of nodes and cluster-heads (CHs) and validated in a simulated environment. The CHs are inherently more robust than regular nodes in terms of energy expenditure for communication and computation, and hence aggregate data from the nodes in the cluster and forward it to a central base station or sink, where the end-user interface makes higher-level decisions from the gathered data from the network of nodes and CHs in the sensing field. Depending on the densities of nodes and CHs, we design power-conserving modes of operation and perform adaptive density control of nodes and CHs to maximize coverage of the deployment region. We show that although clustering increases vacancy in the deployment region, an understanding of clustering properties can be efficiently leveraged to take advantage of the energy conservation properties offered by the clustering approach in dense WSNs.

The properties of naturally clustered WSNs are analyzed using the theory of coverage processes. The theorems presented here provide the foundation for a study of varying densities of nodes and CHs encountered in real-world deployment scenarios, where the densities of nodes and CHs are dictated by device failure, battery energy exhaustion or other causes that can occur in remote and hostile deployment regions. For each of these scenarios of naturally clustered WSNs, we provide algorithms for power optimization and present results on capacity and latency in these networks.

While the nature of naturally clustered networks encompasses varying definitions of network topologies, this proposal is highly focused, employing just that subset of topologies necessary to establish the findings of this proposal. The purpose of studying clustered WSNs arises from the need for sensitivity analysis to the topology of nodes in the network, which initially sparked our interest during the Master's project where we studied the impact of mobility of nodes on power performance studies of MANETs. The development and related analysis led to the study of impact of topologies on performance of wireless sensor networks, which are characterized by stricter power constraints that limit their communication and computation abilities. This in turn calls for algorithms that consider this impact of topologies to optimize network performance for naturally clustered WSNs.

1.2 Organization of this Dissertation

Section 1.3 of this chapter summarizes relevant literature on clustered WSNs and highlights the differences between existing research and our proposal. Chapter 2 reviews background necessary for naturally clustered WSNs and explains prerequisite concepts, particularly the nature and scope of power-constrained WSNs, clustering and coverage, capacity, latency and power consumption metrics of WSN performance. Chapter 3 presents the analytical framework for optimizing the tradeoff between coverage and power consumption of nodes and presents results of network operation validating the study and consideration of clustering in networks. In Chapter 4, we present the queuing analysis in clustered WSNs that takes into account the problems of edge effects and starvation in clustered WSNs. Finally, Chapter 5 presents directions for further research in naturally clustered WSNs and proposes a framework for cognitive WSNs.

1.3 Background

The resource-constrained nature of WSNs in terms of their size, cost, weight and lifetime is a primary area of concern for most potential applications using WSNs. At their best, the constraints of size, weight and cost of individual nodes have propelled their use in a wide variety of military and civilian applications. At their worst, constraint of the power-limited nature of nodes which also constrains their computational, communication and sensing capabilities calls for research into optimizing tradeoffs between reliability and prolonged network operation. Coupled with the inherent unreliability of the wireless channel, possible hostile environment in certain application-specific deployment regions and device unreliability of individual nodes, WSNs are subject to unique challenges for efficient power management to prolong network lifetime in addition to fulfilling sensing objectives of the application.

Energy efficiency and achieving reliability of data collection is a key issue in WSNs. Energy efficiency has been investigated widely and the various approaches to achieve an energy efficient network include scheduling sensor nodes to alternate between energy-conserving modes of operation, efficient routing algorithms, clustering, incorporating intelligence and use of spatial localization at every sensor node to reduce transmission of redundant data. These approaches draw upon theories from mathematics, game theory, physics and even observation of biological phenomena. The unreliability of the wireless channel also poses security challenges in WSNs similar to those encountered in other ad hoc networks. Clustering has frequently been cited as a hierarchical approach to reduce energy expenditure of networks by data aggregation, reducing number of transmissions from individual nodes to the sink and promoting scalability in dense networks. The parameters for cluster formation and cluster-head selection are chosen from a subset of or a combination of factors such as residual energy, node degree and mobility. A survey and of various clustering schemes in WSNs and mobile ad hoc networks can be found in (Dechene, 2006) and (Yu and Chong, 2005) respectively, where the authors classify the existing literature on clustering in WSNs and mobile ad hoc networks (MANETs) and discuss key features of these algorithms. Another survey of clustering in ad hoc networks is presented in (Wei and Chan, 2006), where the authors survey clustering schemes for ad hoc sensor networks and mobile ad hoc networks. While the parameters for cluster formation focus on energy efficiency and load balancing in these surveys, a key difference is the mobility of the nodes in MANETs which significantly changes the protocol development for energy efficiency and routing in ad hoc networks. Below we provide a brief overview of various clustering schemes in dense, stationary networks of homogeneous, power constrained wireless sensor nodes and highlight the major difference between them and our proposal: the uniqueness and prevalence of naturally clustered networks and yet lack of a framework that studies the properties of naturally clustered WSNs.

1. 4 Related Work

One of the earliest literature on clustering in WSNs in LEACH- Low Energy Adaptive Clustering Hierarchy (Heinzelman, Chandrakasan and Balakrishnan, 2002), where cluster formation is designed to achieve prolonged network lifetime by local data processing, rotation of the CH position among nodes and low energy MAC access. The probability of becoming a CH is function of the node energy level relative to the total residual energy level in the network. Since the CH is responsible for data aggregation and data transmission to the sink (communication and computation tasks) that are more energy-intensive than the tasks of sensing and communication to a CH that occur at a regular node, rotation of the CH position relative to node energy levels achieves distribution of the computation and communication as well as cluster maintenance tasks of the CH. The authors also present a modification of LEACH, called LEACH-C (LEACH- Centralized), where the sink centrally coordinates cluster formation and CH selection. In LEACH-C, the base station takes over the tasks of node energy computation, cluster formation ad CH assignment. The authors also provide an analytic framework to determine the optimal number of clusters to optimize the communication and computation energy expense at nodes. The authors assume a network model where nodes are continuously transmitting sensed data to the nearest CH (LEACH) or the sink (MTE). Simulation results show that the LEACH clustering algorithm reduces the energy dissipation and data transfer latency in the network compared to an MTE (Minimum Transmission Energy) approach. In the MTE approach, a node selects the nearest node as its next hop to relay its data to the sink. This is in contrast to the clustering approach, where the nodes communicate to the sink via the CH and thereby reduce the number of transmissions to the sink. They also study the quality of the clustering algorithm in terms of amount of data reaching the sink, since a large amount of data reaching the sink enables accurate reproduction of the parameters of the sensed environment. Assuming that all nodes in a cluster sense the same phenomenon due to proximity of location, simulation results show that LEACH and LEACH-C sense higher amount of data per unit energy than MTE. This is due to the fact that LEACH and LEACH-C enable local data processing through the clustering mechanism.

In (Vlajic and Xia, 2006), the authors provide analytic results to validate the need for clustering in WSNs. They show that when the monitored phenomenon can be grouped as 'isoclusters' (areas within the sensing field that have similar values of the monitored phenomenon), clustering nodes to lie within such isoclusters helps in achieving network objectives such as prolonged network lifetime. This is because, within the isoclusters, the sensed phenomenon, e.g. temperature in a sub-region of the sensing field has a high probability of being reported by all sensors in that sub-area P with same values. This high correlation between data allows for data aggregation at the CH, which results in shorter messages being transmitted from CH to BS. The authors use the bit-hop metric to evaluate the total energy expenditure of transmissions and receptions of bits across the network as a comparison for the energy expenditure in clustered and non-clustered networks. Non-clustered networks are characterized by direct reporting of measurements from individual nodes to the sink, whereas in clustered networks, nodes report their measurements to their respective CHs, who then transmit the aggregated (if possible, compressed) data to the sink. The cluster formation strategy is dictated by the a) size of cluster b) choice of nodes to be included in cluster (i.e. nodes belonging to an isocluster yield energy savings if they are formed as a cluster). The authors show that clustering is beneficial in the event of data correlation in node's reported values. In the absence of or very low correlation, clustering increases the energy expenditure of the network. The authors assume a dense WSN of homogeneous nodes deployed for continuous monitoring in a sensing area, forming a multi-hop network for relaying data to the sink. With the help of two simplified cases of horizontal and vertical array of nodes, the authors determine the optimal cluster size in each case which reduces the energy expenditure (bit-hop metric) of the nodes. They show that the optimal cluster size is a function of the cluster, and the distance of the nodes in the cluster to the sink node.

In (Shu, Krunz and Vrushula, 2005), the authors study power balancing in clustered WSNs in terms of maximizing the coverage time of CHs. The network model used by the authors consists of clusters of nodes uniformly and randomly distributed in a circular deployment region of size A. Cluster formation is modeled as follows: A node's distance from the centrally located sink determines its association in a ring. The network is deployed for continuous sensing, where nodes continuously transmit data to the CH, which forwards this data directly to the sink or through other CHs. Defining coverage time as the time until the first CH runs out of battery energy, the authors optimize this metric by proposing two algorithms that take into consideration the mutual impact of clustering and routing on the coverage time of the CH. These two algorithms are as follows:

1. Routing aware optimal cluster planning

This approach deals with optimal cluster planning. A CH in the i^{th} ring forwards traffic to the sink from CHs in the $(i-1)^{th}$ ring. By reducing the radius of clusters in the i^{th} ring and thereby accommodating more clusters and hence more CHs in the i^{th} ring, we have an increased number of CHs in the i^{th} ring forwarding the same amount of traffic from the CHs in the $(i-1)^{th}$ ring. This leads to decrease in the forwarding traffic load per CH in the i^{th} ring and hence reduced power consumption at CHs in the i^{th} ring. However, reduction in the radius of the i^{th} ring has to be compensated by increase in the cluster size of another ring j, since the total number of the rings in the deployment region A is constant. This leads to increase in power consumption in ring j. Thus, by trading off cluster radius in a ring with power consumption, cluster planning can help to increase network coverage lifetime.

2. Clustering aware optimal random relay

This approach deals with load balancing at CHs to increase coverage lifetime. In this scheme, a CH may relay data to the closest CH in the next ring, or directly forward it to the sink. Denoting α as the fraction of load that the CH directly transmits to the sink, each CH has a probability relay vector that determines power consumption at the CHs.

The authors model this problem of optimizing coverage lifetime with the aforementioned two algorithms as a standard signomial optimization problem on the average communication power consumption of any CH in a ring. The power consumption for communication is a function of the power consumed in the transmission, reception and the radio interface with the choice of routing algorithm.

Simulation results show that for a given number of rings, the optimal cluster planning algorithm results in longer coverage time and smaller number of clusters than the load balanced scheme. This is due to the fact that the cluster planning algorithm allows for CHs with less traffic forwarding load to carry more traffic from within the clusters, thus expanding cluster size and reducing the number of clusters required to cover the deployment region.

In (Younis and Fahmy, 2003), the authors propose HEED (Hybrid Energy Efficient Distributed clustering], a distributed clustering protocol that uses residual node energy, cluster size and available power levels at a node for communication with the CH as parameters for CH selection and cluster formation. Defining a parameter AMRP (average minimum reachability power) as the mean of power levels used by the nodes in a cluster to reach the CH, they show that using AMRP to select CHs is better than the distance-based CH selection approach. They compare the protocol with LEACH, and show that HEED outperforms an optimized version of LEACH by prolonging network lifetime.

The authors in (Xing and Shreshtha, 2006) propose a scheme to determine the reliability of hierarchical clustered WSNs. Figure 2 shows a sample architecture that illustrated the hierarchical model. The connectivity of nodes in the network is modeled as a graph G= (V,E). The reliability analysis is based on the concept of k-coverage set, which is the set of nodes in a cluster such that all points in the cluster are covered at all times by at least k nodes. The coverage-oriented reliability in a cluster is defined as the probability that at least one of the k-coverage sets is optional. Assuming no overlaps between nodes of various clusters, the reliability of the WSN performance is obtained by analyzing the reliability of each cluster independently using link failure, node and CH failure probabilities. These parameters are then integrated to find the measure of reliability for the whole WSN.

In (Cha, Jo, Lee and Lee, 2007), the authors propose a clustering algorithm SNOWCLUSTER that creates a 3-tiered hierarchy of nodes, clusters and regions. They use a central framework administrator SNOWMAN, proposed in an earlier work that is responsible for maintaining location information of nodes, monitoring node status and making local decisions and policy allocation for individual nodes. The use of this framework allows nodes to rely on a central framework for policy enaction instead of using its own resources for neighbor discovery and other management tasks.

The hierarchical framework for routing is as follows: The data gathered by nodes is transmitted to the respective CH, which in turn performs data aggregation and transmits the data to the next and final higher-level of nodes in the hierarchy, the region heads. The region heads are responsible for communication with the sink, after aggregating data from the CHs. The selection of CHs and region heads is based on the residual energy of nodes, and SNOWCLUSTER periodically performs a check on the residual energy of nodes to select those with highest residual energy to determine CHs, and a similar check on the CHs to determine the region heads.

Since SNOWMAN uses location information of nodes to implement CH and region head selection, simulation results for transmission of management messages from

BS to sensor nodes shows that SNOWCLUSTER requires lesser energy than LEACH. In the absence of location information, LEACH requires greater energy consumption for discovering routing paths. The authors show that SNOWCLUSTER outperforms the energy consumption in LEACH by requiring lesser energy for data transmission to the sink. This is attributed to the presence of region heads that communicate to the sink instead of CHs, and thus reduce the energy expenditure of communication to the sink from CHs.

In (Tian and Coyle, 2007), the authors study the distributed binary hypothesis problem for clusters in sensor networks. The nodes make a binary decision '0' or '1' depending on the occurrence of an event. This decision bit is then transmitted to the CH, which makes a final decision based on all the decision bits received from all nodes in the cluster. The authors study the network performance in terms of the probability of error at individual nodes in making the decision, propagation errors that affect a decision bit while being forwarded to the sink, and decision fusion errors at the CH due to the communication errors while propagation from node to sink. Since nodes at the outer edge of a cluster are more vulnerable to their decision bits being corrupted while travelling to the CH via relay nodes compared to decision bits from nodes closest to the CH, the authors propose a weighted median algorithm at the CH for decision fusion that takes into account the communication errors. With increase in cluster size, the number of decisions arriving at the CH are greater in number than those arriving from nodes closest to the CH. Thus the decision bits from the outer nodes of a cluster form the dominating set of decision bits which are also more vulnerable to errors. The weighted median algorithm for decision fusion at the CH assigns larger weights to decision bits from nodes closest to the CH by duplicating them several times. This algorithm discounts the weight of the error-prone bits and improves the decision performance of the CHs and the sink.

The closest related work to ours is (Comeau, Sivakumar, Philips and Robertson, 2008), where the CHs are not chosen from among the nodes in a randomized rotation manner (Heinzelman, Chandrakasan and Balakrishnan, 2002), or any other algorithm for CH selection from among the nodes. Rather, the CHs are a separate set of nodes that receive data from nodes, perform data aggregation and sensing tasks. The authors present an energy model for clustered WSN, which consists of N nodes randomly and uniformly distributed in the deployment region, The process of choice of CHs or the geometry of deployment in unclear. The authors assume a radio model, where propagation path loss exponent is assumed to vary with the distance of transmission, i.e. $n = 2$ for transmission within the cluster and $N>2$ for transmission outside the cluster. They model the energy consumption at both CHs and regular nodes. They use the optimization of energy at regular nodes to obtain the total number of clusters in the network. The authors use a ratio β/l, where l= length of packet transmitted by CH to sink. The optimum number of CHs denotes the minimum total energy, and increases with an increase in compression. This is because an increase in the compression ration equals an increase in the minimum total energy and hence increase in optimum number of clusters. The optimum number of CHs has also been shown to depend on the crossover distance d_o, which determines the value used for the propagation path loss exponent.

Another closely related work is (Perevalov, Blum and Safi, 2006), where the authors study the impact of cluster density on the capacity of ad hoc networks, instead of the widely used assumption of randomly uniformly distributed nodes distributed according to a stationary Poisson point process in the sensing area. They assume a network model where clustered nodes with density ρ_c, in a 'sea of nodes' of density ρ_s, such that $\rho_s << \rho_c$. They show that the throughput of clustered networks switches at a critical size that is dependent on the sensing area A. Before reaching the critical size, the per-node throughput is almost independent of A, and depends on cluster size and cluster density. They derive bounds on the throughput of clustered networks and help to quantify the concept of 'large' networks, i.e. networks whose size exceed the critical size. Large networks are characterized with increase in capacity as size further decreases.

In the next chapter, we obtain the coverage properties of clustered WSNs using the theory of coverage processes. We show that vacancy decreases in a clustered topology of nodes, and we present results for *k*-coverage in a clustered WSN. These results have significance in positioning applications, situations which require stronger environmental monitoring capability (Huang and Tseng, 2003) and high reliability.

CHAPTER 2

COVERAGE AND CONNECTIVITY PROPERTIES OF CLUSTERED WSNs

Sensing coverage is an important functional metric to a wireless sensor network since it determines how well the sensor network can monitor the environment and generate corresponding data. In addition, the knowledge of coverage and redundancy is essential in developing algorithms (Heinzelman, Chandrakasan and Balakrishnan, 2002) to schedule the listening/sleeping cycle of sensors for optimizing the tradeoff between coverage, communication connectivity and power consumption. Currently the assumption of the uniform Poisson process for node distribution dominate the literature as the foundation of most algorithms designed to optimize network performance. However, the assumption is not practical in many situations. The nature and scale of the most WS applications makes it difficult to arrange the nodes in regular topologies across the deployment region. The deployments for random placements of nodes for environment monitoring (Biagoni and Bridges, 2002), (Mainwaring, Polastre, Szewczyk Culler and Anderson, 2002) or military applications is typically done through spraying nodes from an airborne device or randomly scattering nodes manually. A significant consequence of this process is the clustering or clumping of nodes, where node positions form clusters resulting in redundancy of coverage in certain area and coverage 'holes' in the other area. We call this scenario 'naturally clustered' networks as opposed to the more prevalent notion of clustering by choice. Clustering is one of the widely prevalent topologies of nodes in random deployments of dense networks. To emphasize the concept of clustered topologies in wireless sensor networks, a typical example of a clustered WSN is shown in

Figure 2.1, as opposed to the widely used measure of a stationary Poisson point process of node distribution in the deployment region (Figure 2.2).

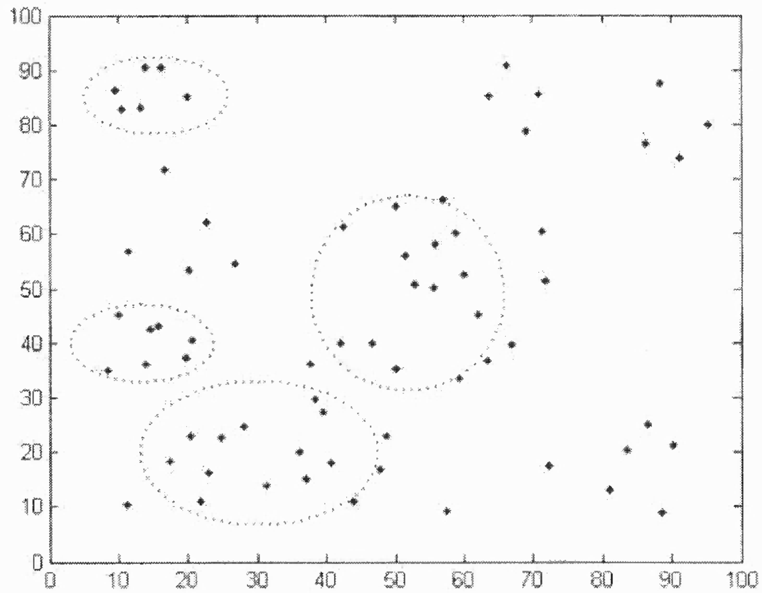


Figure 2.1 Clustering of nodes in WSNs.

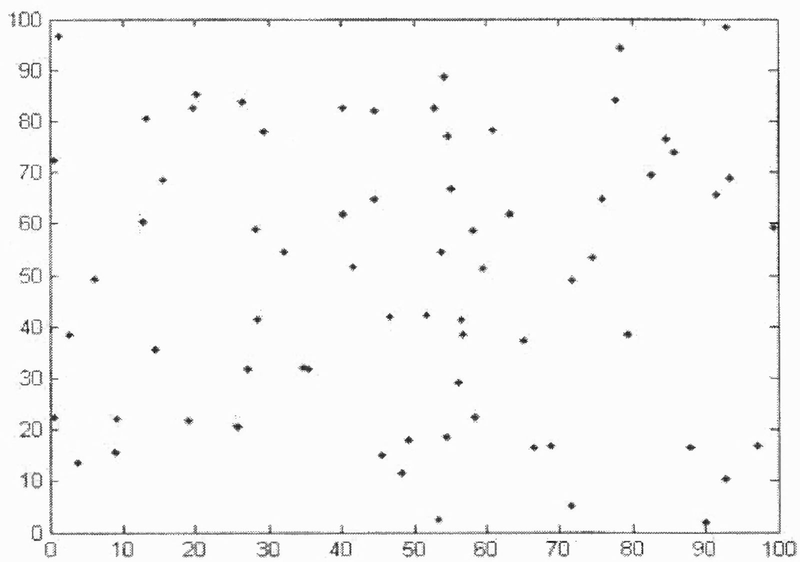


Figure 2.2 Random distribution of nodes in WSNs.

A quick examination of Figure 2.1 reveals the inherent feature of clustered networks: varying coverage in the deployment region. In fact, as we show in the next section, clustering has been shown to increase the area of vacancy compared to uniformly distributed nodes, and this preliminary observation signals the need for analysis of clustering properties to design protocols and algorithms that optimize WSN network performance. In addition to the increased vacancy and vacancy distribution which requires more study, the natural clustering of WSN also have impact on the design of those clustering algorithms (Dechene, 2006), (Shu, Krunz and Vrushula, 2005) for routing, data aggregation and energy conservation. An understanding of clustering properties can be efficiently leveraged to take advantage of the energy conservation properties offered by the clustering approach in dense WSNs.

To sum up, there are fundamental reasons why we investigate the properties of coverage in naturally clustered networks instead of using the widely used theory of uniformly distributed nodes in a Poisson model of node distribution, some of which we enumerate here:

- Models for naturally clustered networks show that coverage properties in clustered networks are significantly altered than those in Poisson models of uniform and random node distribution. As we show in the rest of this chapter, vacancy due to clustering is higher than in the widely used model of a stationary Poisson point process used to model node distribution.
- These models can provide a foundation for future work on placement of nodes in randomly deployed WSNs, thus making it easier to understand and extend the model of clustering.

- Even though clustering exhibits increased vacancy, this vacancy can be compensated by mobile nodes who can travel to the region of vacancy and cover the vacant region.
- With the insights from this work, researchers can create new models of clustering by customizing the properties that are appropriate to the WSN application for which the network is deployed.

In this dissertation, we study 'naturally clustered' WSNs. Random deployments of nodes in WSNs do not have any order in the placement of nodes. The objective of this dissertation is to investigate how to model the randomness in the placement of nodes by examining the coverage attributes resulting from randomness in clustering. In particular, the attributes of coverage in naturally clustered networks are extensions of the Poisson model of node distribution widely used in modeling the distribution of nodes in WSNs. We show how to extend Poisson distribution of nodes to support clustering with an analytical framework using the Poisson cluster point process (PCPP). We analyze the properties of naturally clustered WSNs using the theory of coverage processes (Hall, 1988). This analysis provide the foundation for a study of varying densities of nodes and cluster heads encountered in real-world deployment scenarios, where the densities of nodes and cluster heads are dictated by node failure due to device failure, battery energy exhaustion or other causes that can occur in remote and hostile deployment regions. In addition, we study the affect on the coverage properties of obstacles in clustered WSN. Obstacles exist in a large number of outdoor applications, which are a major portion of WSN applications. The dissertation has the following contributions: (1) study the coverage property of clustered WSNs and provide a foundation for the design to optimize network performance and (2) study the presence of obstacles and how they impact coverage in clustered WSNs.

The remaining of the chapter is organized as follows. Section 2.1 reviews background necessary for naturally clustered WSNs and explains prerequisite concepts, particularly the nature and scope of power-constrained WSNs, clustering and coverage metrics of WSN performance. Section 2.2 discusses vacancy estimation in a clustered network. In Section 2.3, we analyze the impact of clustering on coverage properties. Section 2.4 presents the coverage analysis in the realistic scenario of deployment in the presence of obstacles. In section 4, we present the results of simulation. The performance evaluation of our model is presented in Section 2.5. Finally, Section 2.6 concludes the chapter.

2.1 Problem Statement

Though the assumption of a Boolean model (Poisson process) offers ease of calculation, is not reflective of the coverage and connectivity properties of a real-time random topology. The key assumptions in our formulation are:

- We define naturally clustered networks, where clustering is not facilitated by choice. Rather, it is a consequence of the deployment process in large-scale, dense networks created by scattering/ spraying of nodes.
- To investigate clustering, we leverage the concept of a Poisson cluster point process (PCPP) (Hall, 1988) as opposed to the widely used Boolean model (Poisson driving point process).

- We further assume that the CHs are a distinct set of nodes scattered over the region with a smaller intensity than that of regular nodes. Thus we assume a 2-tier hierarchy comprising of 2 distinct sets of nodes: sensor nodes and CHs.
- The CHs are assumed to be robust, less power-constrained, and larger (akin to localized processing stations) that are capable of intensive processing, computation compared to the sensor nodes. The CHs are also responsible for to other CHs and relaying cluster data to the BS.

The focus of coverage studies in WSNs deployed for environmental modeling has been on random topologies, and the model of choice for the topology is that of Poisson distributed nodes. The coverage problem has also been studied in terms of a set intersection problem using results from integral geometry in (Lazos and Poovendran, 2006). In this dissertation, we use the results from coverage processes, specifically, Poisson cluster point processes (PCPP) to study random topologies of WSNs. The use of PCPP models to model environmental phenomena has been suggested in (Cox and Isham, 1980) and (Kingman, 1993) and has been studied for modeling air temperature and rainfall in (Onof et. Al, 2004), (Kilsby et. Al, 2007) and (Bilgin and Camurcu, 2005). A detailed study of applications of PCPP models to ecological modeling can be found in (Cox and Isham, 1980).

The coverage properties of random topologies in a WSN have been studied with the help of coverage processes previously in (Saito, Shiado and Harada, 2008). In (Saito, Shiado and Harada, 2008), the authors study the coverage in a Poisson process of node topology, where the WSN is deployed for target detection. They consider the scenario of Boolean model of coverage, where a target point is considered to be sensed if it lies within the coverage area of a sensor node and considered to be un-sensed otherwise. They extend this analysis to the interesting case of an expanding target, for e.g. detecting oil spills or infected animals in a herd. Variations of the Poisson process in the study of coverage in WSNs have also been considered in (Manohar, Ram and Manjunath, 2006).

We study the problem where for a given placement pattern for wireless sensor nodes, in a deployment region, we have to find the probability that every point in the deployment region is covered by m nodes, with some probability p, where $0 < p < 1$. We assume that the deployment process results in k-redundancy of nodes, and we find the probability that a given point (x,y) in the region is covered by m-redundancy, where $m < k$. The decrease in the degree of redundancy can be attributed to power management that turns off redundant sensors or to sensors that have run out of battery energy or suffered device failure.

Our research is the first known work that analyzes the interaction between points of the coverage process resulting from a clustered topology. Realistic random deployment patterns result in clustering of nodes. Salient attributes of using PCPP models to study coverage in random topologies are evident, and help us to see the need for using cluster point processes. First, various ecological models display clustering in the spatial and temporal domains. Many spatial cluster processes have been described and modeled in (Neyman and Scott, 1972). Second, realistic deployment models result in clustering of nodes. One of the particular strengths of this dissertation is that it can be used to pre-determine the degree of coverage required to study an ecological model that has been shown to display clustering (Onof et. Al, 2004), (Kilsby et. Al, 2007), (Bilgin and Camurcu, 2005), (Neyman and Scott, 1958). Since the spatial distribution of the phenomenon demonstrates clustering, deploying random topologies in a clustered pattern can help in effectively isolating and capturing the phenomenon. This has been conversely studied earlier in (Vlajic and Xia, 2006) as isoclusters, where the nodes in a geographical region sense same values of the target phenomenon and form a cluster (isocluster) to reduce redundancy in data processing and transmission. The other strength of this analysis lies in the inherent limitation of the Poisson process in approximating realistic random deployments. Most real world deployments of random WSNs display clustering due to the deployment phenomenon and hence a PCPP is more appropriate to study the coverage properties in such topologies.

A clustering process allows for a degree of interaction between the points of the coverage process. In this work, we study the properties of a Poisson cluster point process (PCPP) (Hall, 1988), which possesses a degree of clustering not present in a Boolean model. The properties of coverage and vacancy in a 2-dimensional region R^2 due to clustering processes vary significantly from that of the widely used Boolean model of node placement. Realistic random deployment patterns result in clustering of nodes. The properties of coverage and vacancy in a 2-dimensional region R^2 due to clustering processes vary significantly from that of the widely used Boolean model of node placement. In fact, as we show in the rest of this article, clustering results in increasing the expected vacancy per unit area of the region R^2. We now present some terminology to facilitate our discussion of coverage in cluster point processes.

Terminology:

Stationary point process:

A point process Π is stationary if for each Borel set S, the distribution of the number of points of Π that fall within $x+S$ is independent of x.

Stationary (homogenous) Poisson point process of intensity λ:

A stationary point process is Poisson with intensity λ if

1. the points ξ_i in any Borel subset S of P^2 is Poisson distributed with mean $\lambda\|S\|$, where $\|.\|$ denotes the Lebesgue content (area in 2-dimensions) of a shape.
2. the number of points in any number of disjoint Borel subsets are independent random variables
3. if and only if λ is constant everywhere,
4. mean and variance of number of points in the process equals $\lambda\|S\|$ and
5. probability that no points lie in $S=\exp(-\lambda\|S\|)$.

Let $\Pi\equiv\{\xi_i, \quad i\geq 1\}$ be a stationary Poisson process of intensity λ in P^2. Let $S_1, S_2, S_3, \ldots$ be independent and identically distributed (i.i.d.) random sets independent of Π. Then the coverage model $C = \{\xi_i + S_i\}$, $i\geq 1$. A point *(x, y)* in the deployment region is said to be covered if the point lies within the circular sensing region of a node. In dense networks, *k* (where *k* > 1) nodes can sense any given point resulting in *k*- redundancy. However, power management or node failure can dictate that any *m*, (where *m* < *k*) sensors are sensing that point resulting in actual *m*-redundancy of coverage in the coverage. A Boolean model of coverage in 2-dimensional Euclidean space is R^2 just the coverage pattern created by a Poisson-distributed sequence of random sets. Similarly, *k*-connectivity exists when for any given two nodes, *a* and *b*, multiple (*k*) paths exist between them. Dense networks through their topology create conditions for both *k* /*m*-

redundancy and connectivity. In the rest of this chapter, we will obtain analytical solutions for the probability of coverage in either k or m- redundancy and expected number of connected sensors in the WSN of PCPP process. These results will help us develop an efficient routing protocol that considers the unique coverage and connectivity properties inherent in WSNs of PCPP nodes and CHs.

As we show in this chapter, clustering results in increasing the expected vacancy per unit area of the region R. We now present some terminology to facilitate our discussion of coverage in cluster point processes.

A clustering process allows for a degree of interaction between the points of the coverage process. In this work, we study the properties of a Poisson cluster point process (PCPP), which possesses a degree of clustering not present in a Boolean model.

In a PCPP P, the points of P are the 'children of parent' points. The parent points form a stationary Poisson process in R^2 with intensity λ_0, given by $\{\eta_i, \quad i \geq 1\}$. Each parent point produces progeny represented by points in space in an i.i.d. manner. The number N_i of progeny born to a parent point η_i, which is independent of i. Let $p_n = \Pr(N = n)$.

The jth child of η_i is the point $\eta_i + \eta_{ij}$, $1 \leq j \leq N_i$. Conditional on all N_i and η_j, and on the locations of all progeny of all parents other than the ith, the vectors η_{ij} are i.i.d. with density h defined on P^2. The points $\left\{\eta_i + \eta_{ij}, \quad i \geq 1, \quad 1 \leq j \leq N_i\right\}$ comprise a PCPP $\Pi \equiv \{\xi_i, \quad i \geq 1\}$.

We assume the particular case where the progeny N has a Poisson distribution with mean μ, i.e $\mu^n e^{-\mu}/n!$. The total density of random sets in C per unit content of R^2 equals $\mu\lambda_0$, which we henceforth call the clump factor. This is also the average intensity of the driving point process *P*. A point (x, y) in the deployment region is said to be covered if the point lies within the circular sensing region of a node. In dense networks, k (where k >1) nodes can sense any given point resulting in k- redundancy. However, power management or node failure can dictate that any m , (where m <k) sensors are sensing that point resulting in actual m-redundancy of coverage in the coverage. A Boolean model of coverage in 2-dimensional Euclidean space R is just the coverage pattern created by a Poisson-distributed sequence of random sets. Similarly, k-connectivity exists when for any given two nodes, a and b, multiple (k) paths exist between them. Dense networks through their topology create conditions for both k or m-redundancy and connectivity. A systematic evaluation of the maximum likelihood estimation for a PCPP and demonstration of the convergence of the procedure with a sample small data set has been presented in (Castelloe and Zimmerman, 2002). We refer the interested reader to (Castelloe and Zimmerman, 2002) for an analysis empirical quantification of similarity in actual node distribution to the one predicted by the PCPP. In the rest of this chapter, we will obtain analytical solutions for the probability of coverage in both k or m- redundancy and expected number of connected sensors in the WSN of PCPP process. These results will help us develop an efficient routing protocol that considers the unique coverage and connectivity properties presented in WSNs of PCPP nodes.

2.2 Vacancy Estimation in a Clustered Network

The vacancy V within P^2 is defined to be the 2-dimensional content of that part of P^2 that is not covered by any of the random sets of C, where C is the coverage process $= \{\xi_i + S_i, \quad i \geq 1\}$.

$$X(x) = \begin{matrix} 1 & \forall i, x \notin \xi_i + S_i \\ 0 & otherwise \end{matrix} \tag{2.1}$$

The expected vacancy within a region $E(V)$ is given by [13],

$$E(V) = \|R\| \exp(-\lambda \|S\|) \tag{2.2}$$

where, λ is the intensity of the point process for nodes, $\|R\|$ is the area of the deployment region and $\|S\|$ is the expected area of the node coverage. This vacancy denotes that part of deployment region that is not covered by any node.

This vacancy denotes that part of deployment region that is not covered by any node. Let $S \subseteq P^2$ be a fixed set. Conditional on $\eta_i = x$ and $N_i = n$, the chance that none of the points $\eta_i + \eta_{ij}$, $1 \leq j \leq N_i$ lies within $-S$ is given by $p_1(x)^n$,

where,

$$p_1(x) = 1 - \int_{-x-S} h(y)\,dy = 1 - \int_S h(-x-y)\,dy \tag{2.3}$$

Conditional only on $\eta_i = x$, the chance that none of the progeny of η_i be within $-S$ is given by $p_2(x)$,

where $$p_2(x) = E\left\{p_1(x)^N\right\} \tag{2.4}$$

Since the points η_i comprise a stationary Poisson point process Π_0 with intensity λ_0, then the number of points M of η_i, which have at least one child lying within $-S$ must be Poisson with mean v,

$$v = \int_{R^2} \lambda_0 \{1 - p_2(x)\} \tag{2.5}$$

The probability that no random sets in the coverage process $= \{\xi_i + S_i, \quad i \geq 1\}$ cover the origin equals the chance the M takes the value zero, i.e. it equals e^{-v}.

$$\therefore E(V) = \|R\| e^{-v},$$

where
$$v = \lambda_o \sum_{n=1}^{\infty} p_n \int_{R^2} \left[1 - \left\{ 1 - \int_S h(-x-y)dy \right\}^n \right] dx \tag{2.6}$$

If the distribution N of the progeny of parent points has a Poisson distribution with mean μ, i.e.

$$p_n = \mu^n e^{-\mu} / n!, \qquad n \geq 0 \tag{2.7}$$

Then,

$$v = \lambda_o \int_{R^2} \left[1 - \exp\left\{ -\mu \int_S h(-x-y)dy \right\} \right] dx \tag{2.8}$$

Since $1-(1-x)^n \leq nx$, if $0 \leq x \leq 1$,

$$\frac{v}{\lambda_o} \leq \sum p_n . n \int_{R^2} dx \int_S h(x-y)dy = \mu \|S\| \tag{2.9}$$

where, $\mu = E(N)$,

Now, the total density of random sets in C per unit content of $\|R\|^2$ equals $\mu\lambda_0$. This is also the average intensity of Π. But

$$\|R\|\exp\left(-\mu\lambda_0\|S\|\right) \tag{2.10}$$

equals expected vacancy for a Boolean model having same type of set and same density of sets as C. Hence clustering increases the expected vacancy per unit area.

Since obtaining the density if the progeny points $\eta_i + \eta_{ij}$ as well as classifying the nodes as parents and progeny in the deployment region is not feasible, an alternate way to determine the expected vacancy is as follows.

Vacancy can be determined alternately by finding the expected number of sets that intersect a given set $v(S_o)$, where S_o is some convex subset of $v(S)$. Let $v(S_o)$ be the mean number of coverage disks of nodes intersecting any fixed coverage disk S_o in the deployment region *R*. Let $\mu(S_o, S)$ be the mean area of the region into which centers of coverage disks intersecting S_o must fall. Consider the set *A* of all points **x**, $x \in R$ such that $\mathbf{x}+S$ intersects S_o. If the coverage disks distributed as *S* are centered at points of a stationary point process with intensity λ, then expected number of random sets intersecting S_o equals

$$v(S_o) = \lambda E\left\{\int_R f(x,S)\,ds\right\} \tag{2.11}$$

where, $f(x,S)$ is a coverage function denoted as

$f(x,S) = \{1 \quad if \quad (x+S)\cap S_o \neq \phi$ and 0 otherwise. Hence,

$$v(S_o) = \lambda E\{\mu(S_o, S)\} \tag{2.12}$$

Let $\alpha = E\left(\|S\|_2\right)$ be the area of the coverage disk and $\beta = E\left(\|\partial S\|_1\right)$ denote the perimeter of the coverage disk. This gives the probability that no disks intersect the coverage disk S_o as

$$e^{-v(S_o)} = e^{-\alpha\lambda} E\left[-\lambda\left\{\|S_0\|_2 + (2\pi)^{-1}\|\partial S_0\|_1 \beta\right\}\right] \tag{2.13}$$

In this dissertation, we study clustering of nodes in random deployments with the help of the PCPP process. Modifying this analysis to account for the PCPP process, we substitute the intensity λ , for the intensity of the PCPP process $\mu\lambda_0$, which we call the clump factor.

Hence in a PCPP with average intensity $\mu\lambda_0$, the expected vacancy [8] is given by

$$E(V) = e^{-\mu\lambda_0} E\left[\exp\left\{-\mu\lambda_0 \|S\|_2 + (2\pi)^{-1}\|\partial S\|_1 \beta\right\}\right] \tag{2.14}$$

where, S is a disk of random radius r. $E\left(\|S\|_2\right)$ =area of S= $\pi E\left(r^2\right)$ denoted as α .

$E\left(\|\partial S\|_1\right)$ = perimeter of S= $2\pi E(r)$ denoted as β .

The mean number of sets that intersect a given set gives the probability of forming intersected coverage areas and depends on the area of S . In a PCPP with average intensity $\mu\lambda_0$, the expected vacancy is given by

$$E(V) = \|R\| e^{-\mu\lambda_0} E\left[\exp\left\{-\lambda_o\mu\|S\|_2 + (2\pi)^{-1}\beta\|\partial S\|_1\right\}\right] \tag{2. 15}$$

where, S is a disk of random radius R .

$E\|S\|_2$ = expected area of S = $\pi E\left(R^2\right)$, denoted as α .

$E\|\partial S\|_1$ = mean perimeter of S = $2\pi E(R)$, denoted as β .

Equation (2.15) gives the expected vacancy in PCPP. Figure 2.3 shows the expected vacancy in a deployment region of 300 nodes as a function of the intensity of the deployment process.

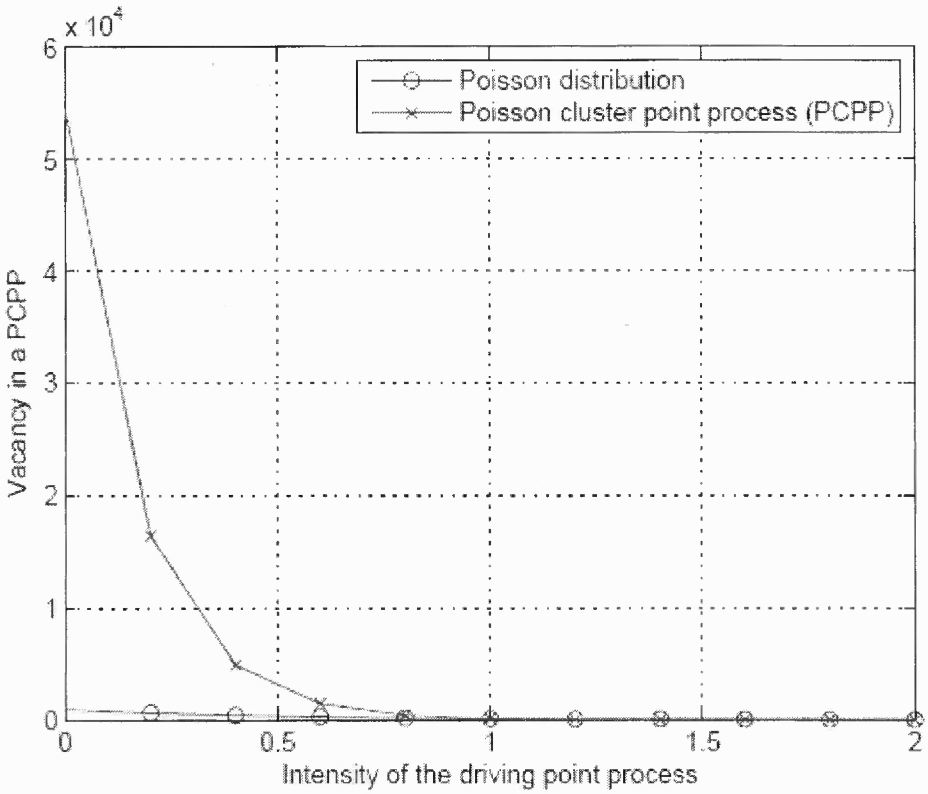


Figure 2.3 Expected vacancy in Poisson and PCPP distributions of 300 nodes without obstacles

The vacancy decreases with increase in the intensity of nodes. However, this vacancy can be further decreased by increasing the degree of clustering.

2.3 Impact of Clustering on Coverage Properties

In this section, we obtain the properties of clumping of the nodes scattered as a PCPP. A realization of a PCPP is a pattern of voids and clumps as shown in Figure 2.4.

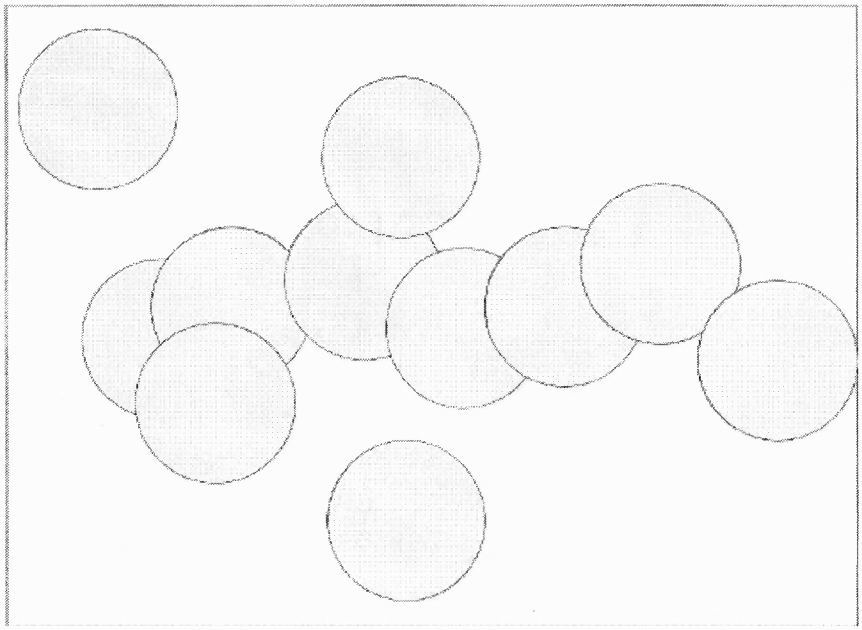


Figure 2.4 Pattern of clumps of coverage areas of sensor nodes and coverage voids due to absence of sensors

We denote the clumps as the coverage area of a pattern of redundant nodes sensing a given point in the region. Defining the number of m-redundancy for a given point as the order of the clump, the area covered by a clump is simply the order of the clump multiplied by the expected coverage area of a single node. In a perfect Poisson process of nodes, the distribution results in nodes that 'avoid' each other (Shu, Krunz and Vrushula, 2006), thus distributing the nodes throughout the deployment region to achieve uniformity of coverage properties. Though this assumption offers ease of calculation, a random deployment can easily result in formation of clumps and voids in the region. The voids denote coverage voids due to sensors that are no longer sensing due to possible battery energy exhaustion, sensor nodes in power-saving sleep states or sensors that have stopped working due to device failure. To obtain the properties of clumping of coverage disks in the deployment region, we use the principle of Euler characteristic of a figure.

Once again, we start with the derivation for a Poisson model for the nodes and then extend it to a PCPP model to reflect the clumping. The Euler characteristic of a figure equals the number of disjoint components minus the number of voids. The Euler characteristic of a figure $x(S)$ equals the number of disjoint components minus the number of voids.

Let $R(C)$ be the set formed by intersection of sets from the Boolean model $C \equiv = \{\xi_i + S_i, \quad i \geq 1\}$ within a given region $\mathcal{R}$. Let $\mathcal{R}$ denote a connected oriented polygonal region without voids.

From the above figure, $R(C) = (2\pi)^{-1}$ {expected curvature of shaded sets}

This quantity is different from the 'expected visible curvature of the pattern within $\mathcal{R}$', because the former includes contributions to curvature arising from boundary of $\mathcal{R}$

Expected visible curvature of sets centered within $\mathcal{R} = 2\pi x\lambda \|R\| e^{-\alpha\lambda}$. (2.16)

Expected total curvature of patterns within $\mathcal{R} = 2\pi\left[x\lambda - (4\pi)^{-1}(\beta\lambda)^2\right]\|R\| e^{-\alpha\lambda}$ (2.17)

Hence, mean Euler characteristic per unit area of this pattern

$$= \left[x\lambda - (4\pi)^{-1}(\beta\lambda)^2\right]e^{-\alpha\lambda} \quad (2.18)$$

The mean total curvature of $R(C)$ =

(a) + (b) +(c),

where, (a) = expected contribution to total curvature arising from uncovered crossings of boundary of $\mathcal{R}$ from boundaries of random sets,

(b) = expected contribution to total curvature from curvature of boundary of $\mathcal{R}$ and

(c) = Expected total curvature within $\mathcal{R}$

In a deployment region, the Euler characteristic is thus the number of isolated coverage disks (those that do not intersect with other disks due to overlapping coverage areas) minus the number of areas that are vacant and bounded by the perimeters of the coverage disks of surrounding nodes. Since the intensity of coverage disks is Poisson with intensity λ, the expected visible curvature of the coverage disks per unit area is $2\pi\chi\lambda e^{-\alpha\lambda}$, where $\chi = x(S)$ denotes the Euler characteristic of the set S. Assuming that the coverage areas are isotropic, the number of disjoint coverage disks per unit area Expected number of clumps minus voids in a PCPP per unit area is given by A. If we know that the coverage disks have smooth boundaries, then any discontinuities in the Boolean model can be identified as an uncovered region which can be removed from the calculation of total curvature. Hence the expected total curvature from uncovered crossings of random coverage disks centered in the deployment region R is given by

$$-\frac{1}{2}(\beta\lambda)^2 e^{-\alpha\lambda} \tag{2.19}$$

Thus the expected number of clumps minus voids in the deployment region of Boolean model of nodes following the Poisson distribution is given by

$$2\pi\left(\chi\lambda-(4\pi)^{-1}(\beta\lambda)^2\right)e^{-\alpha\lambda}$$

Thus the expected number of clumps minus voids (m-redundancy) in the deployment region with PCPP distributed nodes is a straightforward extension of the above equation by substituting the clump factor $\mu\lambda_0$ for λ. Thus the expected m-redundancy per unit area in the coverage in a deployment region with PCPP distribution of nodes is given by

$$2\pi\left(\chi\mu\lambda_0-(4\pi)^{-1}(\beta\mu\lambda_0)^2\right)e^{-\alpha\mu\lambda_0} \tag{2.20}$$

For a 2-D region R populated with PCPP nodes, expected area of coverage α, perimeter of node coverage β, and binary function for coverage χ denoting the presence/absence of a node that covers a point (x, y), and λ is the intensity of the Poisson process of Boolean model denoted by $C(\delta,\lambda)$, where, δS is the distribution of coverage areas and η,λ and δ are related as $\eta=\delta^2\lambda$. Finally, we obtain the expected number of clumps of coverage disks of sensors per unit area (denoting the k- redundancy in the region). The expected number of coverage disks in a Boolean model C that intersect a fixed coverage disk S is given by equation (2.13). The probability that no sets from C intersect S is given by $e^{-\frac{1}{2}v(S)}$. Hence the mean number of coverage disks per unit area with no sets intersecting them is given by the expected number of clumps per unit area is given

$$v_1=\lambda e^{-0.5\alpha}E\left[\exp\left\{-0.5\eta\left(\|S\|_2+(2\pi)^{-1}\beta\|\partial S\|_1\right)\right\}\right] \qquad (2.21)$$

Once again, we extend this analysis to that of the PCPP model for clustered nodes and present the formula for the k-redundancy in a region with the clump factor given by

$$v_1=\mu\lambda_0 e^{-0.5\alpha\eta}E\left[\exp\left\{-0.5\eta\left(\|S\|_2+(2\pi)^{-1}\beta\|\partial S\|_1\right)\right\}\right] \qquad (2.22)$$

2.4 Coverage Properties in the Presence of Obstacles

We now present the properties of a PCPP WSN node placement in the presence of obstacles in the 2-D deployment region R (Figure 2.5).

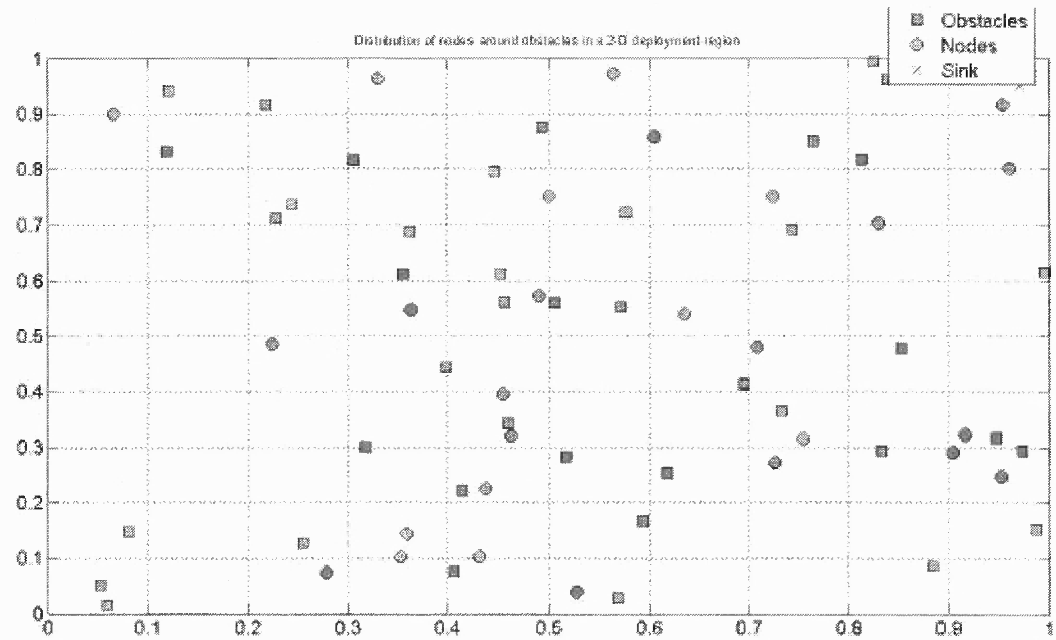


Figure 2.5 Illustration of node deployment in a 2-D region with obstacles

Even though the positions of some nodes are very close to the obstacles, in these cases, the coverage area of a node has been reduced. However, the nodes are not in the same location as the obstacles. We assume that the area occupied by an obstacle is a disk of random radius r and does not allow the presence of a sensor node in that area. Further, we assume a Poisson distribution, i.e. a Boolean model of coverage for the distribution of obstacles. The subscript 'o' in the expressions for coverage, vacancy and clumps indicate properties in the presence of obstacles in the deployment region. In the presence of obstacles, the vacancy in R is defined as that area of R that is not covered by obstacles. The vacancy due to obstacles V_o is given by

$$V_o = \|R\| \exp\left(-\lambda \|S\|\right) \tag{2.23}$$

This area V_o is the expected area in which we can deploy sensors according to a PCPP of average intensity $\mu\lambda_0$. The vacancy in the region V_s after deployment of PCPP nodes and Poisson distribution of obstacles is given by

$$V_s = V_o e^{-\mu\lambda_0} E\left[\exp\left\{-\mu\lambda_0\left(\|S\|_2 + (2\pi)^{-1}\beta\|\partial S\|_1\right)\right\}\right] \tag{2.24}$$

The expected m -redundancy in the region with nodes and obstacles is given by

$$R_m = 2\pi\left(\chi\mu\lambda_0 - (4\pi)^{-1}(\beta\mu\lambda_0)^2\right)e^{-\alpha\mu\lambda_0}V_0 \tag{2.25}$$

Similarly, the expected k- redundancy in the region with nodes and obstacles is given by

$$R_k = 2\pi V_0\mu\lambda_0 e^{-0.5\alpha\eta} E\left[\exp\left\{-0.5\eta\left(\|S\|_2 + (2\pi)^{-1}\beta\|\partial S\|_1\right)\right\}\right] \tag{2.26}$$

If the m-redundancy is due to the power-saving algorithm implemented to schedule sleep states for nodes, then this redundancy can be increased to achieve n-redundancy to satisfy reliability of data collection in the network, albeit at increased energy consumption. Another technique to achieve increased sensing redundancy in a region of voids present due to node failure is to deploy mobile sensors that can navigate to that sub-region of the deployment grid that has a void in the sensing coverage (Wang, Cao and Porta, 2006).

Next, we obtain the number of neighbors of a node to obtain the connectivity properties of PCPP process of nodes. The expected number of neighbors of a node N is given by the mean number of coverage area disks of other nodes intersecting a given node's coverage area (equation (2.13)). Modifying it for the PCPP process, the number of neighbors is given by,

$$N = \left[\mu\lambda_0\left(\|S\|_2 + \alpha + (2\pi)^{-1}\beta\|\partial S\|_1\right)\right] \tag{2.27}$$

With N neighbors, the probability that a sensor has at least k neighbors, where $1 \le k \le N$ is given by 1-Pr (no neighbors)= 1- Pr($N = 0$). Here, N=0 implies

$$N = 0 \Rightarrow v(S) = 0$$

This implies that a) λ_0 = 0 representing only one sensor in the entire region or b)R=0 denoting that the coverage area of a node is a point.

2.5 Performance Evaluation

In this section, we present the results of our simulation for coverage properties of nodes in a PCPP process over the deployment region. Figure 2.3 shows the expected vacancy in a region without obstacles, assuming the Poisson process and the PCPP distribution of node placement. We compare this with the results in Fig. 2.6, where we assume nodes in a PCPP process in a deployment region with obstacles. A common feature in both these figures is the decrease in vacancy with increase in the intensity of nodes in the region. However, the PCPP process exhibits higher vacancy in the region than a Poisson process of node placement. Although the coverage radius is fixed in real-time deployment, we vary it to show the obvious effect on the vacancy. A smaller coverage area of a node increases the total vacancy.

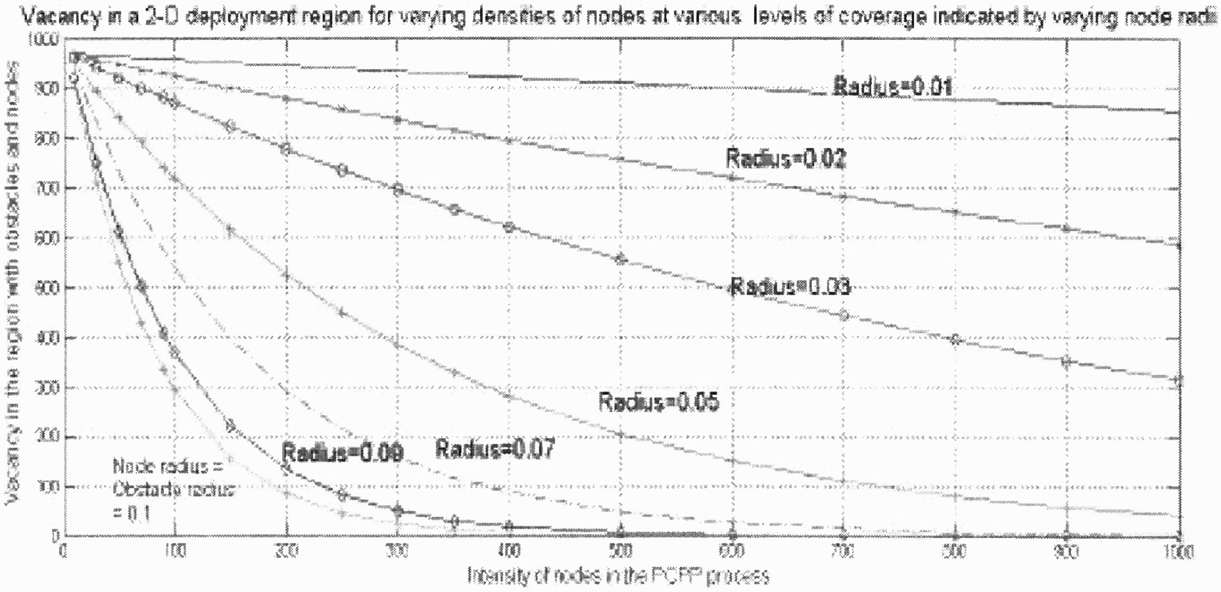


Figure 2.6 Expected vacancy in a deployment region of PCPP nodes and Poisson distributed obstacles with varying coverage.

We also show the results for when the obstacles are small enough and are only about the size of a node. As obstacle radius increases for a given intensity of a PCPP process for nodes, the expected vacancy reduces. Figure 2.7 shows the number of clumps minus voids (m-redundancy) in a region with PCPP nodes and obstacles, where $m < k$ denotes the redundancy that can be increased to a level k.

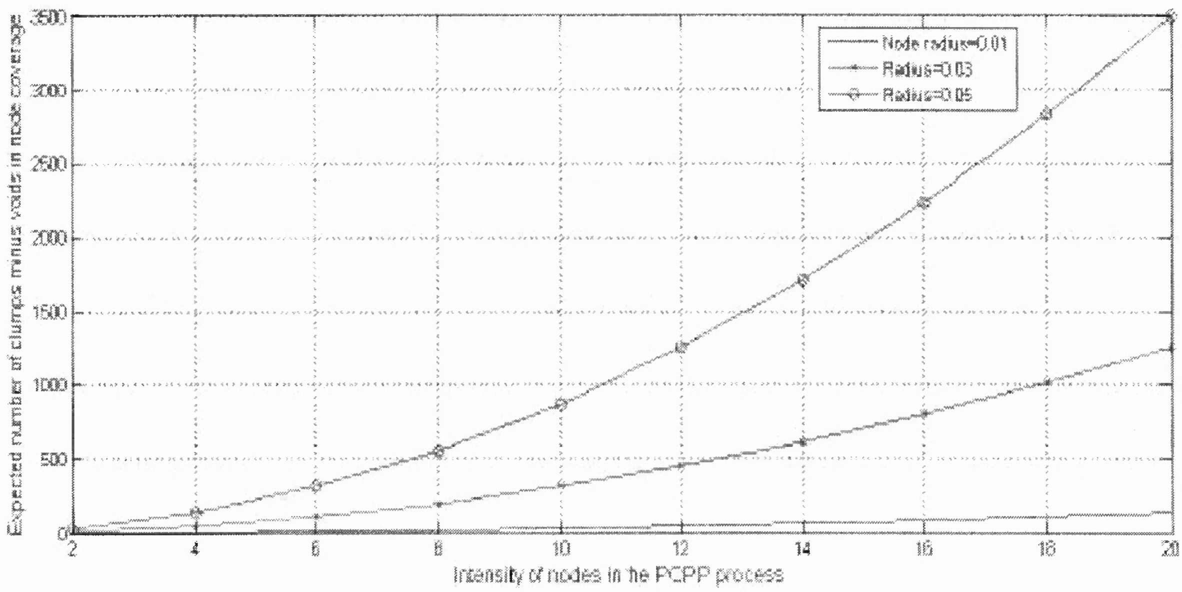


Figure 2.7 Expected m-redundancy in node coverage

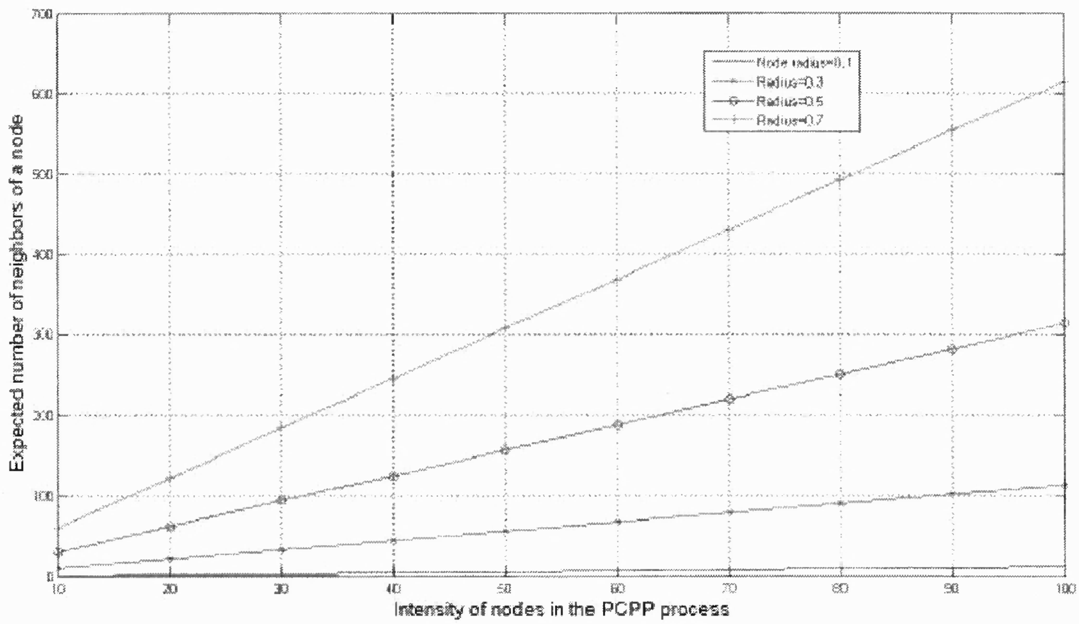


Figure 2.8 Expected number of neighbors of a node

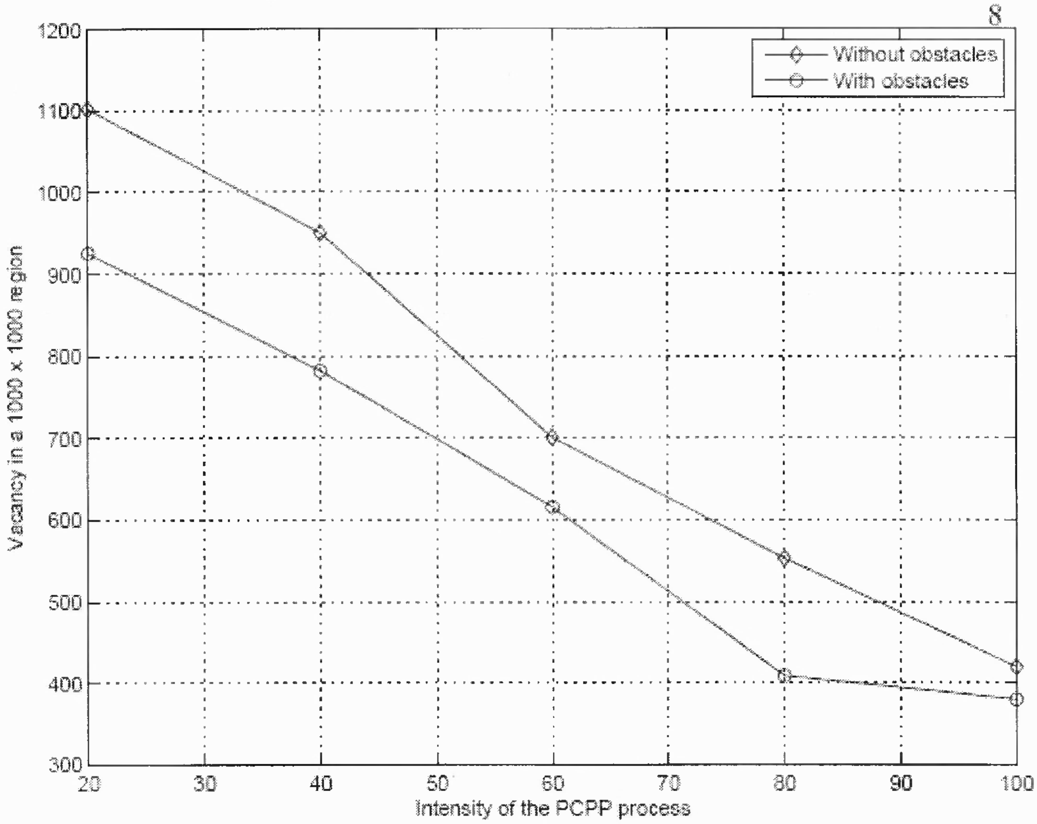


Figure 2.9 Comparison of vacancy in a WSN of PCPP-distributed nodes with and without obstacles

As the intensity of nodes increases, the m-redundancy increases in the region. Finally, Figure 2.8 shows the number of neighbors of a node in a WSN PCPP process of node distribution. As expected, the number of neighbors increases with the intensity of the PCPP nodes. The coverage in the presence of obstacles is compared in Figure 2.9. We assume the obstacles to be 10 times larger in radius than the WSN nodes and we assume that they are Poisson distributed in the deployment region. We also assume that obstacles and nodes cannot occupy the same area, hence the expected vacancy with obstacles is lesser than without obstacles. This is verified in Figure 2.9, where the vacancy with obstacles is significantly lower than without obstacles. These results draw attention to the need for realistic simulation of the placement process of nodes in WSNs by considering the natural tendency of clustering in a random deployment process and the presence of obstacles in the deployment region.

2.6 Conclusions

We have given an introduction to coverage properties in clustered networks of wireless sensor nodes. We looked at coverage in terms of the expected vacancy, m-coverage and k-coverage, ($k < m$) where coverage in m-redundancy indicates the coverage that can be decreased to that achieved by k-redundancy by power management. Having built up the theory for clustered nodes in a deployment region, we analyze the coverage properties in a realistic scenario with obstacles in the deployment region. These results started with an initial guess to the properties of coverage in clustered networks, where clustered networks have larger vacancy in the deployment region which has been verified by simulation results. Although this chapter studies clustered networks of wireless sensor nodes, it can easily be extended to include a structured analytical model for ad hoc networks of mobile nodes. In general this analysis replaces the often used notion of coverage in a Poisson deployment of nodes. The next chapter incorporates exploiting the coverage properties of clustered networks for adaptive density through power management schemes for WSNs.

CHAPTER 3

POWER MANAGEMENT THROUGH ADAPTIVE DENSITY CONTROL

3.1 Introduction

We study active coverage in naturally clustered wireless sensor networks (WSNs), a term which we use to define the topology of WSNs arising as a consequence of the random deployment process as opposed to clustering by choice. We find that the natural clustering can be used to exploit the inherent redundancy in the topology, which can be characteristically used for power management in these networks. By employing coverage processes and optimization theory, we show that any topology of WSN derived from random deployments can result in maximum coverage for the given node density and power constraints by satisfying a set of conditions. Although the framework of naturally clustered networks is not a pre-requisite for the study of coverage optimization and network lifetime extension, we discuss how it plays a key role in determining network behavior. We discover a functional relationship between the redundancy, density of nodes and cluster-heads for active coverage, and the network lifetime. This relationship is much less pronounced in the absence of natural clustering.

Considerable attention has been given to the issue of density control for power management in dense randomly deployed WSNs (Machado and Tekinay, 2007), (Machado and Tekinay, 2008). The motivation for this research area arises from the redundancy afforded by dense WSNs, where k-redundancy refers to k>1 sensors sensing any given point (x, y) in the deployment region at all times. Random deployment procedures may result in such topologies with k redundancy; however, power management and reliability constraints require that we do not need all k sensors sensing the point (x, y). This has given rise to the notion of n-coverage, where at least n $(1<n<k)$ of the k sensors are in the awake mode of operation. This method of scheduling a node to operate in awake/sleep states contributes to power management by reducing the duration of idle mode of transceiver operation in a node. Previous studies (Kahn, Katz and Pister, 1999), (Heinzelman, Chandrakasan and Balakrishnan, 2000) and (Asada et. al. 1998) have shown that the power consumption in the 'awake' state is at least an order of magnitude greater than that in the sleep state. Within the awake mode of operation, the idle mode of listening for transmissions from the BS or other nodes consumes as much energy as the transmit operation. Clustering of nodes (Heinzelman, Chandrakasan and Balakrishnan, 2000), (Vlajic and Xia, 2006) to reduce transmissions of redundant data is one approach for power management in WSNs.

There are two general ways in which clustering may be facilitated. The first is clustering by selection, which is the most common method cited in current literature on clustering in WSNs. The second way to facilitate clustering is manifested in naturally clustered WSNs, which lacks attention. However, naturally clustered sensor networks are quite common due to the uncontrollable deployment in many situations and thus their characteristics can provide valuable reference for sensor network design. In this chapter, we study density control for 'naturally clustered' WSNs. As opposed to clustering by selection, we define naturally clustered networks, where CHs are not chosen from among the nodes. We assume that CHs are a distinct set of nodes scattered over the region with a smaller intensity of distribution than that of regular nodes. Thus we assume a 2-tier hierarchy comprising of 2 distinct sets of nodes: sensor nodes and CHs. The CHs are assumed to be robust, less power-constrained and larger (akin to localized processing stations) that are capable of intensive processing and computation as compared to those of the sensor nodes. The CHs are also responsible for communicating to other CHs and relaying cluster data to the BS. The nodes that lie within the communication region of a CH are assumed to lie within its cluster.

In order to study the impact of natural cluster formation on energy conservation, we formulate two objectives. The first objective is the minimization of vacancy, where vacancy in the deployment region is defined as the area which does not lie within the sensing range of any node. The second is improvement of network lifetime. Mathematically, it is equivalent to the following question: What should be the densities of CHs and active nodes to ensure minimum vacancy and extend network lifetime with given *k*- redundancy of nodes? Note that, as mentioned earlier in the introduction, *k*-redundancy refers to the actual redundancy as a result of deployment, while active coverage resulting from *n*- redundancy ($n < k$) refers to the actual number of nodes that are in the awake mode sensing a given point.

This chapter addresses the problem of density control for active coverage in naturally clustered WSNs. Assuming that the deployment region is covered with nodes and CHs according to Poisson processes with intensity λ_1 and λ_2 respectively, where $\lambda_2 < \lambda_1$, we study density control for the following two cases:

1) All-on network, where all the nodes are continuously on, providing *k*-active coverage in a network with *k*- redundancy.

2) Power management, where a node can be in one of two states- on (awake) or off (sleep), where the off state denotes that the node powering down its sensors and

actuators, transceivers and computation circuitry. The 'on' state denotes that the state can be transmit, receive or idle state while also performing sensing for the duration of the 'on' state. This power management models more realistic deployment scenarios for WSNs to prolong network lifetime.

We analyze both the 'all-on' case and 'power management' cases for various network configurations resulting from combinations of densities of CHs and nodes in the deployment region. Specifically, we analyze the following combinations:

1) Dense networks with high density of nodes and CHs

2) Regular density networks with high density of nodes but low density of CHs

3) Sparse networks with low density of nodes and low density of CHs

4) The fourth case of low densities for nodes and high density of CHs is not feasible, and hence will not be investigated.

The 'all-on' and power management cases are analyzed with respect to meeting power management and coverage objectives. In the 'all-on' case, the emphasis is on efficient network design and coverage by choosing the optimum ratio of intensities for CH and node distributions. In the power management case, the emphasis is on minimizing vacancy (maximizing coverage) by increasing the density of active coverage while satisfying network power constraints to enhance network lifetimes over the 'all-on' case. In this chapter, we make the following contributions: we provide expressions to optimize coverage in the deployment region. We also analyze the optimization of active coverage in a *k*-redundancy WSN with various topologies while ensuring that power constraints of network operation are satisfied. While the latter case of power management does provide closed form solutions to the problem of coverage optimization versus network lifetime extension, we show with the help of numerical simulations that the proposed model for network lifetime extension by optimizing active coverage for various densities of nodes and CHs increases network lifetime while simultaneously achieving maximum coverage. This work lays the groundwork for analysis of coverage properties and power control in various topologies of naturally clustered networks and opens research issues for other topologies of naturally clustered networks.

Related work: One category of related work is the study on network clustering by selection, which is the most common method cited in current literature on clustering in WSNs. We now provide a quick overview of literature on clustering in WSNs. For a detailed section on related work, we refer the reader to Section 1.4 of this dissertation. Clustering of nodes and selecting a cluster-head (CH) for a cluster of nodes are techniques for power management that emerged due to the features of data redundancy arising from the geographical proximity of nodes and *k*-redundancy in WSNs. The CH is chosen based on metrics such as highest residual battery energy (Heinzelman, Chandrakasan and Balakrishnan, 2002), closest to the base station (Shu, Krunz and Vrushula, 2005) and AMRP (Younis and Fahmy, 2003). This approach of clustering and CH selection offers the convenience and economy of in-node/in-cluster processing of data to reduce transmissions of redundant data, power control scalability, and improvement in network lifetime. We call these clustering approaches as clustering by selection where clusters are chosen according to some pre-determined criteria.

The rest of the chapter is organized as follows: Section 3.2 presents the coverage model for various densities of nodes in a WSN. In section 3.3, we develop the analytical model to obtain the optimum ratio of densities of nodes and CHs to maximize coverage in WSNs in an 'all-on' network. We perform this analysis for different topologies offered by combinations of densities of CHs and nodes. Section 3.4 discusses the power management constraint that is to be satisfied while performing coverage maximization for various densities of clustered WSNs. Section 3.5 presents the numerical results of the proposed power management model. Finally, Section 3.6 concludes the chapter and presents future research directions.

3.2 Coverage Model

A process P is said to be a stationary or homogenous Poisson point process P with intensity λ if (Hall, 1988):

1) The number of points ξ_i in any Borel subset S of R is Poisson distributed with mean $\lambda\|S\|$ and

2) The numbers of points in any number of disjoint Borel subsets are independent random variables.

A process is called stationary if and only if the function λ is constant almost everywhere. A Boolean model in k-dimension Euclidean space is just the coverage pattern created by a Poisson-distributed sequence of random sets. Specifically, let $P \equiv \{\xi_i, i \geq 1\}$ be a stationary Poisson process of intensity λ in R, the points ξ_i being indexed in any systematic order. Let $S_1, S_2, \ldots$ be i.i.d. random sets, independent of P. Then,

$$C \equiv \{\xi_i + S_i, i \geq 1\} \tag{3.1}$$

is a Boolean model, where the Poisson process P is said to drive the Boolean model, and the shapes S_i are said to generate the model. The expected vacancy within a region R denoted by $E(V)$ [13] is

$$E(V)=\|R\|\exp\left(-\lambda\|S\|\right) \tag{3.2}$$

where λ is the intensity of the point process for nodes, $\|R\|$ is the area of the deployment region, and $\|S\|$ is the expected area of the node coverage. This vacancy denotes the part of the deployment region that is not covered by any node. In contrast to this moderate distribution of nodes in the deployment region, some WSN applications may call for dense networks with higher concentration of nodes resulting in lesser vacancy in the region. The high intensity of nodes in the deployment region differs from the case of moderate intensity, in that vacant areas of the region are fewer and smaller. The vacancy in a 2-D deployment region due to high intensity distribution of nodes with circular coverage disks is given by [13]

$$E_{V_d}=\frac{\sqrt{\pi}\Gamma(3)}{\Gamma(1.5)}\left\{\frac{2\Gamma(1.5)}{\lambda\Gamma(1)}\right\}^2=\frac{a}{\lambda^2} \tag{3.3}$$

where a is a constant given by

$$a=\frac{\sqrt{\pi}\Gamma(3)}{\Gamma(1.5)}\left(2\Gamma(1.5)\right)^2$$

In the other case of sparse networks with low intensity distribution of nodes, where the vacancy in the 2-D deployment region R is almost equal to the area of the region R, the probability that any two coverage disks will not intersect each other is very high. In such a scenario, an approximation to the vacancy in a sparse network is given by [13]

$$E_{V-sparse}=\|R\|-E(N)\delta^k E\left(\|S\|\right) \tag{3.4}$$

where N is the number of nodes in the deployment region, $E\left(\|S\|\right)$ is the area of the coverage disk of any node S, and δ denotes the scale parameter as a function of the intensity λ of distribution of nodes. We will use these results from the theory of coverage processes for varying densities of nodes in a Boolean model for optimizing the tradeoff between coverage and network power consumption in the rest of this chapter.

3.3 Coverage Optimization in All-On WSN

In this section, we perform coverage optimization in WSNs of various topologies to obtain the maximum coverage with given intensities of distribution of nodes and CHs in the deployment region. The optimization for each topology follows the simple procedure below:

1) Obtain the objective function $f(\lambda_1, \lambda_2)$ in each of these cases the objective is to minimize vacancy for the given topology.

2) Obtain the constraint function $g(\lambda_1, \lambda_2)$. In this section, since we are assuming an 'all-on' network, the constraint is that all nodes are in the 'on' state.

3) Finally, we perform convex optimization of the vacancy subject to the all-on constraint. In the mathematical analysis some of the objective and constraint functions are non-convex, quadratic and/or conic. We follow the standard procedures outlined in (Jensen and Bard, 2002) and (Kliemann and Srivastav, 2008) to linearize the optimization problems. We now present the final results of the optimization.

Dense Networks

Owing to the high density of nodes and CHs, we expect the vacancy in the deployment region to be low (approximately equal to zero). We perform this optimization subject to the constraint that area no more than that of the sensing region of a node should be vacant.

$$E_{V-Cluster} - E_{V-Node} \leq A_{node}.h \tag{3.5}$$

where h is some constant greater than the number of nodes, $E_{V-Cluster}$ is the vacancy in the region after deploying the CHs in the deployment region and E_{V-Node} is the vacancy in the region after deploying the nodes, and A_{node} is the area of the circular coverage disk of a node with radius R_1. The vacancy due to high density λ of nodes in a 2-dimensional deployment region is given by (3.3) from Section 3.2. For densities λ_2 for CHs and λ_1 for nodes, the objective function of vacancy in the 2-D deployment region becomes

$$a\left\{\frac{1}{n_2\lambda_2^2} - \frac{1}{n_1\lambda_1^2}\right\} < \pi h R_1^2 \tag{3.6}$$

where n_2 and n_1 are the number of CHs and nodes, respectively, in the deployment region. The objective function $f(\lambda_1, \lambda_2)$ is given by

$$f(\lambda_1, \lambda_2) = \frac{1}{n_2\lambda_2^2} - \frac{1}{n_1\lambda_1^2} - bR_1^2 \tag{3.7}$$

where $b = \pi h/a$ is a constant subject to the constraint that all nodes are 'on'. Applying the Lagrange duality theory for the original problem, we take the constraints into account to formulate the Lagrangian of (3.5). The Lagrangian optimization (Boyd and Vandenberghe, 2004) is thus

$$\Delta(\lambda_1, \lambda_2) = \frac{1}{n_2\lambda_2^2} - \frac{1}{n_1\lambda_1^2} - bR_1^2 + \lambda\left(\frac{e^{-\lambda_1}\lambda_1^{n_1}}{n_1!} + \frac{e^{-\lambda_2}\lambda_2^{n_2}}{n_2!}\right) \tag{3.8}$$

Regular Networks

We call regular networks as WSNs with high density λ_1 of nodes and low density of λ_2 of CHs in the deployment region. In such a network, we approximate the vacancy in the region after deployment of CHs and nodes to be approximately equal to zero. To determine the vacancy, we use the equations from vacancy for low density of disks for CHs and high density of nodes from Section 3.2. Thus the objective function f for vacancy minimization is

$$f(\lambda_1, \lambda_2) \approx 0$$

$$E_{V-Cluster} - E_{V-Node} \approx 0 \tag{3.9}$$

The objective and constraint functions for sparse networks are as follows:

$$\begin{aligned} f(\lambda_1, \lambda_2) &= \|R\|\left(1 - n_1\lambda_1^{\,2}\pi R_1^2\right) - \frac{a}{\lambda_2^{\,2}} \\ s.t.\, g(\lambda_1, \lambda_2) &= \frac{e^{-\lambda_1}\lambda_1^{n_1}}{n_1!} + \frac{e^{-\lambda_2}\lambda_2^{n_2}}{n_2!} \end{aligned} \tag{3.10}$$

Simplifying the constraint function using expressions from inequality theory (Kazarinoff, 1961), we get

$$\lambda_1 = 1 - \frac{2a}{\|R\|\eta} e^{\frac{2}{3}(n_2 - n_1)} + e^{n_2 - n_1} \tag{3.11}$$

for the density of nodes, and,

$$\lambda_2 = \left(\frac{2a}{\|R\| e^{(n_2 - n_1)} \lambda_1^{\,2} \pi R_1^2} \right)^{1/3} \tag{3.12}$$

for the density of CHs. Thus, the ratio of densities for efficient coverage of the deployment region in WSN applications for regular networks is given by λ_1 / λ_2.

Sparse Networks

Due to the low density of nodes and CHs, we expect the vacancy in the deployment region to be high, but no larger than that of the sensing range of a CH to ensure connectivity. We perform this optimization subject to the constraint that area no more than that of the sensing region of a node should be vacant.

$$E_{V-Cluster} - E_{V-node} \leq A_{CH}.c \quad (3.13)$$

where c is some constant equal to the number of CHs, and A_{CH} is the area of the circular coverage disk of the CH with sensing radius given by R_2. Using the equations for sparse networks from Section 3.2, the objective function for minimizing vacancy is given by

$$f(\lambda_1, \lambda_2) = \pi\left(\lambda_1^2 n_1 R_1^2 - \lambda_2^2 n_2 R_2^2\right) \quad (3.14)$$

Minimizing $f(\lambda_1, \lambda_2)$ subject to $g(\lambda_1, \lambda_2)$ which is the same as those in previous two sections, we get

$$\lambda_1 = 1 + \frac{\eta_{node}}{\eta_{CH}}(\lambda_2 - 1) \quad (3.15)$$

where, $\eta_{CH} = \lambda_2{}^2 \pi R_2^2$ and $\eta_{Node} = \lambda_1{}^2 \pi R_1^2$.

This gives us the ratio of densities for the case of all on WSN for maximizing coverage with given topology of sparse nodes.

3.4 Coverage Optimization in a WSN with Power Management

A key challenge in energy optimization for densely deployed WSNs is selecting the set of sensors that remain awake for a given cycle. Some of the criteria developed for choosing the set of active nodes are environment probing (Ye, Zhang, Lu and Zhang, 2003), *k*-coverage (Wang et. al. 2003), and connectivity-based participation in multi-hop network (Estrin and Cerpa, 2004). In an on-demand network, the BS can query the network on either a random schedule or in response to the changes in the underlying phenomenon monitored by the WSN. For example, a rapidly changing physical parameter calls for higher number of 'awake' nodes that can observe and report the change in phenomenon. In this case, the rate of change of the environmental parameter influences the energy consumption at nodes, causing a higher number of transmissions from nodes to CHs or to the sink through other nodes that act as relays. While we do not consider the pattern of environment variation that triggers queries from the BS, prior work in (Machado and Tekinay, 2008) develops an energy model which considers reliability of WSN operation and impact of sensing environment variation and studies their impact on the network lifetime. However, we use the number of broadcast messages as an indication of network activity, through which we study the latency and network lifetime performance of the WSN with and without power management.

Problem Formulation

How do we ensure that the power consumption of the network ψ with n nodes does not exceed a threshold λ, while still minimizing vacancy for different topologies? We assume that a node j can be in either one of two states: on with a probability p_j or off with a probability $1 - p_j$ for an amount of time t. We also assume the power consumption for a node j in either state is given by w_j, where $w_{j\text{-}off} \square\ w_{j\text{-}on}$, i.e. power consumption in off state is much less than that in on state and p_j denotes the probability of node j being in either on state and $1 - p_j$ denotes probability of node being in off state.

To proceed with the formulation of the power constraint ψ, we define the power consumption ψ as the sum of the power consumption of very node j in the on/ off state. The state of very node in the network is represented by X_j, where for all j= 1; 2,...N, the states of any two nodes A and B are mutually independent of each other. We assume this for simplicity of calculation, since in practice the decision to switch a node to the on/off state depends on various factors such as the amount of coverage desired for the application, residual battery energy and the reliability constraints. Since the states X_j alternate between one of two states (on/ off), the power constraint ψ can be formulated as a binomial random variable with mean $\bar{\lambda} = np$ and variance $\sigma^2 = np(1 - p)$. Hence,

$$\psi = \sum X_j \tag{3.16}$$

Since the power consumption of the network should satisfy the constraint of being $< \lambda$, we need to find the probability of

$$P(\psi < \lambda)$$

which is equivalently given by

$$1 - P(\psi \geq \lambda) \tag{3.17}$$

Since for some t,

$$P(\psi \geq \lambda) = P\left[\exp(t\psi) \geq \exp(t\lambda)\right] \tag{3.18}$$

$$\leq E\left[\exp(t\psi)\right] \tag{3.19}$$

$$= \prod_j E\left[\exp\left(tw_j X_j\right)\right] \tag{3.20}$$

where w_j is the power consumption of node j.

But $\forall j \in [n]$, where n is the number of nodes in the deployment region

$$E\left[\exp\left(tw_j\psi_j\right)\right] = p_j \exp\left(tw_j\left(1-p_j\right)\right) + \left(1-p_j\right)\exp\left(-tw_j\psi_j\right) \tag{3.21}$$

With further simplification, we get,

$$P(\psi \geq \lambda) = \prod E\left(1 + p_j\left(\exp\left(tw_j\right)-1\right)\right) \tag{3.22}$$

$$\geq \prod\left(1 + p_j tw_j (e-1)\right) \tag{3.23}$$

$$\leq \prod \exp\left(1 + p_j tw_j (e-1)\right) \tag{3.24}$$

Hence,

$$\therefore E\left(\exp(t\psi)\right) \leq \prod \exp\left(1 + p_j tw_j (e-1)\right) \tag{3.25}$$

$$\leq e \exp \sum_j (e-1)\, p_j tw_j$$

Thus, the complement of the power constraint becomes

$$P(\psi \geq \lambda) = P\left(\exp(t\psi) \geq \exp(t\lambda)\right) \tag{3.26}$$

$$\leq \frac{E\left[\exp(t\psi)\right]}{\exp(t\lambda)}$$

Substituting (25) into (26), we get

$$P(\psi \geq \lambda) \leq e \exp\left(t \sum_j (e-1)\, p_j w_j - t\lambda\right) \tag{3.27}$$

By letting $t = \lambda = \dfrac{(1/e)-1}{\sum_j p_j w_j}$, the LHS of (3.26) becomes

$$P(\psi \geq \lambda) = P\left(\frac{\psi - \overline{\lambda}}{\sigma^2} \geq \frac{\lambda - \overline{\lambda}}{\sigma^2}\right) \tag{3.28}$$

$$= 1 - \phi\left(\frac{\lambda - \overline{\lambda}}{\sigma^2}\right) \tag{3.29}$$

The RHS of (3.26) becomes

$$e \exp\left(1 - \left(\frac{(1/e) - 1}{\sum_j p_j w_j}\right)^2\right) \tag{3.30}$$

Neglecting the power consumption of nodes in the 'off' state since it is very small as compared to that in the 'on' state, the operand of the summation in the denominator of the RHS is dominated by the power consumption of nodes in the on state. Denoting w_{on} as the power consumption in the on state, and λ_p as density of nodes in the 'on' state, the RHS can now be re-written as

$$e \exp\left(1 - \left(\frac{(1/e) - 1}{p w_{on}}\right)^2 \frac{((n-1)!)^2}{e^{-2\lambda_p} \lambda_p^{\ 2n}}\right) \tag{3.31}$$

Let

$$\zeta = \frac{(1/e) - 1}{p w_{on}} (n-1)! \tag{3.32}$$

Using slack variables as in [28] to convert (26) to canonical form, we get,

$$\therefore 1 - \phi\left(\frac{\lambda - \overline{\lambda}}{\sigma^2}\right) \leq e \exp\left(1 - \zeta^2 e^{2\lambda_p} \lambda_p^{\ -2n}\right) \tag{3.33}$$

which can be written as

$$np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p} \lambda_p^{\ -2n}\right)\right] + np \leq \lambda \tag{3.34}$$

Equation (3.17) can further be written as

$$\lambda < 1 - np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p}\lambda_p^{-2n}\right)\right] + np \tag{3.35}$$

which gives us the power constraint for the power management problem for clustered WSNs.

We now summarize the coverage maximization vs. power management problem for various densities of nodes and CHs. Unlike the case for an all-on network, we cannot provide straightforward closed form equations for the ratios of densities of CHs to that of the nodes in the on state. This is due to the difficulty of obtaining a closed form solution for the problem of minimizing vacancy to that of maximizing network lifetime. In the next section, we provide numerical results for Monte Carlo simulation of the WSN with the constraints discussed in Section 2 and equation (3.35). In each case, we minimize vacancy subject to the power constraint in (3.35).

- **Dense WSNs**: From Section 3, the vacancy in a dense network of nodes and CHs given by (3.7) is optimized w.r.t. (3.35), i.e.,

$$f(\lambda_1, \lambda_2) = \frac{1}{n_2\lambda_2^2} - \frac{1}{n_1\lambda_1^2} - bR_1^2$$

$$\text{s.t. } \lambda < 1 - np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p}\lambda_p^{-2n}\right)\right] + np \tag{3.37}$$

- **Sparse WSNs**: From Section 3, the vacancy in a sparse network of nodes and CHs given by (3.15) is optimized w.r.t. (3.35), i.e.,

$$f(\lambda_1, \lambda_2) = \pi\left(\lambda_1^2 n_1 R_1^2 - \lambda_2^2 n_2 R_2^2\right)$$

$$\text{s.t. } \lambda < 1 - np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p}\lambda_p^{-2n}\right)\right] + np \tag{3.38}$$

- **Regular density WSNs**: From Section 3, the vacancy in a regular network of nodes and CHs given by (3.10) is optimized w.r.t. (3.35)

$$f(\lambda_1,\lambda_2) = \|R\|\left(1 - n_1\lambda_1^2\pi R_1^2\right) - \frac{a}{\lambda_2^{\,2}}$$

$$\text{s.t. } \lambda < 1 - np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p}\lambda_p^{-2n}\right)\right] + np \qquad (3.39)$$

- **Moderate density WSNs:** From Section 3, the vacancy in a moderate network of nodes and CHs is given by (3.2) and optimized w.r.t to (3.35)

$$f(\lambda_1,\lambda_2) = \|R\|\left(\exp\left(-\lambda_2^2 R_2^2\right) - \exp\left(-\lambda_1^2 R_1^2\right)\right)$$

$$\text{s.t. } \lambda < 1 - np(1-p)\phi^{-1}\left[1 - e\exp\left(1 - \zeta^2 e^{2\lambda_p}\lambda_p^{-2n}\right)\right] + np \qquad (3.40)$$

3.5 Results

First we present network performance results after density optimization in clustered networks without power management. Figure 3.1 shows the network lifetime in a WSN of randomly deployed nodes without taking into account of the clustering phenomenon. Defining network lifetime as the time until the first node runs out of battery energy, we obtain results for network lifetime with varying levels of network activity. We see that as the network activity (number of BC messages) increases, the network lifetime decreases due to the increased radio power consumption at nodes. The network lifetime also significantly decreases with the increase in the network size. For network size of up to 100 nodes, with fourfold increase in network activity (i.e. BC messages=10 vs. BC messages equal to 40), the network lifetime decreases almost four times as much. For network sizes greater than 150 nodes, as network activity increases, the network lifetime rapidly tends to zero.

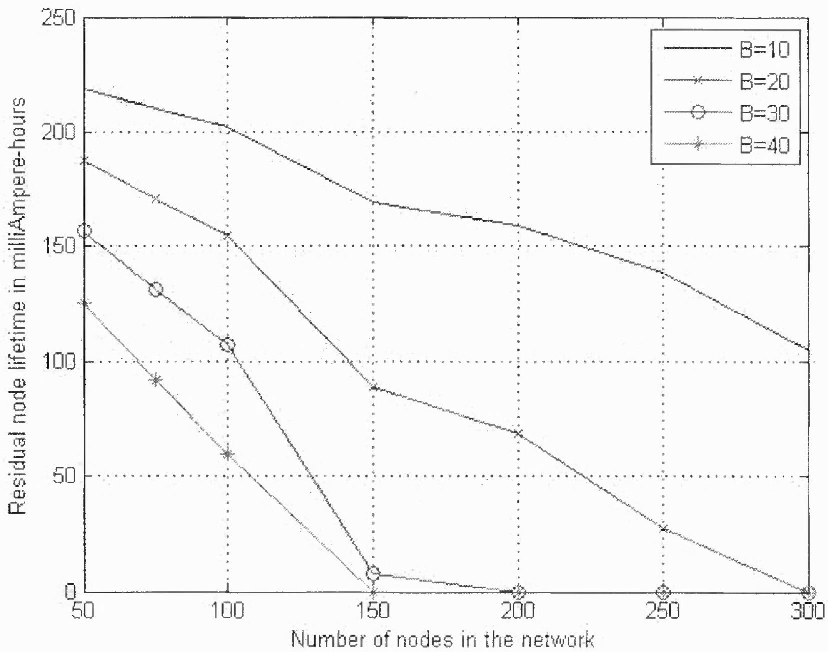


Figure 3.1 Network lifetime in a random deployment.

Figures 3.2 and 3.3 show a comparison of network lifetime simulation results for network performance obtained by density optimization versus those in random networks for the case of a mostly 'on' network, where the networks do not perform any power management through energy-saving modes of operation. In our model, nodes relay their data to the nearest CH, which then performs data processing and aggregation, and forwards it to the nearest CH. With clustering, the end-users of the data can benefit by reducing the amount of data-processing to obtain relevant information at the BS. Figure 3.2 shows the results of network lifetime in random and density optimized networks. For all levels of network activity, we see that density optimization results in higher lifetime than random networks.

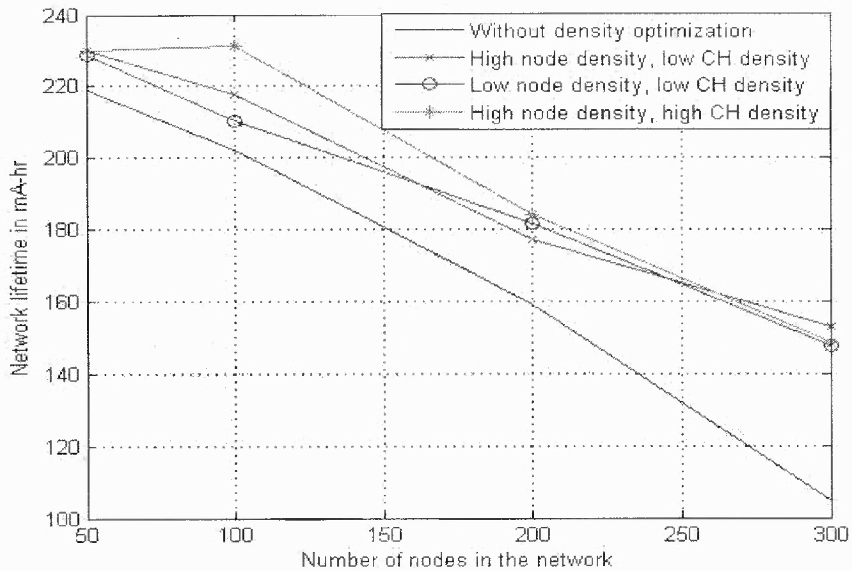


Figure 3.2 Network lifetime in a clustered WSN without power management, BC=10.

The improvement in network lifetime is significant for lower network activity (number of BC messages =10). For increased network activity (BC=30), the improvement in network lifetime is less significant. Within density optimized networks, we see that for low network activity, dense networks have higher network lifetime than sparse networks and networks with high density of nodes and low density of CHs. This is because for low network activity, network lifetime is greatly dependent on the node's radio consumption and microprocessor power consumption is much smaller than the node radio consumption.

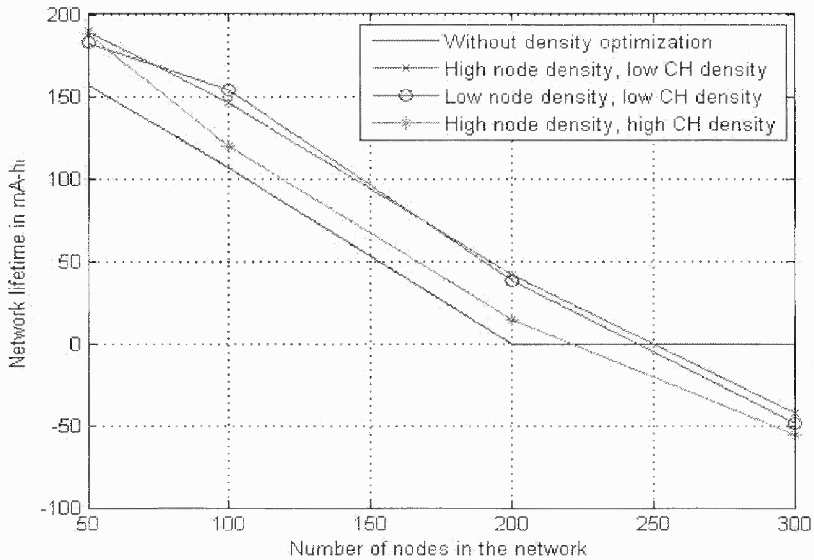


Figure 3.3 Network lifetime in a clustered WSN without power management, BC=30.

For higher activity, sparse networks have larger inter-node distances, while networks with high density of nodes and low density of CHs have larger cluster sizes. The large inter-node distances in sparse networks prevent communication between nodes, and hence resulting in higher network lifetime. Dense networks have the lowest network lifetime for high network activity since the increased number of clusters and higher activity cause faster depletion due to the radio and microprocessor activity. The best case to satisfy coverage and connectivity is a high density of nodes and low density of CHs, since it results in a small number of clusters that dense networks and provides the same level of coverage and connectivity.

Figures 3.4 and 3.5 presents results for the time until the last node runs out of battery energy. Similar to the network lifetime results (Figures 3.2 and 3.3), density optimization increases the time until the last node runs out of battery energy for all levels of network activity. Within density optimization, sparse networks still have the longest

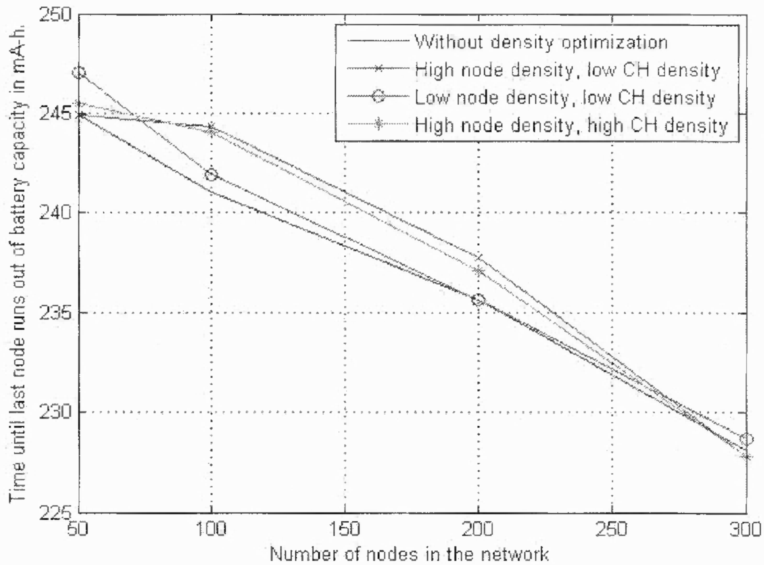


Figure 3.4 Last node lifetime in a clustered WSN without power management, BC=10.

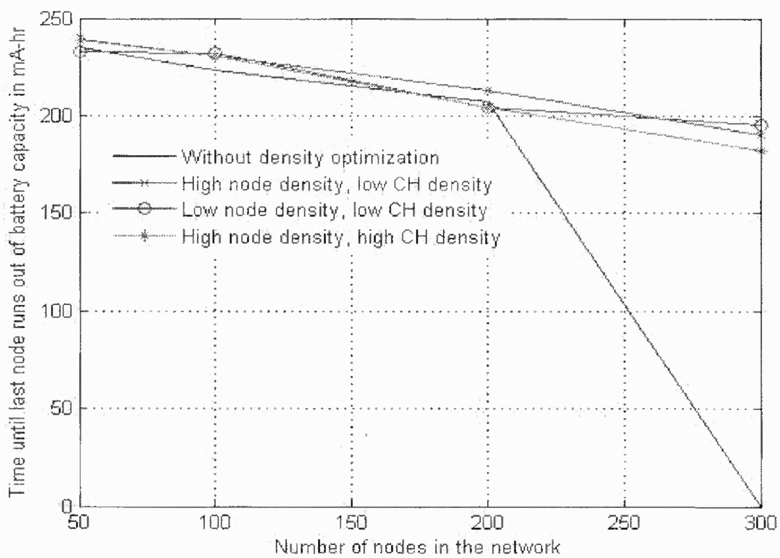


Figure 3.5 Last node lifetime in a clustered WSN without power management, BC=30.

time until the last node runs out of battery energy. However, this scenario is not feasible due to the reduced coverage and connectivity in the WSN. Dense networks and regular density networks both have comparable time until the last node runs out of battery energy due to high network activity, with the latter case exhibiting slightly higher network lifetime due to reduction in number of clusters.

Next, we present network performance results after density optimization in clustered networks with power management. In this section we present results for the case where power management is implemented in the network such that nodes can be in one of two states: 'on' or 'off'. We use the following simulation parameters for obtaining the expected battery lifetime of sensor nodes and CHs and their impact on network lifetime and latency. These specifications are obtained from the product specifications for the MICAZ 2.4 GHz, IEEE/ZigBee 802.15.4 wireless modules for low power wireless sensor networks. Model 1 refers to the state where nodes are in the 'on' state all the time (continuously sensing and data gathering and transmission), whereas Model 2 refers to the case where nodes stay in the 'on' state according to some duty cycle. We present simulation results for different probability p that a node is in the 'on' state. The optimization here is performed for the highest network activity (number of BC messages = 40) with respect to minimizing the vacancy for each scenario of node and CH densities, and subject to the power constraint imposed by the given value of p.

Figures 3.6 and 3.7 present comparison of network lifetime between random and density optimized networks for different values of p. Similar to WSNs without power management, sparse networks exhibited the highest network lifetime due to the minimum number of node connections as compared to other networks. With the increase in p from 0.2 to 0.7, the network lifetime reduces due to increased activity of nodes in the 'on' state. Dense networks had the lowest network lifetime due to the increased cluster maintenance and intra- and inter-cluster activity.

Networks with dense nodes and low density of CHs reported highest network lifetime with power management. A comparison between Figures 3.3 and 3.7 show that power management results in higher network lifetime for WSNs. Table 3.1 shows the simulation parameters used in calculation of network lifetime for the two models (all-on network and power-management network) using the IEEE 802.15.4/ZigBee model.

Table 3.1 Simulation parameters for battery life in clustered WSNs

Currents			**Duty Cycles**		
	Value	**Units**	**Model 1**	**Model 2**	**Units**
Micro Processor (Atmega128L)					
Current (full operation)	6	Ma	100	0.5	%
Current sleep	8	Ua	0	99.5	%
Radio					
Current in receive	8	Ma	75	0.4	%
Current xmit	12	Ma	25	0.1	%
Current sleep	2	Ua	0	99.5	%
Logger					
Write	15	Ma	20	0	%
Read	4	Ma	20	0	%
Sleep	2	Ua	60	100	%
Sensor Board					
Current (full operation)	5	Ma	99	0.5	%
Current sleep	5	Ua	1	99.5	%
Battery Specifcations					
Capacity Loss/Yr	3	%			
Computed mA-hr used each hour			**Model 1**	**Model 2**	
uP			0.06	0.0380	
Radio			0.09	0.0460	
Flash Memory			0.003	0.0020	
Sensor Board			0.0550	0.0300	
Total current(ma-hr) used			**0.2375**	**0.1159**	

Source: http://www.xbow.com/Products/productdetails.aspx?sid=164, accessed March 12, 2009.

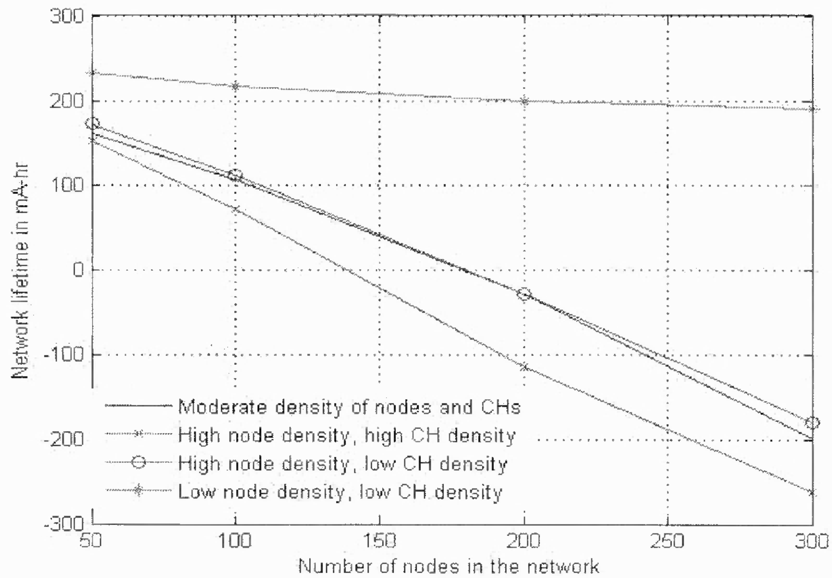


Figure 3.6 Network lifetime in a clustered WSN with power management for p=0.2.

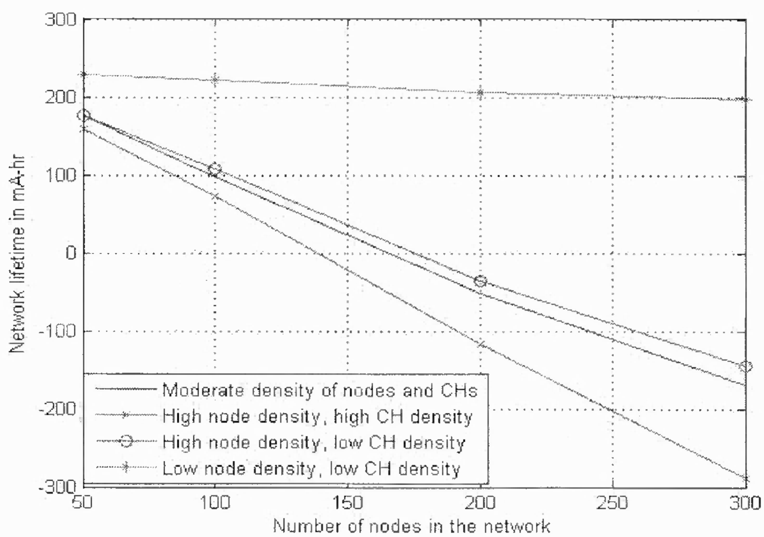


Figure 3.7 Network lifetime in a clustered WSN with power management for p=0.7.

Figures 3.8 and 3.9 compare the time until the last has run out of battery energy for random and density optimized networks for different values of p. With increase in p, the time until the last node runs out of battery energy drops due to the increased battery exhaustion in the 'on' state.

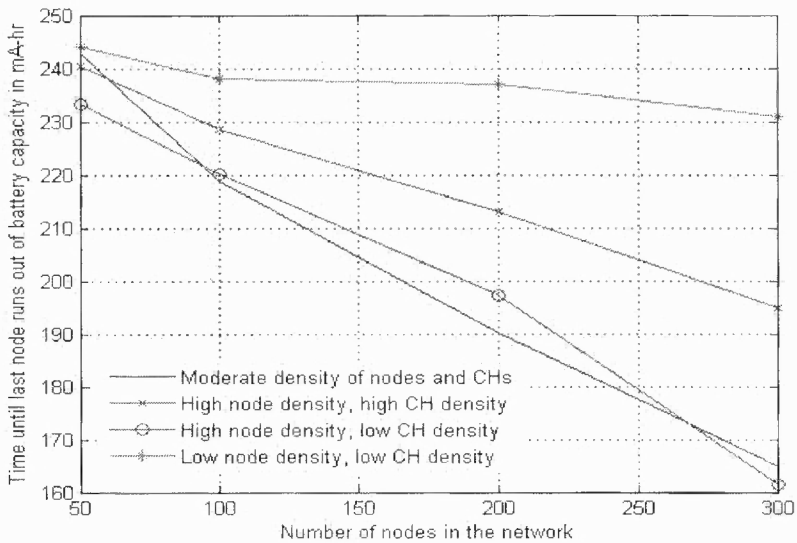


Figure 3.8 Last node lifetime in a clustered WSN with power management for p=0.2.

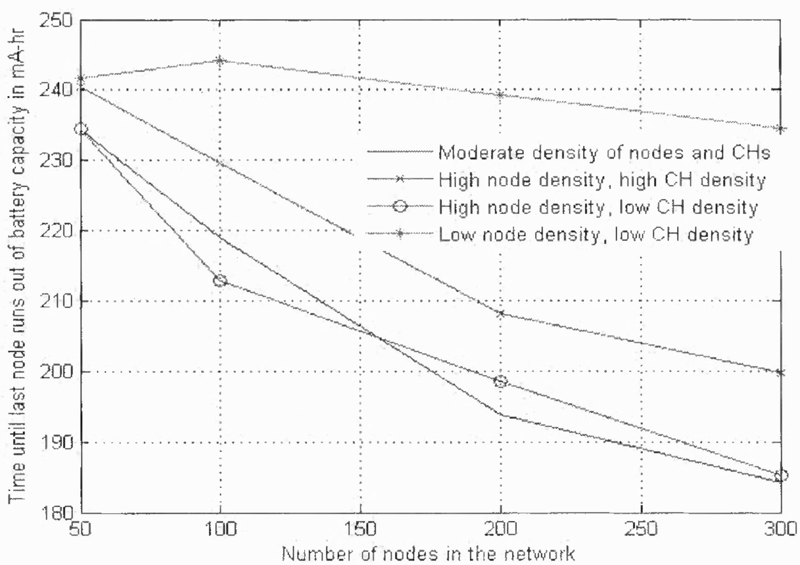


Figure 3.9 Last node lifetime in a clustered WSN with power management for p=0.7.

Similar to the network lifetime results (Figures 3.6 and 3.7), sparse networks have the longest time until the last node runs out of battery energy. Dense networks have the highest network lifetime with the exception of sparse networks, closely followed by networks with high density of nodes and low density of CHs.

3.6 Conclusions

In this chapter, we have used the concepts of coverage processes and optimization theory to explore coverage in various topologies of naturally clustered WSNs. We show that in naturally clustered WSNs, where cluster formation and CH selection are a consequence of random deployment procedures. While the definition of naturally clustered networks encompasses many different topologies, we focus on the topologies generated by various combinations of densities of nodes and CHs. In each case, we provide expressions to optimize coverage in the deployment region. We also analyze the optimization of active coverage in a k-redundancy WSN with various topologies while ensuring that power constraints of network operation are satisfied. While the latter case of power management does provide closed form solutions to the problem of coverage optimization versus network lifetime extension, we show with the help of numerical simulations that the proposed model for network lifetime extension by optimizing active coverage for various densities of nodes and CHs increases network lifetime while simultaneously achieving maximum coverage. This work lays the groundwork for analysis of coverage properties and power control in various topologies of naturally clustered networks and opens research issues for other topologies of naturally clustered networks. Our future work in this area will be analyzing the network lifetime for dense WSNs, where the definition of network lifetime provides a more accurate representation of the residual sensing and communication capacity, as opposed to the conventional definition of network lifetime which uses the time until the first node runs out of battery energy. In the next chapter, we analyze the queuing properties of clustered networks that address the issues of edge effects and starvation in WSN operation.

CHAPTER 4

CONNECTIVITY AND QUEUING IN CLUSTERED WSNs

This chapter concerns the study of connectivity from nodes to CHs and the impact of edge effects on admission control at CHs. In the first section, we investigate the amount of randomness in establishing a link from any node in the network to a CH. We present tight bounds on this randomness for different scenarios of network density. The knowledge of the entropy to establish connectivity is crucial in determining the connectivity graph of dynamic networks. The bounds presented verify the impact of cluster density on routing in WSNs. In the next section, we study the impact of edge effects on admission control at CHs. We formulate the directed ignoring model and evaluate the performance of a clustered network. We show that the directed ignoring model improves system performance by optimizing the tradeoff between packet loss and waiting time in large networks.

The rest of this chapter is organized as follows: Section 4.1 studies the entropy E_c to establish connectivity from a node to a CH in the WSN. describes related work in admission control and queuing policies in wireless networks. Section 4.1.1 presents bounds on E_c for various scenarios of clustered networks. In Section 4.2, we present the background for queuing analysis in wireless networks. Section 4.3 describes related work in queuing admission control. Section 4.4 presents the directed ignoring model for heavy traffic in clustered networks. As in previous chapter, we perform this analysis for varying topologies (dense/ sparse/moderate) of WSNs. Finally, Section 4.5 presents the numerical results to evaluate the performance of the proposed directed ignoring model.

4.1 Connectivity in Clusters

In this section, we study the following problem: What is the entropy of establishing connectivity E_c to a CH from any node in the WSN? Nodes can connect to a CH through multiple nodes that act as relays. Intuitively, the sparser the distribution of CHs in the WSN, the larger will be the cluster sizes of individual CHs. We provide an analytical framework for deriving the dependence between E_c and the distributions of CHs and nodes in the deployment region. Since the stochasticity of the wireless channel plays an important role alongside node locations in determining the connectivity graph of the network, we model the wireless channel with randomness introduced by a lognormal shadow fading environment. This implies that a link between two nodes u and v separated by a Euclidean distance $s(u,v)=d_l$ exists only if the signal attenuation between the nodes does not exceed the threshold attenuation ratio for communication between the nodes. Knowing the Euclidean distance between the nodes u and v, we denote the probability of forming a link between the nodes by $\mathrm{P}(\Lambda(u,v)\,|\,s(u,v))$. In a shadow fading environment, the expression for $\mathrm{P}(\Lambda(u,v)\,|\,s(u,v))$ is given by (Bettstetter and Hartmann, 2005)

$$\mathrm{P}(\Lambda(u,v)\,|\,s(u,v))=\frac{1}{2}-\frac{1}{2}erf\left(\frac{10\alpha}{\sigma\sqrt{2}}\log_{10}\frac{s(u,v)}{r_0}\right) \tag{4.1}$$

where, α is the path loss exponent due to the deterministic geometric component of attenuation in a shadow fading environment. σ denotes the standard deviation of the stochastic component chosen from a normal probability density function of attenuation.

r_0 is the normalization term denoting the maximum distance granting a link in the absence of shadow fading. For threshold attenuation β, r_0 is given by

$$r_0 = 10^{\left(\frac{\beta}{\alpha.10db}\right)} \tag{4.2}$$

We model the links between nodes and the base station as a connected random graph, where the nodes and the CHs comprise the vertices of the random graph, and the links between nodes comprise the edges of the random graph (Figure 4.1). This is shown in Figure 4.1, where the numbered circles denote the coverage area of the wireless sensor nodes, while the circles labeled CH denote coverage area of CHs in the WSN. The links between nodes represent the connectivity between nodes and CHs and the number of nodes attached to a CH comprise the cluster size. We assume that a node can be either in 'sleep' or 'awake' states. In the sleep state, a node's transceivers are turned off and hence cannot form links with any other nodes. In the awake state, a node can actively form links with other nodes and can belong to multiple clusters by even forming links with nodes that lie beyond the distance d_l that allows nodes to communicate in the presence of attenuation due to fading. This is because lognormal shadow fading environment allows nodes to create longer links by taking away shorter links in the vicinity of the node. The subsequent random graph then looks like Figure 4.2. Figure 4.2 shows the connectivity graph with power management for sleep-mode scheduling. The nodes labeled with subscript denote nodes in sleep state. Links to and from these nodes are shown by dashed arrows. The dotted arrows represent the links between nodes and CHs due to lognormal fading. The random graph from Figure 4.1 is transformed as Figure 4.2.

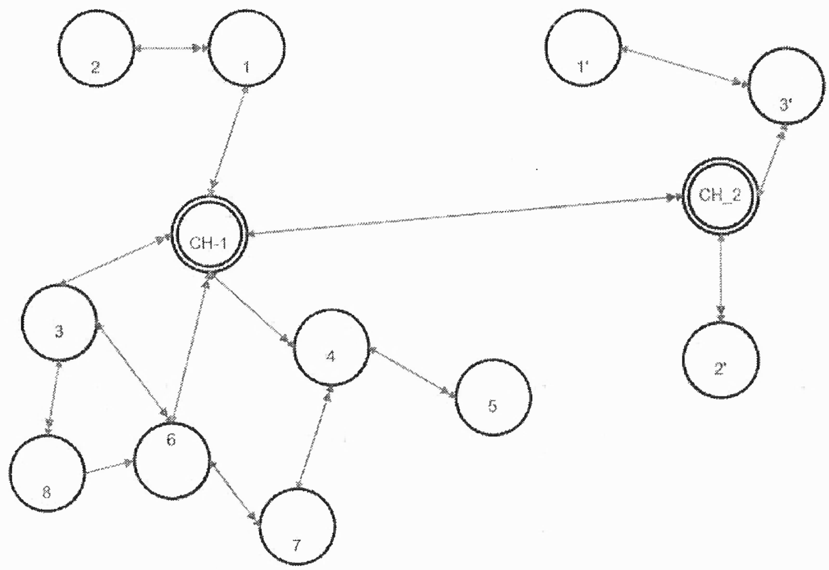


Figure 4.1 Connectivity of all-on WSN

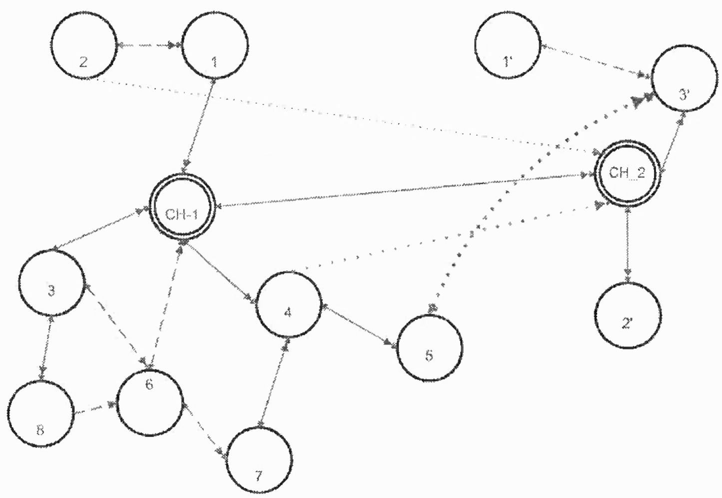


Figure 4.2 Connectivity graph of WSN with sleep scheduling for power management

Next, we model the entropy to establish connectivity as a random sequence of vertices that a node i traverses as it proceeds to establish connectivity with the base station. The probability of choosing another node j as the next hop node is proportional to the weight of the edge linking nodes i and j and is given by P_{ij} . The weight of an edge is given by the probability of forming a link between the nodes i and j subject to the shadow fading environment. P_{ij} can be expressed as the ratio of the weight of edge W_{ij} between nodes *i* and *j*, to the total weights of all edges W_i emanating from node *i*. Thus P_{ij} is given by

$$P_{ij} = W_{ij} / W_i \tag{4.3}$$

Additionally, since nodes are assumed to be randomly assigned the 'sleep' or 'awake' states and since a node in the sleep state cannot form links with other nodes, the weight of an edge linking node *i* to another node *j* in the sleep state is taken to be zero. We also assume that node *i* knows the number of neighbors it has, by counting the number of links it can form. The node *j* with the highest edge weight (lowest signal attenuation) is chosen as the next hop node for node *i*. The sequence of nodes that a node *i* uses to reach the base station is modeled as the sequence of random states $\{S_i\}$, where the maximum value of *n* is given by the number of nodes in the network. The sequence of states can be expressed as

$$S_o = 0 \tag{4.4}$$

$S1 = P_r$ (Randomly choosing any node in the cluster as the starting vertex)

$$S_{n+1} = S_n * P_{ij} \tag{4.5}$$

Thus the entropy to establish connectivity E_c is the entropy of the random sequence of states $\{S_i\}$ and is given by,

$$H(S_1, S_2, \ldots S_n) = \sum_{i=1}^{n} H(S_i \mid S^{i-1})$$

$$= H(S_1) + \sum_{i=2}^{n} H(S_i \mid S^{i-1}) \tag{4.6}$$

$$= H(S_1) + \sum_{i=2}^{n} H(W_{ij} \mid W_i) \tag{4.7}$$

where, (40) is due to the chain rule of entropies, (41) is due to property of Markov chains and (42) is obtained from (39). Let l be the number of edges emanating from node i, i.e the probability of forming a link to l other nodes exists. Thus, the second term of the expression can be expressed as,

$\sum_{i=2}^{n} H(W_{ij} \mid W_i) =$ (probability of forming a link from node i to jth node)/ sum of probabilities of forming a link from node i to all l nodes.

where l is the number of awake neighbor links that a node has in presence of shadow fading environment. The entropy of starting the graph at any node is given by

$$H(S_1) = -1/n \log 1/n \tag{4.8}$$

where n = number of nodes in the cluster. To obtain the second term of the expression for E_c, we note that $\mathrm{P}(\Lambda(u,v) \mid s(u,v))$ is given by (4.) and W_i is obtained as the sum of the probabilities $\mathrm{P}(\Lambda(u,v) \mid s(u,v))$ on all links emanating from node i.

4.2 Bounds on E_c

In this section, we provide upper and lower bounds on *Ec* and show its dependence on the intensity of CH distribution as well as on the probability of connectivity between nodes, $\mathrm{P}(\Lambda(u,v) \mid s(u,v))$. To study this, we consider the clustered WSN model of two types of nodes: a homogeneous set of wireless sensor nodes that perform sensing and another homogeneous set of CHs, where each CH aggregates data from the nodes belonging to its cluster. The deployment region is assumed to be a 2-dimensional Euclidean space of area

A in which for simplicity of calculation, the wireless sensor nodes are distributed as a Boolean model formed by a Poisson-distributed sequence of random sets. These random sets are the disk-shaped circles of coverage of individual nodes with radius r. The coverage circles are assumed to form a stationary Poisson process of intensity λ_1. We define another similar stationary Poisson process of intensity λ_2 for the CHs. If the WSN is designed for operation such that all wireless sensor nodes as well as CHs are awake at all times, the probabilistic nature of a node being in the 'awake' or 'sleep' states is eliminated. The sequence of states $\{S_i\}$ thus depends only on the probability of forming links between nodes, i.e. when the signal attenuation stays below the threshold required for communication. The upper bound on the entropy $E_{c-\max}$ is obtained when all the nodes are awake and every node i maintains links to all its neighbors who lie within the one-hop communication range (Fig. 1a). Additionally, the assumption of the log-normal distribution allows for forming links with nodes located greater than distance d_l away from a node i. The sequence of states $\{S_i\}$ can then be modeled by a random walk on a connected graph with a stationary Markov chain, and its entropy $E_{c-\max}$ is given by

$$\begin{aligned} E_{c-\max} &= H(S_1, S_2, \ldots S_n) = H(S_2 \mid S_1) \\ &= \sum_{i=1}^{n} \mu_i H(S_2 \mid S_1 = i) \end{aligned} \tag{4.9}$$

where μ_i is the stationary distribution of the Markov chain. The lower bound on the entropy $E_{c-\min}$ can be similarly obtained. When the attenuation due to fading results in zero probability of connectivity for any node pair, the graph formed by the wireless sensor nodes and CHs does not contain any edges. Thus the lower bound $E_{c-\min}$ is just the entropy of choosing any given node as the starting vertex to analyze the entropy of connectivity to the CH.

$$E_{c-\min} = H\left(S_1\right) \tag{4.10}$$

While the above analysis holds for a given intensity λ_2 of distribution of CHs, we can also present bounds on E_c for varying levels of CH distribution. The bounds in this case are readily obtained. If the intensity of distribution of CHs λ_2 , is increased to be equal to the intensity λ_1 of wireless sensor nodes while keeping the area of the deployment region constant, the distribution of CHs relative to that of the nodes becomes a high -intensity distribution and the expected number of nodes per cluster is one. In this case the entropy of the sequence of states, assuming connectivity between nodes and CHs, is just the entropy of choosing one out of n nodes in the WSN and provides the lower bound on entropy for equal distributions of CHs and wireless sensor nodes. Thus,

$$E_{c-\min} s.t.\left(\lambda_2 = \lambda_1\right) = H\left(S_1\right) = -1/n \log 1/n \tag{4.11}$$

Similarly, when the distribution of CHs is much less than that of nodes, the expected cluster size per CH increases. The largest cluster size is obtained when the intensity of distribution equals zero. This results in a WSN with only one CH for all $n = kA/A_s$ wireless nodes, and the entropy E_c is the highest. Thus the upper bound on E_c, assuming connectivity among nodes and CHs is given by

$$E_{c-\max} s.t.\left(\lambda_2 = 0\right) = H\left(S_1, S_2, \ldots S_n\right) \tag{4.12}$$

4.3 Queuing Analysis in Clustered WSNs

This section concerns the problem of edge effects and the resulting starvation in queuing access in clustered WSNs. The problem of edge effects and starvation has been studies in terms of the unfairness in channel access in the IEEE 802.11 MAC protocol (Durvy, Dousse and Thiran, 2008). This problem arises due to the topology of large wireless networks, where nodes at the borders of the network get increased access to the channel due to lesser interference than nodes in the center of the network. This results in edge/border effects, where the nodes in the center of the network are starved off channel access due to increased interference from more neighbors. However, the problem of edge effects is not confined to channel access alone. The topology of the network and the routing algorithm can also result in edge effects in queuing of data at the central base station to which all the network data is routed. This problem is more relevant in clustered topologies, where clusters of nodes route their data to respective CHs.

Clustered WSNs are miniatures of the order of the whole scale of dense WSNs. Instead of reporting the sensed data to a central base station, individual nodes report the sensed data to local processing stations like cluster-heads (CHs) which are assumed to be more robust, computationally intensive and less power constrained than individual nodes. The problems of edge effects and starvation in channel access, commonly studied in large WSNs, are also present in clustered networks, due to the same reasons of increased interference at the center of the cluster. The density of clusters in the networks leads to the propagation of edge effects from every cluster, impacting the entire WSN throughput. We study edge effects in admission control and queuing in clustered networks and present the motivation for this study in this section.

We continue with the assumption of naturally clustered WSNs, where the deployment process of CHs and nodes results in cluster formation. We assume disk model of coverage for both CHs and nodes, where R_{CH} and R_{node}.

In clustered WSNs, the density of CHs dictate the size of a cluster, and nodes at the edge of a cluster can 'belong' to more than one cluster. In clustered networks, with given densities of nodes and CHs, the cluster size affects the distance of a border node from its CH. A dense network with high density of nodes and CHs has a smaller *d*-hop distance between a border node and a CH than in a network with low density of CHs and high density of nodes. In the latter case, a larger average cluster size results in higher value of the *d*-hop distance between a border node and CH.

An illustration of the edge effect in shown in Figure 4.3. The nodes at the edge of a cluster A lying at a *k*-hop distance from CH A, may also lie at the intersection of perimeters of clusters A and B, and be at some *d*-hop distance from CH B. In the event of data routing, nodes in the center of a cluster have access to only one CH, where nodes at the edge of a cluster can have access to more that one CH. We call the nodes at the center of the cluster as 'core' nodes, compared to the nodes at the edge of a cluster which we denote as 'border' nodes. In Figure 4.3, nodes *b, c, d* and *g* are the core nodes, while nodes *f, h, a* and *k* are the border nodes.

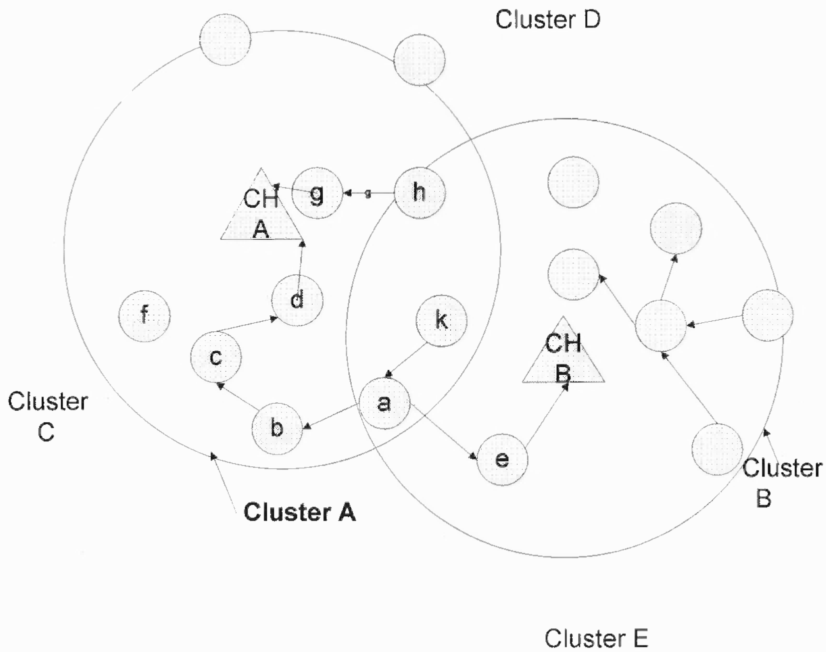


Figure 4.3 Illustration of the edge effect in clustered WSNs. Node *a* at the perimeters of clusters A and B can choose to route its data in 4 hops to CH *A* (*a*-*b*-*c*-*d*-CH *A*) or in 2 hops to CH *B* (*a*-*e*-CH *B*).

The data from border nodes may end up being processed multiple times in the data aggregation algorithms being carried out at the CH, thus affecting the reliability of the information obtained from data processing in the cluster.

One way to address this problem is through strict cluster formation strategies, where nodes are assigned to a cluster for the duration of the network lifetime. In the scenario of Figure 4.3, this ensures that nodes of cluster A report only to CH A. However, in the event of device failure or battery failure at CH A, we need to run centralized algorithms to redesign the cluster strategy for load balancing throughout the network. The large scale of WSN operation and the data intensive operations carried out at CHs also impacts the queuing at CHs. Heavy traffic, characterized by a traffic intensity almost close to unity resulting in system capacity occupying almost all available bandwidth is a significant consequence of both on-demand and continuous sensing operation scenarios in WSNs. In this dissertation, we address the problem of queuing at the CH for data arriving from two types of nodes, core nodes and border nodes in the presence of heavy traffic through the network. We use a diffusion-based model for obtaining the expected queue length in a heavy traffic scenario and evaluate the performance of a optimal control problem to improve the throughput of clustered WSNs.

We formulate our heavy traffic model for queuing analysis in a clustered WSN as follows: We characterize a cluster as having two types of nodes: core nodes and border nodes. These nodes are expected to share the same CH for data processing; however border nodes may resort to choosing a different CH to send their data based on knowledge of hop-distance to nearest CHs. In order to avoid potential redundancy information processing from border nodes in multiple clusters, we consider an admission control scheme for the border and core nodes. The core nodes are characterized by best-effort (BE) admission policy, similar to the model adopted in the Internet. The border nodes are characterized by a guaranteed-performance (GP) admission control policy. We call this model as the 'directed ignoring' model, where redundant messages from border nodes are ignored in the admission control policy. Here, we realize that although the aim is to eliminate/ reduce redundant processing of data from border nodes with minimum control overhead, a stringent control policy can result in a larger number of GP packets from border nodes being dropped. The goal therefore is to minimize the loss of GP packets from border nodes while reducing the waiting time for BE packets from the core nodes. Since the nodes in a cluster are located in geographical proximity, the potential loss of GP packets from border nodes due to the admission control policy does not greatly impact the information obtained from data processing in dense WSNs. Thus, the proposed directed ignoring model can provide a convenient approach for admission control to reduce edge effects in clustered WSNs.

4.4 Related Work in Queuing in Wireless Networks

The problem of scheduling in networks has been widely studied in the context of queuing and scheduling (Bharghavan, Lu and Nandagopal, 1999). One of the earliest works in analysis of scheduling in queues is (Tassiulas and Ephremides, 1992), where the authors study the problem of scheduling N parallel queues to be served by a single server. At any given time slot, the connectivity between queues and the server depends on the value of a connectivity variable which can be 0 or 1. The allocation of a queue to the server depends on this connectivity variable and the queue length. The authors propose an allocation policy for stability (finite queue length) based on parameters such as buffer length, arrival and service policies and connectivity. They obtain the necessary and sufficient conditions for stabilizability and show that the allocation policy that serves the longest queue stabilizes the system when stabilizability conditions hold.

In (Wu, Srikant and Perkins, 2007), the authors study the efficiency of greedy scheduling policies for link scheduling in wireless networks. They study the category of greedy algorithms, where a node attempts to independently schedule transmission on a link. If it finds the link busy, it randomly picks another link. This process continues until all attempts have failed or a link is found free. They obtain bounds on the efficiency of distributed scheduling policies for the greedy scheduling algorithm for the case of traffic passing in one-hop networks and then extend their analysis to that of data traversal in multi-hop networks.

In (Lin and Rasool, 2006), the authors study a distributed link scheduling problem for obtaining the set of active links that are free of mutual interference and yet achieves a large capacity region. As opposed to most distributed scheduling algorithms where the time taken to compute a schedule increases with the network size, the authors propose a constant-time policy that requires only one round of computation and achieves comparable data rates as other non constant-time scheduling policies.

Other scheduling policies for distributed wireless networks have been discussed in (Joo, 2008), (Joo and Shroff, 2007) and (Sanghavi, Bui and Srikant, 2007) with the emphasis on parameters such as reduction of control overhead, scalability, throughput and computation time. Our work focuses on the queuing admission control policy at the CH to reduce edge effects in clustered WSNs. The next section presents the directed ignoring model and key assumptions.

4.5 Directed Ignoring Model

The paradigm of directed ignoring is derived from analogous processes in human cognition (Cavanagh, 2004), where the human cognitive system selectively ignores data gathered from the sensory system while processing information. This is similar to filtering out noise except that in the case of directed ignoring, the filtered information is not noise, but relevant data that is not considered while making a decision. Such activity gives tacit support to the underlying cognitive system to make informed decisions based on a subset of total available data. We use this paradigm to design the directed ignoring model for clustered WSNs, where a CH selectively ignores data from the border nodes and always processes data from the core nodes. Since the border nodes are capable of routing their data to multiple CHs, selectively ignoring their data only minimally affects the reliability of data gathered from the cluster. We further assume that the border nodes are characterized as guaranteed performance (GP) nodes, where every node is guaranteed a fixed bandwidth for the duration of this session. We also assume that the remaining BW is available to share by BE nodes, however there is an upper limit to the BW that can be shared. This assumption of an upper limit on the BW accounts for the loss in usable BW to control overhead, noise and channel randomness. The random number of border nodes that access the processing services of a given CH affects the BW available for core nodes. The fraction of nodes in a cluster at any given time slot that are communicating with the CH depends on the number of active nodes allowed by the power management algorithms and the interference model. In our work, we use the node exclusive model, where a node cannot simultaneously transmit or receive, and cannot communicate with two or more nodes in the cluster. We use the adaptive density control algorithms from Chapter 3 to obtain the subset of active nodes. Thus in any given scenario of dense/sparse/moderate networks, the number of packets from core/border nodes is a fraction of the cluster size.

We use controlled reflected stochastic diffusion approximation to study the performance of the clustered WSN with border nodes and core nodes in the presence of heavy traffic. The assumption of heavy traffic creates a system that is built to handle the processing demands resulting from response to queries for data from the BS. However, the heavy traffic assumption results in systems that are not always Markovian. Even if the system can be resolved into a set of Markovian states, the number of states is large to be modeled. The reflected diffusion approximation makes use of the central limit theorem for large numbers and allows for the formulation of state equations that are linear. These linear state equations and limit equations enable the development of algorithms for admission control in queuing with the help of cost functions that optimize the various processes that compose the state and limit equations. Specifically, in our case, as we shall show, the state and limit equations comprise of the following:

1. Wiener processes for arrival and service processes for packets from border and core nodes at the CH
2. Initial conditions of the network, i.e. number of packets initially queued at the CH from BE and GP nodes.
3. Number of packets from border (GP) nodes not admitted by time t, and number of packets from core (BE) nodes denied admission due to the bandwidth limitations.

The goal is to estimate the number of packets $x(t)$ in the queue at the CH at some real time k. We give some background in the heavy traffic estimation for a simple M/M/1 queue before developing the directed-ignoring models for two types of packets in a clustered WSN. For a M/M/1 queue, the reflected diffusion process to estimate the number of packets $x(t)$ in the queue at the limits of heavy traffic can be written as

$$x(t) = x(0) + bt + w^a\left(\overline{\lambda}^a t\right) - w^d\left(\overline{\lambda}^d t\right) + z(t) \tag{4.13}$$

where, $x(0)$= number of packets at time k= 0 (initial condition) of the queue, $w^a(.)$ and $w^d(.)$ are mutually independent Wiener processes for the arrival and service processes

$\overline{\lambda}^a$ and $\overline{\lambda}^d$ respectively. The terms $w^a(.)$ and $w^d(.)$ represent the asymptotic effects of the randomness in the arrival and service processes. The term $z(t)$ is called the reflection term which considers the fact that there might not always be customers in the queue. $z(t)$ can only increase when $x(t)$ is zero or is scaled by the limit of large time defined by the central limit theorem, where $k = nt$ and t represents scaled time. Thus the reflection term $z(t)$, which is non-decreasing and continuous keeps the other terms from driving $x(t)$ negative. The parameter b represents the scaled and asymptotic difference between input and service arrival rates.

We now present the development for the directed ignoring model for clustered WSNs. We use the subscripts b and g to denote BE and GP packets. The bandwidth is normalized so that each GP packet gets one unit of bandwidth. We assume the arrival process for packets of the BE and GP users are Poisson, so the variance of the $w^a(.)$ and $w^d(.)$ processes are $\sigma_b^2 = 1$ and $\sigma_d^2 = 1$. The service times for the packets of GP nodes are assumed to be mutually independent, exponentially distributed with rate $\overline{\lambda}^d$. We assume that GP packets denied by the admission control algorithm at the CH disappear from the system. To satisfy with the assumption of heavy traffic, the basic system variables are scaled by $1/\sqrt{n}$, where n is the order of the mean number of GP packets and the arrival rates of GP and BE packets. Let $F_g^n(t)$ denote $1/\sqrt{n}$ times the number of GP packets not admitted by time t. Let $U_b^n(t)$ denote $1/\sqrt{n}$ times the number of BE packets that are rejected by time t, because on their arrival there were $\sqrt{n}B_b$ users already in the system, where we suppose that there is a $B_b < \infty$ such that the maximum number of BE packets in the system at any time is $\sqrt{n}B_b$. Suppose that $B(t)$ is the total bandwidth unused by the GP packets in time *t*, and there are $N(t) > 0$ BE packets in the system. We assume that the maximum bandwidth that any individual BE packet can use is C_b. Define $x_b^n(t)$ to be the number of BE packets in the system at time *t* minus the scaled deviation that is centered around a mean value due to the restriction on the bandwidth usage.

$$x_b^n(t) = \frac{1}{\sqrt{n}} \{ \text{ number of BE packets at } t \text{ - } n\overline{\lambda_b}^a \Big/ \left(C_b \overline{\lambda}^d{}_b\right) \} \tag{4.14}$$

where, $\overline{\lambda_g}^d$ is the exponentially distributed rate of service times for GP packets. However, the service time for the BE packets depend on the history of available bandwidth during their stay in the system. The conditional probability that any particular BE packet will depart the system in the interval $[t, t+\delta)$ is

$$\frac{\overline{\lambda_b}^d \delta B(t)}{N(t)} + o(\delta) \tag{4.15}$$

We set the scaled number of GP users to be equal to $x_g^n(t)$, where

$$x_g^n(t) = \frac{1}{\sqrt{n}} \{ \text{ number of BE packets at } t \text{ - } n\frac{\overline{\lambda_g}^a}{\overline{\lambda_g}^d} \} \tag{4.16}$$

Thus $x_g^n(t)$ is the scaled number of GP packets, centered about the mean that would hold if there were no rejections and an infinite channel capacity. For the heavy traffic condition, suppose that there is a constant *b* such that the channel capacity is defined by

$$C_n = n\left[\frac{\overline{\lambda_g}^a}{\overline{\lambda_g}^d} + \frac{\overline{\lambda_b}^a}{\overline{\lambda_b}^d}\right] + b\sqrt{n} \tag{4.17}$$

The term $n\overline{\lambda_g}^a / \overline{\lambda_g}^d$ accounts for the mean GP packets usage. Rewriting the limit equation (4.1) for the case of a clustered WSN with GP and BE users, we get for the BE users

$$x_b(t) = x_b(0) - \overline{\lambda_b}^d \int_0^t g_1(x(s))ds + w_b{}^a\left(\overline{\lambda_b}^a t\right) - w_b{}^d(t) - U_b(t) \tag{4.18}$$

where we define

$$g_1(x) = \min\{b - x_g, C_b x_b\} \tag{4.19}$$

and the integral term arises due to the Doob-Meyer decomposition of the sub-martingale of the departure process $w_b{}^d(.)$ into a martingale and a continuous increasing function for either class of packets (GP or BE). A detailed development is presented in (Kushner, 2001).

Similarly, the limit equation for the expected queue length of the GP packets at the CH is given by

$$x_g(t) = x_g(0) - \overline{\lambda_g}^d \int_0^t x_g(s)ds + w_g{}^a\left(\overline{\lambda_g}^a t\right) - w_g{}^d(t) - F_g(t) \tag{4.20}$$

Thus we see from (4.18) and (4.20) that the GP traffic affects the performance of BE packets at the CH.

Next we formulate a discounted cost function with controls c_i for admission control that obtains the number of lost GP packets in the queue. Let $\beta > 0$, where β can be any small number. Let $k(.)$ be a non negative continuous function with $k(0) = 0$. The discounted cost function is defined by

$$C_\beta^n\left(x, F_g^n\right) = E\left(\int_o^\infty e^{-\beta s} k\left(x_b^n(s)\right) ds\right) + E\left(\int_0^\infty e^{-\beta s} \sum_i dF_i^n(s)\right) \tag{4.21}$$

where i denotes the two classes of packets from the BE and GP nodes. The second term penalizes the rejections. The loss U_g^n is not penalized, since it tends to zero in the limit as $n \to \infty$, irrespective of the controls. If $k(.)$ is linear, then it penalizes the waiting time for packets from BE nodes. Thus the allowed generality of the cost function enables flexibility in the design of controls for various classes of nodes in more realistic scenarios.

Since n depends on the density of CHs and nodes in the network scenario (dense/sparse/moderate), the first step in the modeling of the clustered WSN with cost controls is to obtain the value of n in various clustering scenarios. We use the theory of intersecting sets from Chapter 2 to obtain the number of border and core nodes in each scenario and summarize the results here for convenience.

- Dense networks
  - $b_{dense} = \lambda_{node}\left\{\|R\|_2 + E\left(\|S\|_2\right)\right\}$
  - $g_{dense} = \left(\dfrac{a/\lambda_{CH}^2 - b/\lambda_{node}^2}{\|R\|_2 - a/\lambda_{CH}^2}\right)\dfrac{A_{CH}}{A_{node}} - b_{dense}$

where, $\|R\|_2$ denotes the area of the 2-D deployment region, $\|S\|_2 = A_{node}$ denotes the disk model of coverage area of a node with radius R_{node} and A_{CH} denotes the disk model of coverage area of a CH with radius R_{CH}. The intensity of nodes and CHs is given by λ_{node} and λ_{CH} respectively. The constants a and b for a 2-D deployment region are given by $a = \dfrac{\sqrt{\pi}\Gamma(3)}{\Gamma(1.5)}\left(2\Gamma(1.5)\right)^2$ and $b = \pi h/a$.

- Sparse networks

- $b_{sparse} = \lambda_{node}\left\{\|R\|_2 + E\left(\|S\|_2\right)\right\}$
- $g_{sparse} = \dfrac{\eta_{node}}{\eta_{CH}}\left(\dfrac{\lambda_{node}}{\lambda_{CH}}\right)^2 - b_{sparse}$

where, $\eta_{node} = \lambda_1^2 \pi R_{node}^2$ and $\eta_{CH} = \lambda_2^2 \pi R_{CH}^2$.

- Moderate networks
  - $b_{\mathrm{mod}} = \lambda_{node}\left\{\|R\|_2 + E\left(\|S\|_2\right)\right\}$
  - $g_{\mathrm{mod}} = \dfrac{e^{-\lambda_{CH} A_{CH}}\left(1 - e^{-\lambda_{node} A_{node}}\right)}{1 - e^{-\lambda_{CH} A_{CH}}}$

In the next section, we present the simulation model and results for queuing control in WSNsS. We show that a simple linear queuing control results in considerable savings in global performance with minimum rejection of packets from GP nodes.

4.6 Simulation Results

We evaluate the performance of the directed ignoring model for queuing admission control in clustered WSNs. We compare their performance under the lognormal shadowing model for dense, sparse and moderate intensities of clustered networks. We assume the traffic intensity is generated according to a Poisson process, and the ratio of arrival and service rates is close to unity (in our case, 0.98). Any packet that is rejected at the CH due to the queuing admission control of the directed ignoring model is considered to disappear from the system. We use the IEEE 802.15.4 ZigBee power model of the MICAZ mote for the sensor nodes. We use a network graph generated in a circular deployment region with radius 1000 m by randomly placing nodes and CHs according to varying levels of intensity. This generates the different scenarios for dense, sparse and moderate networks. Two nodes are considered by a link if they are within distance of 2 meters. We assume that the nodes are 'on' with a probability of 0.7; this changes the connectivity graph dynamically at both the cluster- and network-level. Each link has unit capacity, i.e. it can transmit one packet of data when active. We assume that the slotted time transmission. We use a linear cost function $C_l(t) = cx_b(t) + F_b(t) + 5F_g(t)$ for the simulation of the directed ignoring model. $cx_b(t)$ penalizes the waiting time for BE packets from core nodes. $F_b(t) + 5F_g(t)$ penalizes the rejections of the GP packets from border nodes. We compute the fraction of lost GP packets from border nodes as $F_g / \left(\lambda_g \sqrt{N}\right)$. We assume that the arrival rates for both GP and BE packets are equal to one per second. We assume the variance of the Wiener processes used to model the arrival and departure rates under heavy traffic is unity. Further, we take the service rate of GP packets to be equal to 0.5 and that of BE packets to be equal to 1. Figures 4.4 and 4.5 show the results of simulation of the directed ignoring model for clustered WSNs in various scenarios of dense/sparse/moderate density of nodes and CHs. From Figure 4.4, we see that for large number of nodes (~40) in the cluster, the percentage of lost GP packets is of the order of 0.78%. Also, as the control variable c in the cost function increases from 2 to 7, the percentage rejection of lost GP packets decreases due to the fact that the controls only decrease x_g, the number of GP packets in the queue at the CH.

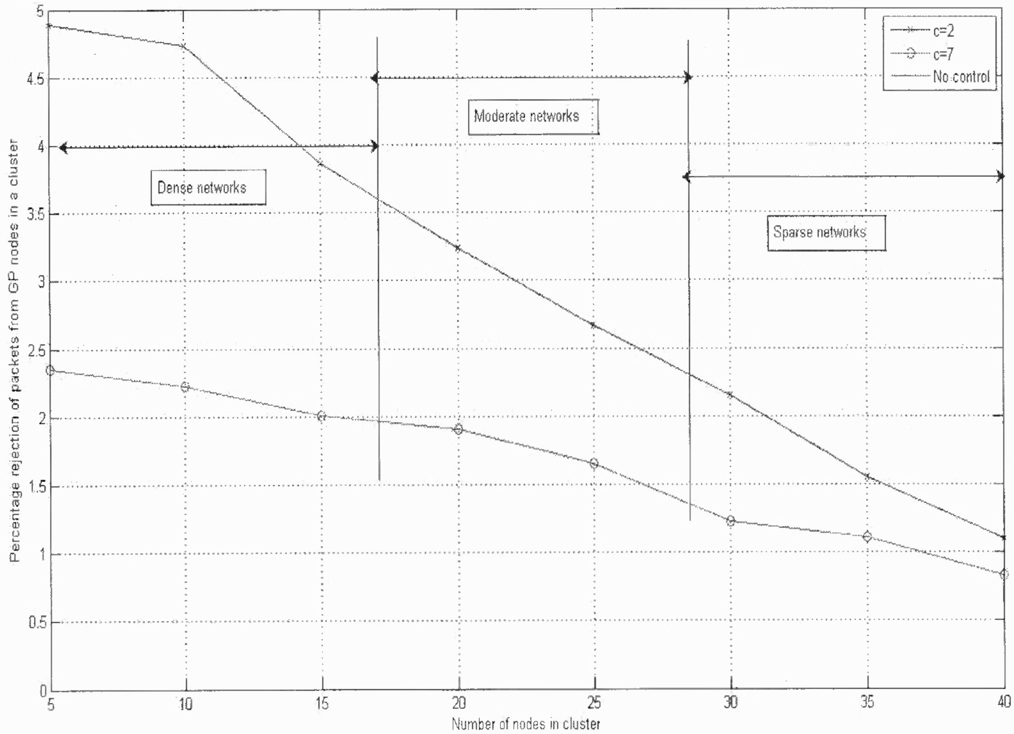


Figure 4.4 Percentage rejection of GP packets from border nodes in a cluster.

Figure 4.5 shows that similar to the behavior observed in a cluster, the percentage rejection of GP packets decreases with increase in network size.

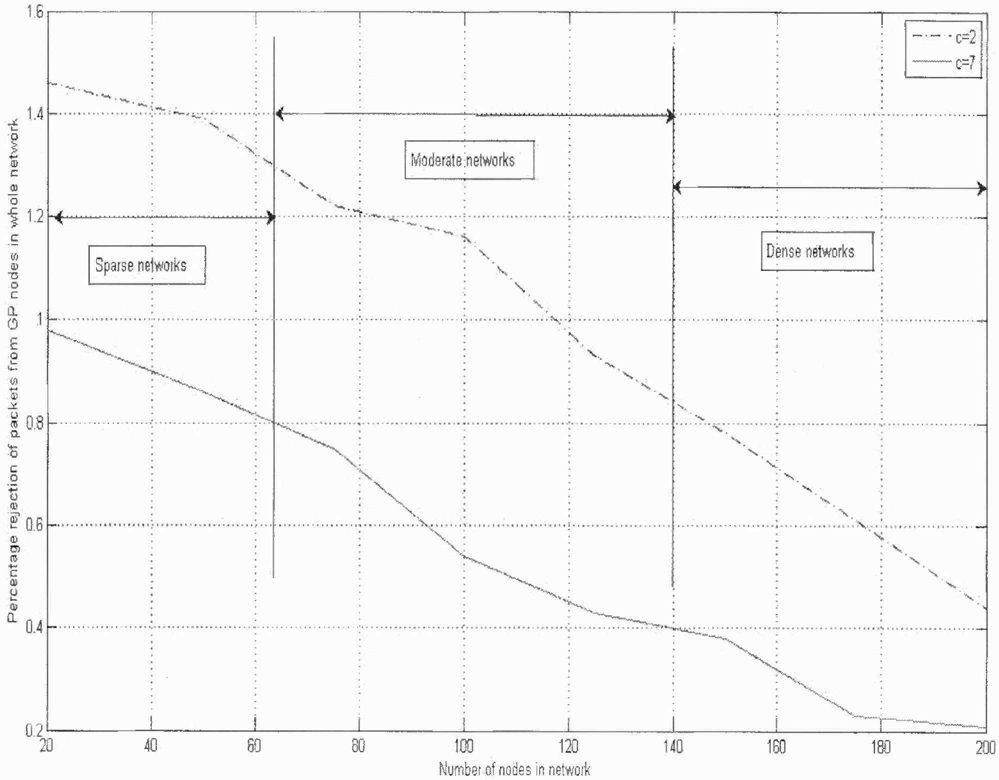


Figure 4.5 Percentage rejection of GP packets from border nodes in a WSN.

We now present results for comparison of reduction in wait time of BE packets versus the percentage rejection of GP packets. Table 4.1 indicates the tradeoff in potential loss of GP packets versus reduction in wait times for BE packets. With no control, i.e. $c = 0$, the percentage rejection of GP packets is 0. However, the results in Table 4.1 indicate that $c = 0$ also corresponds to the case where the queue lengths are the longest. This results in larger wait times for the BE packets. The introduction of controls results in shorter wait times for the BE packets at the CH, and also lowers the percentage rejection of GP packets for larger network sizes.

Table 4.1 Tradeoff of waiting time for BE packets versus loss of GP packets.

	Expected queue lengths for BE packets from core nodes, x_b	Percentage rejection of GP packets from border nodes for varying N (N = number of nodes in a cluster)			
		N=5	N =10	N = 20	N = 40
No control	0.793	0	0	0	0
$c = 2$	0.452	4.889	4.737	3.170	1.235
$c = 7$	0.267	2.316	2.202	1.985	0.796

With regards to network scenarios, although sparse networks offer the lowest rejection of GP packets, they also have larger cluster sizes and the connectivity graph in sparse networks omits a number of nodes due to nodes being outside of the CH's coverage area. We thus conclude that in moderate networks with optimal control and operating in the heavy traffic regime, we may gain considerably in system performance under the directed ignoring model. At the cost of rejection of small amounts of GP packets from border nodes, the directed ignoring model mitigates the effects of unfairness in queuing admission control for clustered networks. In the next chapter, we present a framework for cognitive WSNs and conclude this dissertation.

CHAPTER 5

COGNITIVE WIRELESS SENSOR NETWORKS

5.1 Introduction

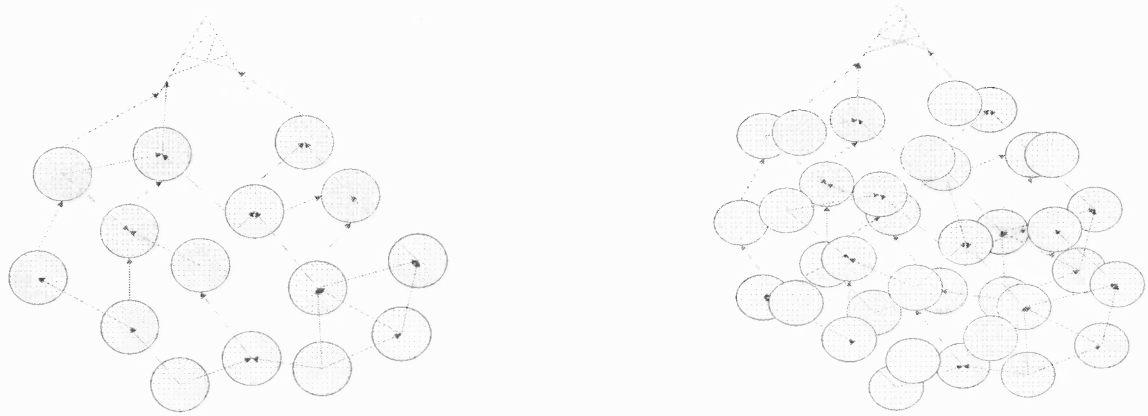
The large, rapidly growing field of wireless sensor networks (WSNs) offers the ability to collect and process massive amounts of information from various environments. This distributed data gathering and computation with the help of tiny, power-limited devices enables their use in surveillance, target detection and various other monitoring applications. In the previous chapters, we analyzed a realistic scenario of clustered topologies in WSNs deployed for applications like environmental monitoring. We studied coverage in clustered topologies, and showed that clustering increases vacancy. However, by exploiting the redundancy to design sleep scheduling algorithms for adaptive density control, it was shown that coverage in clustered WSN could be optimized while still improving network lifetime. The problems of starvation and edge effects commonly observed in large wireless networks were investigated for queuing at CHs. While the scenario of clustered topologies studied in this dissertation is not unique in that clustering can be modeled using various processes, for e.g. Cox processes, we showed that topology modeling plays an important role in network design and management. Also, the studies on coverage, power management and queuing in WSNs form a subset of the many research issues that confront large-scale, distributed networks. As the range of applications envisioned for WSNs increases, the need for smart networks that utilize algorithms for intelligent data gathering and processing also increases. In this context, the role of a sensor network can be viewed as that of a system that pays attention to a phenomenon of interest. Thus, the current body of literature on WSNs falls into two major categories: developing networks that a) pay attention to the environment to detect the phenomenon under consideration and b) improving the quality of attention paid by WSNs to these phenomena. In this chapter, we lay the foundation for a theoretical framework for the context of attention in WSNs. This dissertation is the first step in understanding the association between the nature of attention in WSNs and their real-world applications. Although we structure this framework for cognitive WSNs around clustered WSNs, it can easily be extended to various topologies of WSNs. Through the rest of this chapter, the terms clustered WSNs and WSNs will be used interchangeably.

5.2 WSNs: Developing an Analogical Framework to the Nature of Attention

In this chapter, we introduce the concept of attention in clustered wireless sensor networks by framing a relationship between the nature of attention at the cognitive level and the parallel data-gathering and processing functions carried out by WSNs. Wireless sensor networks are aptly named for their ability to sense the deployment region, gather data and use it for higher levels of processing. Multi-hop links or a single direct link is used to route this gathered data to a central base station (sink) in order to reconstruct the desired parameters of the deployment region (Marco, Duarte-Melo, Liu and Neuhoff, 2003). The power-limited nature of sensor nodes effectively constrains the processing and data dissemination that are necessary to achieve sensing objectives of reliable network operation while also prolonging network lifetime. This constraint has spawned research in deployment, signal processing, communication and networking within WSNs.

In particular, these issues can be classified within the context of attention into two main categories. The first category deals with developing networks that pay attention to the environment: i.e. the range of WSN applications. This is evident in the study of WSNs developed for habitat monitoring (Mainwaring, Polastre, Szewczyk, Culler and Anderson, 2002), weather detection (Sims, Kurose and Lesser, 2005) and structural monitoring (Li and Liu, 2007) to name a few. The other category deals with improving the quality of attention paid by the WSN to the phenomenon under consideration. Deployment, density control, routing, data processing and security are themes used to improve the quality of attention paid by the WSN to the environment. Our work unifies current research in terms of attention: the fundamental ability of sensor networks to pay attention and process data gathered from attentive sensing to fulfill sensing objectives. In our knowledge this is the first work that addresses WSN applications and performance as a function of attention paid by the network. Below, we provide a brief introduction to the nature and scope of WSNs and then outline the analogy between the limits of attention in human cognitive science and the limits of data gathering, processing and routing in WSNs.

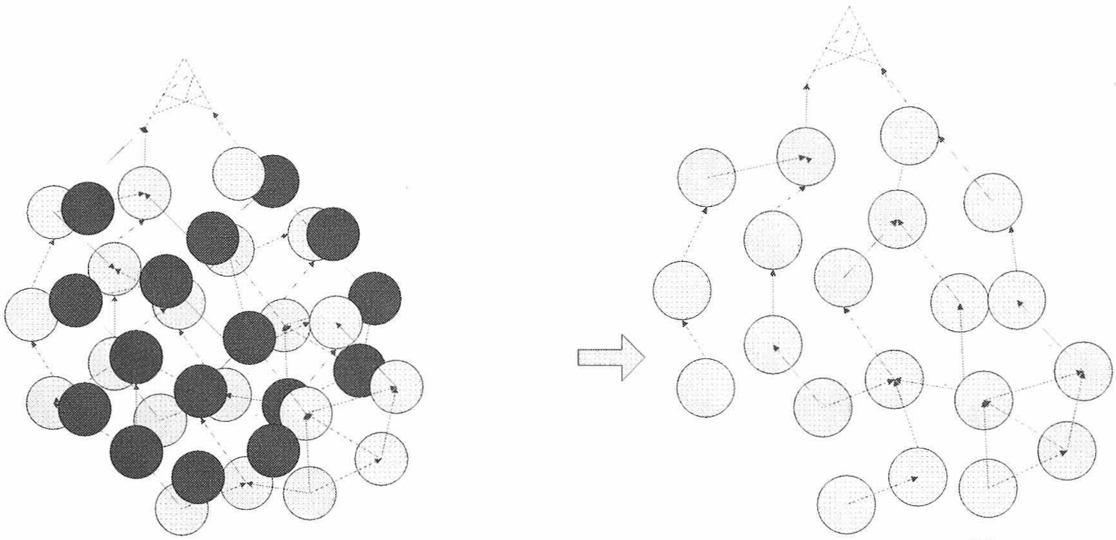
Clustering in WSNs has emerged as an efficient model for data aggregation and processing, especially in redundant WSNs. A sample depiction of a clustered WSN is shown in Figure 5.1, where the nodes are represented by their circular coverage areas. Figure 5.1 can also be used to depict the model of a general WSN, where nodes send their data to a central sink. There are two major sensing scenarios: *continuous* sensing in which the nodes continuously gather data and route it to the sink and *event-driven* sensing where the nodes respond to the base station's request for data, viz. what was the temperature in region A of the deployment region at 10 am? For a WSN to be efficient, it has to satisfy the sensing objectives, viz. temperature measurement, intrusion detection, etc. in the deployment region while achieving maximum possible network lifetime.



(a) (b)

Figure 5.1 A clustered wireless sensor network (WSN). (a) shows a WSN with a CH and wireless sensor nodes. The arrows indicate possible routing paths in the network. (b) shows redundancy in a cluster in the WSN.

This redundancy may arise in random deployment strategies (scattering nodes from a height on remote terrains) or deterministic deployments, where dense networks of nodes are deployed in the deployment region, e.g. networks of cameras for intrusion detection. In the absence of redundancy, all nodes in the network might have to stay in the 'awake' state to achieve coverage and connectivity in the network. Redundancy presents ways to let some nodes 'sleep', while others stay 'awake' to perform data gathering, computation and routing. Figure 5.2a shows redundant nodes in the 'sleep' state (darkened circles). The equivalent network without the sleeping nodes is depicted in Figure 2b. As demonstrated in Chapter 3, this alternation between the 'sleep' and 'awake' modes' of operation helps in increasing network lifetime.



(a) (b)

Figure 5.2 Power management by 'sleep' scheduling. The darkened nodes indicate nodes in the 'sleep' state. The equivalent network is shown in (b).

From the above brief introduction to the structure and operation of WSNs, we see an analogy between the working of clustered WSNs and human cognition in terms of the data gathering, computation and routing (Figure 5.3) from clusters of neurons. Though the human cognitive system does not face similar constraints of working with power-limited data gathering units, it encounters constraints on the attention that can be paid to the environment. In this dissertation we examine the analogy between cognitive attention that deals with the visual sensory input and WSNs that gather data from the deployment region for various applications. The relevance of attention to WSNs merits a series of questions that we frame to set the tone of the rest of this chapter.

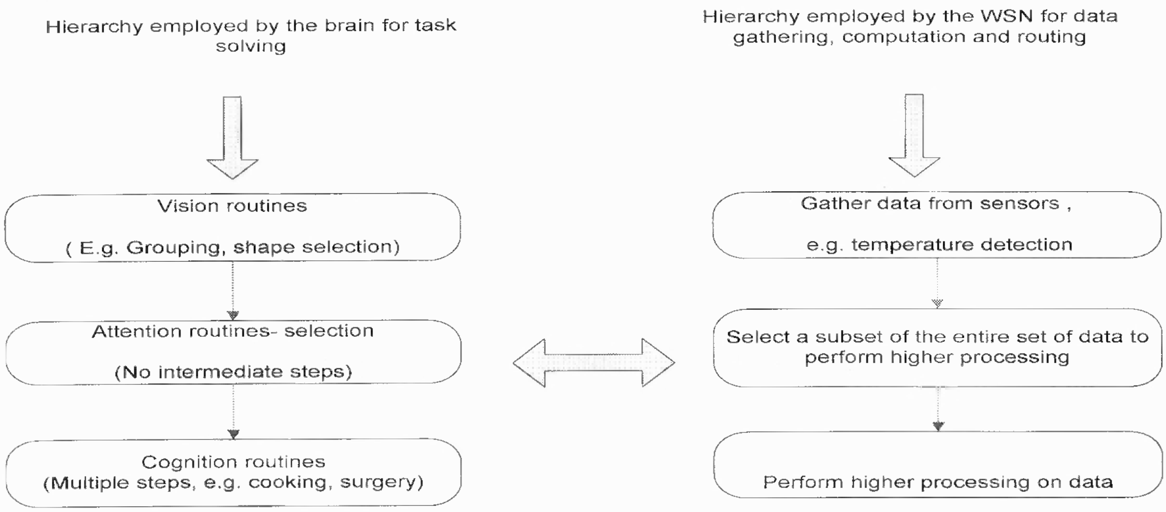


Figure 5.3 Analogy of task solving in human cognition (Cavanagh, 2004) and the WSN

The first question that the framework evokes is: *How do we extend the concept of attention to wireless sensor networks?* One of the essential prerequisites for WSN applications is to create architectures for reliable data gathering and processing, so that the network fulfils sensing objectives while achieving longer network lifetimes with nodes that have constraints on battery energy and processing power. The scope of WSN applications includes data gathering in environment monitoring, surveillance, target detection and intrusion and medical applications. Though these application scenarios are unique, they all display a common feature: the WSN pays attention to the deployment region to obtain information about the parameter of interest in the sensing application.

For instance, a temperature monitoring WSN pays attention to the temperature in the deployment region. In an intrusion detection system, nodes are supplied with the data set corresponding to intruder identification and the network attentively scans the environment and reports intruders to the base station. This paradigm of attention can be applied to many other sensing scenarios as well.

Having extended the concept of attention to WSNs, the next question that arises is: *How do we quantify attention in WSNs?* The best interpretation of this is the density of 'awake' nodes that sense the environment for any of the two main sensing scenarios: event-driven and continuous. An 'awake' node gathers data from the area covered by its sensing radius, communicates the data to the nearest node or base station. A higher density of 'awake' nodes results in a network that is *k*-connected and depending on the deployment pattern in the region, it is also *k*-redundant. In this interpretation, attention in WSNs can be used to study efficiency of WSN operation as a function of node deployment, data processing algorithms and routing protocols. Similar to attention in humans, where a higher amount of it is linked to greater efficiency, creating attention-paying WSNs improves the network operation. This may be only trivially true, and we elaborate on this in Section 5.5 of this chapter.

Finally, how do we improve attention? It is helpful to understand the structure of attention to answer this question. The structure of attention routines defines limits to the amount of information available for higher processing and hence limits the amount or the capacity of attention (Cavanagh, 2004). In this dissertation, we draw on the work of (Cavanagh, 2004) where the author summarized three independent limits on the information available for higher processing. These three limits are the capacity, acuity and the coding singularity of the selection region which commands attention. While the framework of attention described is not unique in that, there exist different types of attention, we focus on the attention routines that lie as an intermediate step between vision routines and cognition routines. The vision and cognition routines represent the first and last steps of a hierarchy that the brain employs to solve tasks. Within the set of attention routines, (Cavanagh, 2004) focused on one particular routine, selection and described it with the help of the three limits of capacity, acuity and coding singularity. We use the same approach to quantify attention limits in WSNs and detail them in Section 5.3 of this chapter.

The idea of employing cognition to wireless networks is not new; cognitive radio (Haykin, 2005) is already being researched for wireless communication as a means to improve the utilization of scarce radio spectrum. In the tradition of WSN research, cognition can be applied to a broader framework where network applications resemble the attention paid by human sensory systems to the environment. Although this is the first formal attempt to defining cognitive WSNs, the existing research in WSNs is wide enough to be encapsulated in the framework of cognitive WSNs. The understanding of what constitutes cognitive WSNs and using the analogy between the limits of attention in human cognition and the limits of data gathering and processing in WSNs shapes the rest of this chapter.

The objectives of the study on the analogy between attention in human cognition and WSNs are summarized below. The study of wireless sensor networks within the context of attention is important to achieve the following three objectives:

Capacity: If the network is deployed for continuous sensing, what is the density of information that can be sensed by the network? What element of it can be used for higher processing that reliably fulfils the objectives of the sensing operation?

Acuity: In case of multiple objects in a tracking application, what is the minimum spacing between objects that can permit access and detection of the object of interest?

Coding singularity: A third and less obvious objective is to study the sensing resolution of the network. How do we focus on the features of the desired phenomenon from the entire selection region? The answer to this lies in accurate recognition of the phenomenon despite its seemingly sparse nature of description as encountered in most real-world sensing applications and developing '*attention-paying*' WSNs.

The organization of this chapter with respect to each of the above limits is as follows: Section 5.3 describes the capacity limit of attention. In section 5.4, we address the acuity and coding singularity limits and show the relationship between them. Section 5.5 provides emerging directions for future research and concludes the dissertation.

5.3 The Capacity Limit

In (Cavanagh, 2004), the author showed that the capacity limit of attention in human cognition is set by the constraints of representing the initial and final routines in awareness. In WSNs, the capacity of a WSN may refer to the amount of information sensed by the network for the duration of network operation, network throughput or the transport capacity. In addition to being a function of the deployment pattern in the sensing region (Moscibroda, 2007; Machado and Tekinay, 2007), we show that the capacity is also a function of the reportability. With respect to data gathering networks, the capacity is often measured in terms of the transport capacity or network throughput.

In a WSN with a given density of 'awake' nodes that are sensing the environment in event-driven or continuous sensing applications, the information capacity of the network is proportional to the number of 'awake' nodes. However, the reportability required of nodes to transmit data to a sink reduces the capacity, in part due to the receiver encoding ability. This feature of the capacity limit in attention is also shown in (Marco, Duarte-Melo, Liu and Neuhoff, 2003). In (Marco, Duarte-Melo, Liu and Neuhoff, 2003). the authors show that the amount of data received at a single receiver from the network of sensors in the deployment region depends on the density of sensors. They consider a data gathering applications, where the receiver reconstructs a snapshot of the sensed field from the data received. The compression rate at the encoder poses a constraint on the reconstruction of the sensed field, since this rate is less than the transport capacity of the network. They show that as the sensor density increases, there is more correlation in the data leading to greater compression at the encoder. However, since the single-receiver transport capacity of the receiver remains constant, the amount of time it takes to transport the sensed field/ reconstruct a snapshot of the field does not decrease, but goes to infinity.

The other factor contributing to reduction in capacity is the requirement to accurately reproduce the spatial and temporal nature of the sensed environment from the data gathered. Without this constraint, the data obtained from nodes would be compressed at the sink after an amount of time dictated by the density of nodes and efficiency of the compression algorithms used, surpassing even the encoding limit at the receiver.

5.4 The Effects of Crowding

In this section, we show the effect of crowding on attention paid by WSNs with the help of the acuity and the coding singularity limits.

5.4.1 Acuity

Acuity in human cognition refers to the limit imposed by crowding on selecting an object from a region of interest. In WSNs, acuity has been studied in terms of visual acuity of networks of camera sensors (Miao, Qi and Wang, 2005). However, acuity in the context of an attention limit can have further implications. Acuity is an important issue for detecting/tracking applications in WSNs. In the case of a multiple target tracking application, what is the extent of crowding permissible in the selection region that can permit access and reporting of the desired target? This problem holds for the case of both crowding of multiple desired targets or a single desired target in a crowd of other objects. In order to detect more than one target, a widely used approach is to incorporate multiple transducers of the same type on board to indicate the presence of multiple targets (Mainwaring, Polastre, Szewczyk, Culler and Anderson, 2002; Chen et al., 2006; Werner- Allen, Johnson, Ruiz, Lees and Welsh, 2005). While the inclusion of multiple target detectors on-board is a way to increase the detection capacity of the WSN, there is a clear difference between this method and the method of detection using an increased density of 'awake' nodes with a single target-detector on board. This can be illustrated by an example: in a habitat monitoring application to spot a certain species, two organisms of the same species in close proximity might register as one organism with the sensors in the nearby area. Unless the sensors are equipped with collocated multiple target detectors, an increased density of sensors might be less effective than a single sensor with efficient detecting/tracking abilities. This brings us back to the problem of crowding. Since the probability of target detection across the deployment region is non-uniform and since activating multiple detectors on-board is not energy-efficient, one way to accommodate a sensitivity to acuity would be to develop intelligent networks that study the pattern of variation of the target and then perform adaptive density control. The analysis of coverage properties on clustered WSNs helps to resolve the acuity limit through the use of clustering techniques for data gathering and processing. In the context of target detection applications, WSNs of mobile nodes that adaptive form clusters to track properties of a mobile target is a solution to the acuity problem.

5.4.2 Coding Singularity

The coding singularity is relevant in understanding the coverage paradigm in WSNs, where coverage and connectivity are the primary factors in obtaining reliable network operation. In human cognition, the coding singularity limit refers to the constraint of selecting a given object or attributes of an object from the selection region. It differs from the acuity limit in that while the acuity limit focuses on the minimum spacing between items that allows access to individual items, coding singularity refers to the sparse description of the target in the selection region. Coding singularity in WSNs refers to the sensing resolution of the network which is defined by the resolution of the fundamental sensing unit: the sensor nodes. The area covered by a node that lies within its sensing radius is the finest level of detail that can be accessed by the sink for data processing. The next higher level of detail that can be accessed is the data from a CH. This data and the equivalent information is obtained from data aggregation and represents higher reliability than relying on the data from a single sensor.

Given this, the next question is: what should be the sensing resolution? The answer to this is application and objective dependent, although having data available at the finest resolution increases the reliability. This comes at a cost, since a high level of reliability requires a greater density of nodes sensing and transmitting data to the base station for further processing. Within this reliability constraint, the coding singularity poses two more issues. Firstly, there is the issue of what to transmit in a continuous sensing application like environment monitoring. Secondly, in an event-driven application like a target tracking/intrusion detection application, how do we recognize the target? Does merely increasing the density of 'awake' sensors guarantee an accurate response?

In a continuous sensing application, the uninterrupted nature of sensing and data dissemination has led to research into determining the subset of actual data that may be transmitted to the base station. Redundancy in deployment patterns has been exploited to reduce the transmission of redundant data due to spatial correlation in sensor locations or temporal correlation due to the pattern of variation in the sensed environment. While the coding singularity limit for attention in the neural system refers to the inability to process the features of more than one object in a selection region, this limit does not apply to WSNs. This is due to the presence of multiple transducers on board a sensor node that can sense multiple parameters of the sensed environment. However, coding singularity plays a role in information selection when the data processed at the base station is required to yield more information than merely the variation of the sensed parameters. Equivalently, this is a case of more unknowns than parameters, where the sensed parameters are processed to provide more information about the sensed field than can be obtained from transducer data in individual nodes. Coding singularity in a continuous sensing application is thus more relevant at the base station than at the nodes where the base station has to intelligently decide the amount of processing to be done on the gathered data to obtain relevant information. Alternately, in case of networks where nodes perform processing, it increases the complexity of determining what is relevant, since a node by itself has access only to the data within its sensing radius and to know the data from other nodes, it has to resort to increased inter-node communication which results in faster battery energy depletion and consequently affects network lifetime.

In response to the second issue, we recall that in the introduction, we mentioned the correlation between attention and performance. While increased attention improves performance, it does not hold true in the absence of a selection region. This is best illustrated in the case of a WSN deployed for target tracking or intruder detection application. If the features of the target are not provided to the network, there can be no awareness of the target even though all sensors are 'awake' and are transmitting gathered data to the sink. This holds also in case of inadequacy of the supplied features. If the target features are accurately outlined, it increases the efficiency of the target detection application in terms of decreasing/ eliminating the data propagation time from nodes to sink and the processing time at the sink to identify the target. Alternately, a faulty selection region that focuses on detecting objects other than the desired target have the same effect of resulting in loss of network resources such as battery power due to increased density of 'awake' sensors. The adequacy of supplied features acts like cues to the network to aid in efficiency of detection. The same argument can be used for continuous sensing scenario such as environment monitoring applications such in weather detection and temperature monitoring; however, the nodes do not have to perform the same level of processing as in detection applications to sense and report temperature. In other words, coding singularity is more relevant to tracking/detection applications with an emphasis on accurate selection. Figure 5.4 shows a cognitive WSN with the capacity, acuity and coding singularity limits that impact WSN performance.

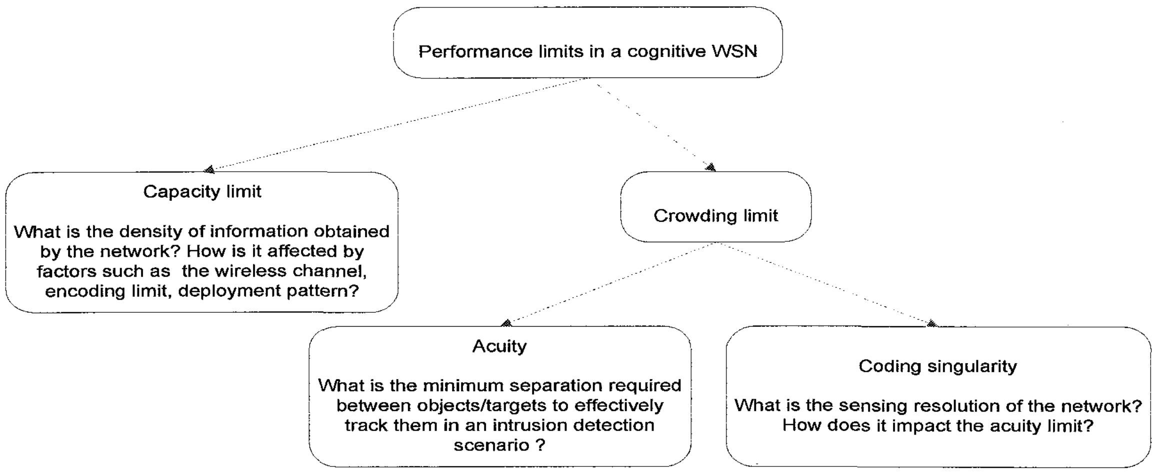


Figure 5.4 Guidelines for developing a cognitive WSN considering the capacity, acuity and coding singularity limits that impact WSN performance

5.4.3 Relationship between Coding Singularity and Acuity

In this section, we illustrate the relationship between acuity and coding singularity limits for tracking application in WSNs. Acuity and coding singularity both derive from the issues of sensing resolution in the network. In the absence of a limit for coding singularity, the base station would have access to infinite amount of data obtained from the base station and not perform any compression to process the information from the raw data. The finest resolution of sensing would thus determine the quality of the sensing operation. However, in WSNs, clustering and in-network data processing performed at nodes allow for a certain leniency in estimating the information content from a given region of the deployment region. For example, spatial and temporal correlation from sensor locations and knowledge of variation in sensing field can be used to extrapolate the data from sensors that have been turned off due to power-saving mechanisms implemented at the nodes. The acuity limit is related to the crowding of targets in the selection region. While the region of interest (ROI) can be densely covered with an increase in the number of 'awake' sensors, they do not capture the amount of detail as fewer sensors with multiple transducers on-board. Thus similar to attention in neuroscience, the acuity limit for detection exists only because of the coding singularity that defines the sensing resolution of the network (due to coverage). However, the coding singularity does not determine the minimum separation between targets, i.e. limit for the acuity of detection.

5.5 Concluding Remarks

The nature of WSN operation by distributed data gathering and processing in large-scale networks of nodes suggests that the primary goal of a WSN is to pay attention to the environment to sense the phenomenon of interest. The concept of attention in cognition can be leveraged to understand the nature of data gathering in WSNs. The knowledge of the limited nature of attention has led neuroscience research to explore among many avenues, the cognitive impact of limited attention. In this chapter, we showed that the limits of capacity, acuity and coding singularity that limit attention in human cognition are also found in clustered WSNs. In WSNs, these limits are manifested in the form of capacity of the network, ability for multiple target detection and sensing resolution of the network. We believe this framework of attention limits, which has been illustrated in this chapter with the help of comparisons to the problems encountered in clustered WSNs, will provide a unifying framework for studying the performance of WSNs. This study is worth pursuing in order to develop application-specific WSNs that do not just pay attention to the environment, but also adaptively learn to harness different 'types' of attention to provide the highest reliability of operation. The insights gained from an attention-oriented study can be used to develop self-organizing WSNs that allow for a combination of dynamic network topology, power management and routing techniques according to the variation of the sensing field.

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