University of Alberta

Base Station Positioning and Relocation in Wireless Sensor Networks

by

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To my lovely parents: Shahnaz and Hamid

Abstract

Base station (BS) positioning is considered an effective method to improve the performance of a Wireless Sensor Network (WSN). The goal of this dissertation is to minimize total energy consumption and to prolong lifetime of a WSN. First, the idea of the BS positioning in WSNs through our exhaustive search algorithm is evaluated; where it is shown that the BS position has an undeniable effect on the energy efficiency and lifespan of a WSN. Then, a metric-aware optimal BS positioning and relocation mechanism for WSNs is proposed. This technique locates the BS with respect to the available energy resources and the amount of traffic travelling through the sensor nodes at the time. Moreover, a BS relocation technique is presented in response to the dynamic environment that the sensor nodes operate in. Specifically, two optimization strategies based on the value of the path loss exponent are analyzed as weighted linear or nonlinear least squares minimization problems. Lastly, a distributed algorithm is proposed that can effectively handle the required computation by exploiting the nodes' cooperation. The simulation results demonstrate that the proposed BS positioning and relocation method can significantly improve the lifespan and energy efficiency in WSNs.

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LIST OF SYMBOLS

Symbol	Definition	First Use
α	Path loss exponent	1
n	number of the sensor nodes	6
λ	Wavelength	11
$\lVert\cdot\rVert$	Euclidean norm	14
H	Hessian matrix	15
$\mathcal{J}$	Jacobian matrix	16
γ	Poisson packet generation rate	34
δ	two-norm regularization factor	42

List of Abbreviations

Description (Abbreviation)……………………………………………………………………………………………………**First Use**
Application node (AN) 7
Arrival of Angle (AOA) 7
Base Station (BS) 1
Boundary-Constraint Nonlinear Least Square (BCNLS) 17
Constant Bit Rate (CBR) 34
Medium Access Control (MAC) 5
Sensor and Actor Networks (SANETs) 9
Universal Mobile Telecommunications System (UMTS) 6
Wireless Sensor Networks (WSNs) 1

Chapter 1

1 INTRODUCTION

1.1 OVERVIEW

The next generation of wireless communication needs independent mobile users to operate by exchanging information among themselves while keeping the communication cost a low as possible [1]. In such networks, the topology of the network changes rapidly due to the mobility of the users and the dynamic number of active users at a time. Therefore, wireless systems are migrating toward ad hoc networks to take advantage of the dynamic infrastructure and the absence of centralized control and management. Wireless Sensor Networks (WSNs), as ad hoc networks, bring all these features together; however, they face several technical challenges in their design and implementation [1]. WSNs are general infrastructure that can be classified into two categories: centralized and decentralized networks. In decentralized WSNs, nodes execute all the operations, such as message routing, decision making and topology discovery, by themselves without relying on a specific management centre. On the other hand, centralized networks operate by having a special powerful node as a centre that organizes and manages the other nodes; as a result, centralized networks face several challenges.

Recently WSNs have been the focus of researchers due to their wide range of applications, such as disaster management, traffic control, battlefield surveillance, medical diagnostics, and environmental and habitat monitoring. Some of the potential goals of such networks are conservation of natural resources, improved manufacturing productivity and improved emergency response [2].

WSNs consist of a large number of tiny and cheap devices with limited energy, processing and communication capabilities to cooperatively monitor physical or environmental conditions, such as temperature, pressure, vibration, sound, motion or pollutants at different locations. A typical task for nodes is to cooperatively gather data from the surrounding environment, make a proper decision accordingly, and send their data to a Base Station (BS). The BS is often a gateway between the sensor network and a wired network like the Internet. In the case of small networks, sensor nodes may be able to send data directly to the BS. However, in large networks multihop communication is required with intermediate sensor nodes cooperating to forward data to the BS, see Figure 1.1. The BS may be fixed but is often mobile. Two main arguments have been proposed in the literature to support multihop routing. First, there is an energy benefit of $n^{\alpha-1}$ when the distance between the source and destination is divided into n hops. Here, α is the path loss coefficient. Secondly, shorter hops lead to higher received signal strength, which results in higher network throughput [3].

Sensor nodes are typically powered by limited battery resources, and the large number of physically dispersed nodes makes it highly impractical to replace sensor nodes' batteries. Thus, the main challenge in any WSN is to employ energy control mechanisms through network management techniques [2]. Hence, energy is a critical issue in the lifetime of a WSN and requires energy to be optimized in order to extend the network lifetime. Although in WSNs energy is consumed by processing and observation, the most energy intensive task is communication [4]. Based on the recent paper by Koomey [5], in future networks, energy requirements for information processing will be insignificant compared to the energy required for transmission which does not scale with process technology and is fixed by Shannon's bound [6].

Due to the scarce energy resources, many studies have focused on energy-aware solutions in order to increase the network lifetime [7-11]. An ideal WSN is scalable, consumes very little energy, is reliable and accurate over the long term, and requires little or no maintenance.

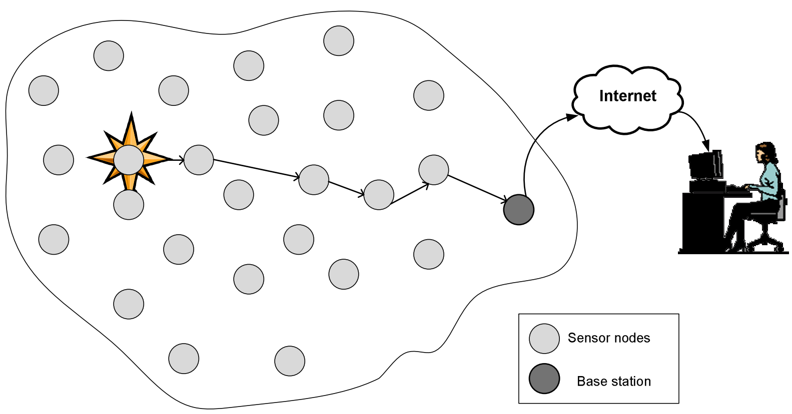

Figure 1.1. A typical form of a WSN field

Recent research results have shown that strategic positioning of the BS can effectively improve the network performance, such as throughput and delay [12]. In this context, several BS positioning techniques have been proposed to conserve energy consumption and to prolong lifetime in WSNs [13-17]. The goal of most published papers is to find a good location for the BS based on initial topological information such as distances between sensor nodes and the BS, density of sensor nodes and traffic flow within a WSN. However, such schemes are not resource-aware and can lead to misplacing the BS in the network.

One of the major characteristics of any wireless system is the reduction in power intensity as the signal propagates through space—called, path loss, which depends on propagation environmental features, such as type of area (urban versus rural); medium characteristics including weather; and antenna properties. Path loss values normally are in the range between 2 to 4, where 2 is for propagation in free space and 4 is for highly lossy environments. Sensor networks may often be deployed where the path loss is greater than 2, such as mountainous forests, on ground and inside buildings. Therefore, BS positioning techniques become important in these environments. Most current literature focuses on environments with path loss exponents of 2, which is not realistic for WSNs.

Furthermore, the majority of the proposed methods [8, 12, 14, 16] rely on centralized solutions for the problem and typically need computationally powerful hardware to perform the required calculations. However, local data processing increases energy consumption in multihop WSNs. In addition, when the algorithm runs on a specialized node, global knowledge is needed. Hence, the system requires that each sensor node reports its geographical information to that node. Several localization mechanisms have been proposed in order to obtain the nodes' location information [18-21]. From a technical perspective, centralized approaches are highly expensive due to limited bandwidth and memory in WSNs.

1.2 Thesis contribution

First, the impact of the BS positioning is investigated using our exhaustive algorithm. Our results show that in general position of the BS has a marked influence on energy efficiency and lifetime of the WSN. Then, as the main building block of this dissertation our study is extended to the optimal placement of the BS in obtaining the least total consumed energy. The objective of this thesis is to establish a BS positioning scheme in a WSN that is:

- optimal. Our method finds the optimal position for the BS in a WSN by providing the least total consumed communication energy.
- inclusive. One of the main problems that previous BS positioning techniques have not addressed is path loss exponent values arising from different environmental conditions that have an essential role in energy minimizations in WSNs. Our method finds the optimum position for a BS with regards to different path loss exponent values.
- resource-aware. This feature enables the BS positioning technique to take into account network resource availabilities and to locate the BS accordingly. We argue that network topology should be considered, and that every sensor node should contribute to the calculations relative to the conditions that it is experiencing at the time.
- distributed. The communication nature of WSNs is based on nodes' cooperation; likewise the BS positioning result should be obtained from the local interaction between the nodes. In fact, our algorithm uses only local information available at each node without the need for global knowledge.
- dynamic. Placing the BS in its initial optimal position leads to a false location over time. Thus, BS relocation needs to be implemented. The BS has to be considered for relocation in case of changes in available network resources, network topology and environmental conditions.

In other words, we aim to find an optimal BS position within a sensor field in a resource-adaptive manner according to node properties at a given point in time. Our goal is to minimize the total energy consumption in a WSN and to prolong network lifetime. Our proposed optimal BS positioning is built upon models of two environments. First, we consider a WSN located in free space where the path loss value is 2. Second, we extend our solution to environments with path loss values greater than 2, where our approach is based on an adaptive algorithm that converges to the optimal solution in a finite number of iterations. This feature makes our method robust to the dynamic changes in a WSN.

1.3 Thesis outline and organization

Chapter 2 presents a review of related solutions to the BS placement problem in WSNs followed by the challenging aspects of the mentioned schemes.

In Chapter 3, some background information is discussed for better understating of this thesis. First, we explain the network model and the energy consumption model of a WSN. Then, we conduct a probability analysis on node neighborhood's connectivity, which provide us with a sufficient number of sensor nodes to be deployed in the network field. Next, we explain the definition of the network lifetime that we use in this work. Finally, we introduce linear and nonlinear least squares optimization. This section serves as the infrastructure for the purposed BS positioning algorithms in Chapters 5 and 6.

Chapter 4 presents our proposed BS positioning and relocation algorithm relative to a known area of interest in WSNs. Our proposed algorithm considers different features for the area of interest in order to position the BS in a place where the network consumes the least energy. This algorithm is an initial elaboration on BS positioning based on an exhaustive search that evaluates and assures us of BS position on network performance in terms of energy consumption and network lifespan.

In Chapter 5, we develop our BS positioning and relocation method by formulating the problem into a weighted linear least squares optimization, where path loss exponent is considered to be 2. Weights include node characteristics that influence the energy consumption of the network. Using this algorithm along with BS relocation method, the energy consumption is minimized and results in network lifetime extension. A detailed explanation of our proposed distributed algorithm can be found in Chapter 5. The distributed algorithm exploits the nodes collaboration in order to perform the needed computation for BS positioning. The proposed distributed method works with local information and removes the need for global knowledge.

Later in Chapter 6, an extension of the proposed BS positioning algorithm in Chapter 5 is presented where a realistic network model with path loss exponent value greater than 2 is considered. An optimal algorithm for BS placement is presented along with an algorithm for BS relocation. The solution is in the framework of weighted nonlinear least squares optimization. Similarly, the weights are taken into account in order to provide a metric-aware solution. The performance of the proposed algorithms is presented for different scenarios in a WSN.

Finally, Chapter 7 concludes the thesis and suggests some potential directions for future work.

Chapter 2

2 KNOWN BASE STATION POSITIONING TECHNIQUES

Researchers have conducted investigations on WSNs at almost every layer of the communication protocol stack [22]. There exist several papers on efficient routing algorithms and data aggregation techniques [23-26], localization techniques [18-21] and medium access control (MAC) methods [27-31]. In addition, researchers take advantage of the flexibility of WSNs by designing protocols that positively affect energy consumption. To address this issue, a number of topology control techniques have been proposed, including clustering algorithms [32-36] and node deployment strategies [11, 36-39]. In recent years, several papers [8, 12, 14, 16] report on BS positioning and mainly design the network to ensure energy conservation and network lifetime extension. Nevertheless, all of these papers are facing some limitations in different aspects including relying on centralized algorithms with global knowledge, considering an unrealistic value for the path loss exponent parameter, overlooking influential metrics on energy consumption, neglecting the importance of BS relocation, and proposing an unscalable strategy restricted to small size WSNs.

In [8], the BS positioning problem is formulated as a maximum flow problem. In order to implement their BS positioning method, they argue that any maximum flow algorithm (e.g. [40]) can compute the needed calculations. In [8], production of data across the network is considered as the metric to be maximized. A fixed data rate for sensor nodes is assumed in the network model. The authors aim to find optimal positions for multiple BSs such that the energy consumed by the sensor nodes is minimized. They also investigate the effect of the BSs' layout on the data production and flow in the network. In [8], it is shown that their method for choosing the BS position can significantly improve the data rate and total energy consumption of a WSN. However, their approach is based on a centralized algorithm where a global knowledge is provided to a single workstation, including the locations of each sensor node in the network. Furthermore, the number of BSs is assumed to be fixed and known in advance. Also, authors have not investigated relocation of the BS, but we will show how this technique can dramatically improve the network performance.

The approach in [16] uses the well known k-means algorithm [41] to cluster the network and then places the BS at the centre of the cluster. However, their method to find a centre of each cluster does not include any power-aware distance metrics. Thus, if there are multiple BSs, multiple clusters need to be created. The authors define the network lifetime as the percentage of dead sensor nodes in the network. The drawback of this approach is that the number of clusters depends on the number of BSs in the network, and a priori knowledge about the number of BSs is needed without having a global view of the network. Their solution is centralized, in that a system designer should calculate the BS position. For this purpose, node locations are assumed to be known before the solution phase. Furthermore, clustering algorithms must be deployed carefully since they significantly increase the computation load on low capacity sensor nodes. Similar to the study in [8], no BS relocation mechanism has been deployed by the authors.

In [14] the authors use a mathematical model to minimize the energy used for communication by deploying the BS where the average distance between the sensors and the BS is minimized. The BS coordinates (x_s, y_s) are given by:

$$(x_s, y_s) = arg \min_{(x,y)} \sum_{i=1}^{n} \sqrt{(x_i - x)^2 + (y_i - y)^2} \qquad 2.1$$

where n is the number of sensor nodes in the network, and (x, y) is the coordinates of the BS initial position. To find the minimum, the authors in [14] calculate unit vectors pointing to the location of every sensor node. Then, the BS coordinates are obtained so that every resultant vector is zero; see Figure 2.1, redrawn from [14]. They also investigate their method on networks with a possibility of multiple BSs. It is shown that in some cases poor BS positioning may result in isolating the BS from the network by moving the BS to a place without sensor nodes. However, the proposed approach relies only on Euclidean distances as a metric for BS positioning without considering other parameters that affect energy consumption in the network. BS relocation methods in [14] use the same metric as for BS positioning. In their method, path loss value is assumed to be 2, which happens when a WSN is located in a free space. We argue that such an environment is not a realistic assumption for a WSN, and we propose a solution for this problem.

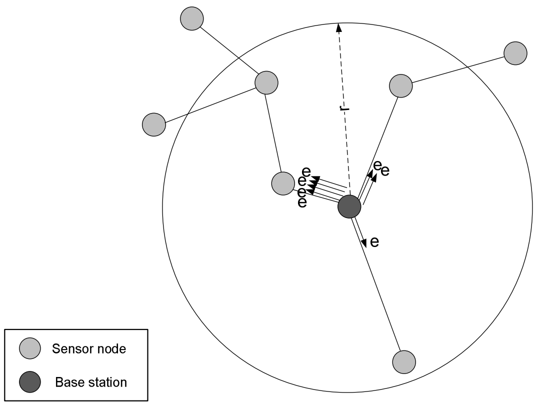

Figure 2.1. Calculating the BS position based on the resultant vectors

The proposed approach in [12] locates the BS by choosing *n* nodes within the one-hop neighborhood of the BS in terms of traffic density to form vertices of a polygon. The BS is positioned at the centroid of the vertices, which is equidistant from the selected sensor nodes. It is shown that BS repositioning reduces the average energy consumed per transmitted data packet while network throughput increases. However, the vertices (nodes) must be chosen with special care, since the solution in [12] fails when the polygon is self-intersecting, i.e. the boundary of the polygon crosses itself. Moreover, their BS positioning method only evaluates a limited region of the network, which is the BS's one-hop neighborhood. Thus, their method ignores other potentially important sensor nodes in the rest of the network. However, in our approach we consider each potentially important node to contribute to the calculations automatically.

The BS positioning problem has also been studied for universal mobile telecommunications system (UMTS) networks [42]. It is worth mentioning that cellular networks generally differ from

WSNs, since nodes in cellular networks are not able to forward messages from other nodes. The method in [42] formulates the BS positioning problem with a polynomial-time approximation scheme such that certain limitations and costs are met. They assume that a subset of possible BS positions is identified by the service provider. Their method should be applied in the planning stage of a new network, when the service provider has to decide about the locations of the BSs. Their method efficiently improves the network performances, but it is difficult to implement.

In [17], the authors investigate the BS positioning problem in a wireless video sensor network, in which tiny video sensor nodes are placed in certain locations in order to monitor and capture the data. Their goal is to maximize the network lifetime by placing the BSs in optimal positions. In their approach, the network lifetime is defined as when the first node runs out of energy. Their method forms a circle which encloses all critical nodes in the network. Critical nodes are defined as a subset of nodes with very low residual energy. The BS is positioned at the centre of the formed circle; see Figure 2.2, redrawn from [17]. They propose two algorithms based on centralized and decentralized schemes. In the decentralized method, node information is calculated based on the measurements of Arrival of Angle (AOA). For more details on AOA methodologies, see [43]. However, in some situations node locations have to be falsified since the circle has to enclose all critical nodes, as shown in the left picture of Figure 2.2. One of the other drawbacks of their approach is that their algorithm is limited to a network with a path loss of 2. Moreover, another aspect that the authors in [17] do not consider is that moving the BS towards the critical nodes (nodes with low energy reserves) is not always beneficial for networks with multihop communication schemes. Hence, their strategy can be detrimental by moving the BS closer to the critical nodes, which increases the burden on these nodes since they have to forward other nodes' messages as well as the data of their own observations. This situation can lead to exhaustion of critical node batteries and BS isolation from the rest of the network. We address this problem in our proposed work.

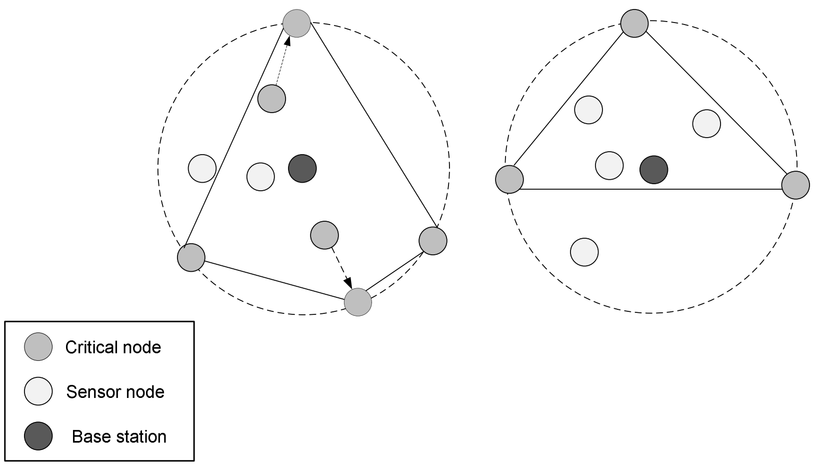

Figure 2.2. Placing the BS in the centre of a formed circle

The authors in [17] extended their work to a two-tiered WSN [35], where sensor nodes exist to capture and transmit the observed data. Sensor nodes form clusters and at least one application node (AN) is responsible for receiving the data from sensor nodes and forwarding it to the BS. It is assumed that ANs are more powerful in terms of energy resources than sensor nodes. In [35] the critical subset contains the first ANs that run out of energy. The lifetime of each node i is defined as l_i. They aim to maximize the network lifetime by maximizing $min(l_i)$ for $1 < i < N$, where N is the number of ANs in the network. The authors argue that maximizing $min(l_i = \frac{E(0)}{d_i^\alpha})$ is equivalent to minimizing the radius d of the enclosing circle as:

$$d = max\left\{d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}\right\} \quad 2.2$$

where (x_0, y_0) is the BS initial position, $E(0)$ is the initial energy allocated to each AN, and α is the path loss exponent which is assumed to be 2. Then, they locate the BS at the centre of a minimal enclosing circle. The focus is specifically on the distances between the ANs and the BS while the data rate of sensor nodes is assumed to be fixed. Their solution is unscalable to large WSNs, since the communication scheme is considered to be a single hop. Moreover, as a solution to large WSNs, it is not cost efficient to assign large number of ANs since these nodes are expensive due to higher energy supplies.

Although BS positioning is advantageous for network performance, such as delay, energy consumption and throughput, it may risk the BS safety by putting the BS in a potentially dangerous location. In [44] authors investigate the BS safety level caused by BS positioning and relocating in the network. This is especially important in disaster management applications, where there is a risk of fire, gas leak or collapsing buildings [44]. The idea is to observe the BS at different locations and to define the parameters of the BS safety levels. They propose a solution for monitoring and evaluating the BS safety and for providing candidate positions for the BS relocation. The authors argue that there is a trade-off between network performance and the BS safety. To address this problem, our BS positioning technique takes BS safety into consideration and has the ability to locate the BS in a pre-specified sub-region within the network. This way, the BS is kept far from the dangerous events in the network.

In this thesis we deal with BS positioning and relocation problems, but we do not elaborate on the literature addressing other problems in a WSN. However, we want to mention the following recent works.

In [45], authors propose a method for propagating the location of a mobile BS to the nodes in WSNs. They exploit the overhearing feature of wireless transmission, in which a node can overhear the packets in the neighborhood that are not destined for itself. In [45], sensor nodes are assumed to be static and know their own position and the location of their neighbor nodes. The BS is considered to be movable. The idea is that the BS sends periodic messages containing its new position to the last forwarder node, from which it received the last data packet. Then, the informed node propagates this message to its neighbors about the BS’s new location. However, their method will be unsuccessful if the last forwarder node runs out of energy before it receives the beacon message from the BS or if the beacon message is lost due to data collisions in the network. Also, the method in [45] may lead to confusion about the current and real position of the BS due to time-synchronization problems. In their approach, all communication links are considered to be bi-directional, which means all nodes have the same communication ranges. Their solution is not applicable for a network containing nodes with different transmission capabilities.

The authors in [46] propose a method for BS placement, node activity scheduling and routing. Their method is based on linear programming with the goal of maximizing the network lifetime. Since the authors argue that the current integer linear programming solvers are not efficient for realistic size problems, they propose a heuristic algorithm to find the solutions in a reasonable amount of time. It should be noted that they have not assumed an energy consumption cost model. The main contributions in [46] are the strategies of finding a subset of sensor nodes that ensures network coverage, and of determining efficient data transmission routes from sensors to BSs. Their approach for BS placement is simple and limited to reduce the distances between sensor nodes and the BSs. For this purpose, they divide the sensor field into equal rectangular sub-regions and place the BSs at the centre of each part. BS relocation is not investigated by the authors.

An upstream (sensors to BS) oriented transport protocol is proposed in [47], which controls the event-to-BS reliability in a WSN. Authors define Event-to BS reliability as the number of packets received by the BS in a certain period of time. Their approach is an enhanced version of the algorithm proposed in [48] when the desired reliability is sufficiently greater than the capacity of the network—called over-demand reliability. They argue that their approach in [47] outperforms the transport scheme in [48] in case of over-demand reliability by detecting this unwanted condition and recursively pushing the algorithm to converge based on the feedback from the network. In such a case, the goal is to approach the maximum reliability point in which the BS has to reduce the desired event reliability. However, the maximum reliability cannot be calculated easily due to several reasons, such as network topology changes and randomness in initial network setup.

In [49], authors introduce a new hybrid simulator for sensor and actor networks (SANETs). SANETs is a combination of two research fields namely, wireless sensor networks and mobile robotics. Their proposed integrated simulator helps to evaluate and measure the efficiency of the new algorithms by creating a realistic physical environment. The authors define the current development status of this simulator as a prototype since it still lacks performing in more complex scenarios. According to their performance evaluation, comparing the proposed simulator in [49] to the currently available simulators, the results obtained from [49] are more precise at the cost of more computation time.

Authors in [50] evaluate number of known ad-hoc routing protocols when applied to dynamic infrastructures in WSNs. They argue that traditional ad-hoc routing protocols have to be deployed for WSNs such that they support the nodes mobility feature. They categorize the existing ad-hoc routing protocols to Table Driven and On-Demand Routing Protocols. Authors argue that Table Driven method, where each sensor node has a routing table, achieves better results in dynamic WSNs compared to the On-Demand Routing Protocols. Nevertheless, Table Driven methods are inefficient due to memory limitations in sensor nodes. The study in [50] also presents a set of required characteristics for the future routing protocols to support mobility in WSNs. Authors believe that by supporting mobility features in WSNs such as phenomenon movement, sensor movement, network movement and user movement, the integration of WSNs with 4G (fourth generation of cellular wireless standards) will be possible.

To the best of our knowledge, no specific mechanism has been proposed to provide an optimal metric-aware BS positioning technique based on a distributed algorithm to reduce energy consumption in WSNs. We argue that centralized solutions are inefficient and unscalable due to limited energy resources, large numbers of deployed sensor nodes and continuous changes to the node properties in WSNs. Therefore, we propose a distributed algorithm where the computation is based on cooperation between the sensor nodes. In this way, our method leverages the information exchange among collaborating sensor nodes, which is the dominant form of communication in WSNs. Table 2.1 compares the features of some selected approaches on BS positioning with our proposed method.

Table 2.1. Comparison of BS positioning approaches

Methods' characteristics	**BS positioning for enhanced performance** [12]	**A efficient heuristic for BS placement** [46]	**Power-aware BS positioning** [8]	**Optimal BS locations in two-tiered WSNs** [35]	**Optimal BS positioning (our proposed method)**
Centralized or decentralized	Centralized	Centralized	Centralized	Centralized	Decentralized
Path loss exponent value	2	N/A	N/A	2	2-4
Evaluated metrics in BS positioning	Traffic density, distance	Distance	Data flow, distance	Nodes residual energy, distance	Nodes residual energy, traffic density, distance
Independency to initial BS position	No	Yes	No	No	Yes
BS relocation	Yes	No	No	No	Yes
Applicable network area	Convex-hull region	Rectangular grid shape	Enclosed polygon	Two-tier (sensor and cluster-head)	No restriction

Chapter 3

3 NETWORK MODEL AND PRELIMINARIES

In this chapter, we describe the system model that is used, including the node deployment and connectivity, energy consumption model and network lifetime definition. Furthermore, a detailed discussion on least squares optimization problems is provided. These definitions will be later used in the following chapters.

3.1 NETWORK MODEL

In this work, we consider a set of battery-powered sensor nodes that are distributed in a field. The BS is assumed to be placed randomly within the network, which is a typical case in a WSN. The sensor nodes are designed to monitor the coverage area and to forward data to a BS. We consider a multihop communication scheme, where intermediate sensor nodes act as relays to forward data to the BS. The BS is also a gateway between the WSN and a wired network like the Internet. For the above transmission and reception energy model, a contention-free MAC protocol is assumed, where interference can be minimized or avoided effectively.

3.2 ENERGY CONSUMPTION

Here, we outline an energy consumption cost model for a WSN that is used in our work. Based on the Friis formula [51]:

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi}\right)^2 \left(\frac{1}{d}\right)^{\alpha} \tag{3.1}$$

where,

- P_t and P_r are the transmitted power and received power respectively,
- G_t and G_r are the transmitter and receiver antenna gains respectively,
- d is the distance between the transmitter and receiver,
- α represents the path loss exponent which is usually between 2-4,
- $\lambda = cf$ denotes the wavelength of the transmitted signal, whereas f is the frequency, and c is the velocity of radio wave propagation in free space, which is equal to the speed of light.

We can express the transmitted power in (3.1) as:

$$P_t = \frac{P_r}{G_t G_r} \left(\frac{4\pi}{\lambda}\right)^2 d^{\alpha} \tag{3.2}$$

The amount of energy that is required to operate for time Δt is:

$$P_t \, \Delta t = K d^{\alpha} \, R \tag{3.3}$$

where K is a constant coefficient that captures basic transmission characteristics and R is the data rate from transmitter to receiver [52]. As mentioned previously, we assume a multihop communication scheme where the BS is situated at a significant distance relative to the sensor nodes. This will result in energy consumption in all intermediate nodes used for message relaying. Any other energy consuming activities in the sensor node is added as an overhead energy Z. Therefore, we can write the transmission energy cost model of each node i as:

$$E_t(R_i, d_i) = (Kd_i^{\alpha})\,.\ R_i + Z \qquad 3.4$$

However, reception energy is independent of d_i, and is given by [52]:

$$E_r(R_i) = WR_i \qquad 3.5$$

in which W is a constant parameter which represents the energy consumed in the reception mode. The total energy consumption of the network with n nodes at time instance t is defined as:

$$E_{total}(t) = \sum_{i=1}^{n}\sum_{j=1}^{n_i}\left\{E_{r_{ij}}(t) + E_{r_{ij}}(t)\right\} \qquad 3.6$$

where n_i is the number of nodes that are cooperating in routing the message of node i to the BS.

3.3 Probabilistic analysis on nodes deployment

Our proposed BS positioning algorithms in Chapters 5 and 6 work in a distributed fashion; thus, it is crucial that all nodes should be able to communicate with each other throughout the network. For this purpose, we present a probabilistic analysis which assures us that each node is connected to its neighbors.

Let *G = (U,V)* be a graph representing the WSN. In this graph, the vertex set *U* stands for the nodes, and the arc set *V* stands for valid communication links. Let n denote the set of sensor nodes in the network, and *A* is the length of the side of the square containing the WSN. Thus, the probability that a node is located in a circular unit area with radius r is (see Figure 3.1):

$$P_n = \frac{\pi r^2}{A^2} \qquad 3.7$$

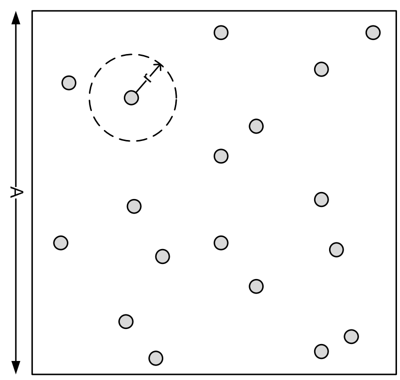

Figure 3.1. Randomly distributed sensor nodes in a square field network

In this scenario, we consider node placements following a Poisson distribution:

$$P(k;\varphi) = \frac{\varphi^k e^{-\varphi}}{k!} \qquad 3.8$$

where φ is the expected number of nodes per unit area, $\varphi = n.P_n$, and k denotes the number of nodes within its communication range. For example, if we assume a range of 4 meters for every sensor node in a field area of 100 m^2, while we require at least 2 nodes in range of every node in the network, i.e. $P(k \geq 2;\varphi)$, then based on (3.8), with 20 nodes the connectivity condition will be met with a probability of 0.99998.

3.4 NETWORK LIFETIME

There exist several definitions for network lifetime in the literature. Basically, network lifetime is strongly related to the lifetime of each individual sensor in the network. In fact, energy depletion of a single node may lead to a partial failure in message deliveries. Therefore, there should be a mechanism to control the sensor nodes' lifetime in order to prolong the lifetime of a WSN. Here, we define our formulation to quantify the lifetime of the sensor network, which will later be used as network performance criteria.

We define the network lifetime as the ratio of unreachable nodes to the total number of nodes in the network [16]. Unavailability is often caused by energy depletion in a node. The network is assumed to be inoperative whenever number of unreachable nodes exceeds a predefined threshold value. The threshold value can be specified according to network specifications. The network lifetime is defined as follows:

$$\mathcal{L}(t) = \frac{number\ of\ unreachable\ nodes\ at\ time\ t}{total\ number\ of\ nodes\ (n)} \qquad 3.9$$

3.5 LEAST SQUARES OPTIMIZATION

The proposed approach in this dissertation for BS positioning is based on weighted linear and nonlinear least square optimization problems. Here, we discuss an overview on the related methods on least squares minimization. The concepts introduced here will be covered later in Chapters 4 and 5 with more technical details.

In practice, many applications are involved with least squares problems including medical image processing, economics and system design where the optimization methods are assisting a human decision maker such as a system designer or an operator. As an answer to this demand, many approaches have been proposed for linear and nonlinear least squares problems, specifically for the unconstrained cases, where there is no limit on the parameters. See [53] for a complete discussion of algorithms for least squares problems. Moreover, many programming softwares contain least squares implementations such as Mathematica and Matlab.

Least squares minimization consists of two sets of problems: linear least squares and nonlinear least squares, when the residuals or errors are in linear or nonlinear forms respectively. The linear least squares problem can usually be solved by data fitting and it has a closed form solution. Basically, in data fitting the goal is to find a model which best fits the observed data. However, nonlinear squares problem has no closed form solution and is solved by iterative refinement. There exist numerical algorithms that find a solution to the unknown parameter, which minimizes the given function. Most algorithms involve choosing initial values for their search process. Then, the parameters are refined iteratively, that is, the values are obtained by successive approximation. At each iteration, the solution is calculated based on a linear regression model, thus it follows a similar approach as linear least squares problem.

If we assume that a model is processed based on a function Q that depends on parameters x, while the actual observations are y_i at time t_i. Thus, we need to find parameters x such that the difference between the predicted and actual measurements is minimized.

$$f_i(x) = y_i - Q(x, t_i) \tag{3.10}$$

where f denotes the random measurement errors of the data, which is assumed to be normally distributed and independent of the errors for other observations

A mathematical procedure to find the curve which best fits the curve of a given set of points is minimizing the sum of the squares of the residuals of the points from the curve. The sum of the squares of the errors is used instead of the offset absolute values because this allows the residuals to be treated as a continuous differentiable quantity. However, because squares of the offsets are used, outlying points can have a disproportionate effect on the fit, a property which may or may not be desirable depending on the problem at hand. The goal of least squares method is to determine the vector of parameters x in order to minimize the sum of squared residuals which is defined as,

$$F(x) = \frac{1}{2}\sum_{i=1}^{n}(f_i(x))^2 \tag{3.11}$$

where f_i: $\mathbb{R}^m \longrightarrow \mathbb{R}$, i =1,…,n are the given functions,

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{bmatrix} \tag{3.12}$$

We want to find x^* such that

$$x^* = arg\,\min_x\{F(x)\} \tag{3.13}$$

However, finding a global minimum is not always trivial and usually this problem is solved by finding a local minimizer for the function.

Find x^* so that, $F(x^*) < F(x)$ for $\|x - x^*\| < a$.

By assuming that each F is a differentiable function, its Taylor expansion can be written as,

$$F(x+h) = F(x) + h^T F'(x) + \frac{1}{2}h^T H h + O(\|h\|^3) \tag{3.14}$$

$\|\cdot\|$ denotes the usual Euclidean norm.

where $F'(x)$ can be calculated as:

$$F'(x) = \begin{bmatrix} \frac{\partial F}{\partial x_1}(x) \\ \vdots \\ \frac{\partial F}{\partial x_m}(x) \end{bmatrix} \quad 3.15$$

And H is the Hessian,

$$H = F"(x) = \left[\frac{\partial^2 F}{\partial x_i \partial x_j}(x)\right] \quad 3.16$$

In the remainder of this section, we shall discuss some basic concepts in optimization and also a brief introduction to the methods for finding a solution for the least squares problems. We will review some theoretical background on linear and nonlinear optimization problems. We also explain unconstrained and boundary constrained cases. Moreover, we introduce some specialized methods for boundary constrained least squares problems.

3.5.1 Linear least Squares minimization

The linear least squares technique is a common form of a linear regression which finds the best fitting straight line through the given set of points. The linear regression model may be written as,

$$f(x) = b - Ax \quad 3.17$$

where matrix $A \in \mathbb{R}^{n\times m}$ and vector $b \in \mathbb{R}^n$ are problem data, and the vector $x \in \mathbb{R}^m$ is the optimization variable. We want to find a vector x such that the function $f(x)$ be minimized. The objective function $f(x)$ contains the prediction errors between the observed data and the predicted values by the model. In this optimization problem, the goal is to find the model parameters that are consistent with the observed data such that the prediction error is minimized. Thus, the objective function is of the form,

$$\min_x \frac{1}{2}\sum_{i=1}^{n}(f_i(x))^2 \quad 3.18$$

Similarly (3.18) can be rewritten as,

$$\min_x F(x) = \min_x \frac{1}{2}\sum_{i=1}^{n}(b_i - a_i^T x)^2 \quad 3.19$$

Where a_i^T are the components of matrix *A*. By setting the gradient of the cost function F to zero,

$$F'(x) = -A^T(b - Ax) = 0 \quad 3.20$$

The above minimization problem can be solved through a set of linear equations as,

$$(A^T A)\, x = A^T b \quad 3.21$$

Thus, the analytical solution is $x = (A^T A)^{-1} A^T b$. The solution to the linear least squares can be found via many algorithms and software implementations which provide a high accurate solution. It worth noting that a solution to some nonlinear least squares methods is found by iteratively solving linear least squares problems. There exist several numerical algorithms for the linear least squares problem, See [54, 55] for more detail.

3.5.2 NONLINEAR LEAST SQUARES MINIMIZATION

The solution to the first order condition of the nonlinear square minimization problem cannot be obtained analytically; therefore solutions for such problems must be computed using numerical methods. In order to find a minimize solution for a nonlinear square function, an iterative algorithm starts by picking an initial value of the argument in the cost function and then next solutions are repeatedly are calculated until an optimum is reached approximately.

It is common to see that the algorithm cannot find the global optimum and it gives the local optimum value as the final solution. However, there exist algorithms which they find the global solution. These algorithms have not been commonly employed due to their high complexity and difficulty of implementation. Thus, the global optimization techniques are used for problems with a small number of variables, in which the computation time is not critical. We will therefore confine ourselves to those commonly used "local" methods.

In nonlinear regression model, the problem has the form,

$$\min_{x} \frac{1}{2}\sum_{i=1}^{n}(f_i(x))^2 \tag{3.22}$$

Our goal is to find,

$$x^* = arg\,\min_{x}\{F(x)\} \tag{3.23}$$

The likelihood of the nonlinear regression model is maximized when the sum of squared residuals are minimized.

We can reformulate as (3.32),

$$F(x) = \frac{1}{2}\|f(x)\|^2 = \frac{1}{2}f(x)^T f(x) \tag{3.24}$$

By assuming that f has second partial derivatives, we can write its Taylor expansion as,

$$f(x+h) = f(x) + \mathcal{J}(x)h + O(\|h\|^2) \tag{3.25}$$

where $\mathcal{J}$ is the Jacobian matrix contains the first partial derivatives of the function *f* as below,

$$(\mathcal{J})_{ij} = \frac{\partial f_i}{\partial x_j} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_m} \end{bmatrix} \tag{3.26}$$

Based on (3.15) and (3.26), the gradient of the function F can be written as,

$$\frac{\partial F}{\partial x_j} = \begin{bmatrix} \frac{\partial F}{\partial x_1}(x) \\ \frac{\partial F}{\partial x_2}(x) \\ \vdots \\ \frac{\partial F}{\partial x_m}(x) \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} \frac{\partial f_i}{\partial x_1} f_i(x) \\ \sum_{i=1}^{n} \frac{\partial f_i}{\partial x_2} f_i(x) \\ \vdots \\ \sum_{i=1}^{n} \frac{\partial f_i}{\partial x_m} f_i(x) \end{bmatrix} = \sum_{i=1}^{n} \frac{\partial f_i(x)}{\partial x_j} f_i(x) \tag{3.27}$$

Thus, we will have,

$$F'(x) = \mathcal{J}(x)^T f(x) \tag{3.28}$$

The Hessian of F can be expressed as,

$$H = F^{"}(x) = \sum_{i=1}^{n} f_i(x) f_i{}^{"}(x) + \mathcal{J}(x)^T \mathcal{J}(x) \tag{3.29}$$

x^* is a local minimizer when,

$$F'(x^*) = 0 \tag{3.30}$$

If x^* is a stationary point and $F^{"}(x)$ is positive definite, then x^* is a local minimizer.

In some case the solution of the nonlinear least-squares problems has to be within a specific boundary as,

$$\begin{gathered} \min_x \frac{1}{2} \|f(x)\|^2 \\ \text{Subject to } l \leq x \leq u \end{gathered} \tag{3.31}$$

In order to solve a nonlinear least squares problem, two types of methods known as large-scale and medium-scale algorithms can be deployed. The former method handles bound constraints in contrary to the latter one. There exist algorithms as a solution to bound-constrained nonlinear least squares such as ASTRAL [56]. In practice, any WSN is restricted to a specific region which forms a boundary for the solution; therefore we utilize large-scale algorithms in our solution for BS positioning based on Gauss-Newton and Boundary-Constraint Nonlinear Least Square (BCNLS) methods.

3.5.3 Weighted least squares minimization

Least squares problem are straightforward to be recognized and be solved; it is only needed to verify that the objective is in a quadratic form and always positive semidefinite. However, there exist several formats of least square optimization in order to increase its flexibility in specific applications such as weighted least squares.

In weighted least squares, the cost function has the form,

$$\min_x \frac{1}{2} \sum_{i=1}^{n} m_i (f_i(x))^2 \tag{3.32}$$

where $m = [m_1, \ldots, m_n]$ are positive values, and is called the weighting matrix. m is often a diagonal matrix and it reflects different emphasis to the residual vector $f(x)$. The weighted least squares problem can solved as a linear or nonlinear least squares problem as explained earlier.

Chapter 4[1]

4 EXHAUSTIVE SEARCH ALGORITHM

4.1 INTRODUCTION

In some WSNs, data from a specific area within the network is critical and is of more interest to the end-user. We call this the “area of interest”. This might be the front line in a battlefield, a portion of a forest supporting a colony of animals or the location of a fire in a city. Sensor data that originates in the area of interest is more important than that from other sensors. The data should reach the BS successfully. Nevertheless, the position of the BS in such networks is crucial as far as energy consumption is concerned. Thus, it is important to deploy the BS at a position with respect to the area of interest such that total energy consumption is minimized. In this Chapter, we propose a new dynamic approach to efficiently place the BS with the goal of reducing the total energy consumption which has a direct effect on the network’s lifetime while guaranteeing successful communication between nodes in the area of interest and the BS.

We begin by describing our algorithm in detail. We then examine the consequences of adding various constraints on the allowable positions of the BS. For instance, in order to validate our results we have considered various types of areas of interest. We have considered placing the area of interest in the centre, corner and side of the network. We have also considered different transmission rates and sizes for the area of interest. Adding constraints to this search must increase energy consumption, and we are interested in the magnitude of these increases.

The results from exhaustive search must, of course, result in the global minimum energy consumption, so it is considered to be useful for comparison. Exhaustive search is relied on here as an expedient way to explore the effects of arbitrary side-constraints that could be very difficult to add to a more efficient method. Although, the exhaustive search is impractical for networks with large number of sensor nodes or BSs, it is intended as a standard by which other more efficient and practically useful algorithms can be judged. We recognize the need for efficient, practical algorithms and develop them in the following Chapters after we have completed this initial survey.

4.2 BS POSITIONING

As mentioned earlier, multihop forwarding is assumed as a communication scheme when the BS is situated at a significant distance relative to the sensor nodes. This results in energy consumption in all intermediate nodes for message reception and transmission. Here, we assume that the BS has a global knowledge of the network including the geographical coordinates of the sensor nodes. Placing the BS in an initial position for a short period of time, the BS can calculate its optimal position by evaluating the incoming packets from other sensor nodes.

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[1] A version of this chapter has been submitted for accepted for publication WiMoNe 2010, Dec. 2010

Let e_{xy} denote the energy consumed when node (x, y) transmits data to the BS, BS_{ij}. U_{xyij} denotes all the sensor nodes along a shortest path to the BS. We use Dijkstra's algorithm for finding shortest paths. In the case of multihop communication, e_{xy} would be the total consumed energy of contributor nodes for all nodes in set U_{xyij}. Figure 4.1 shows such a communication setup.

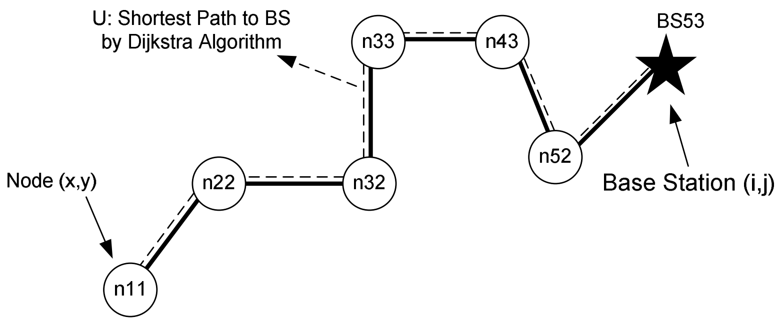


Figure 4.1. Multihop communication scheme

In this example, set U_{xyij} includes:

$$U_{xyij} = U_{1,1,5,3} = \{n_{11}, n_{22}, n_{32}, n_{33}, n_{43}, n_{52}\} \quad 4.1$$

$e_{1,1}$ is obtained as:

$$e_{n_{xy} \to BS_{ij}} = \sum_{n_{kl} \epsilon U} e_{n_{kl}} \quad 4.2$$

In the expression below, let n denote the number of sensor nodes in the entire network. α_{xy} stands for a weight of each sensor node n_{xy} . In this work, we assume the weight of a node is its transmission rate. This parameter could alternatively be used to represent other node characteristics, such as its importance, residual energy, etc.

Once we have deployed the BS somewhere in the network, all nodes start transmitting data to the BS over their shortest paths. The energy reserve of every node which contributed to the data transmission is reduced appropriately. Then the total energy consumption of placing the BS at location *(i,j)* is:

$$E_{ij} = \sum_{x=1}^{n} \sum_{y=1}^{n} \alpha_{xy} \, e_{n_{xy} \to BS_{ij}} \quad 4.3$$

(4.3) is used to calculate the energy consumption of all possible locations for the BS. In order to simplify the analysis, we assume that the possible locations of the BS are exactly the locations of the sensor nodes. By placing the BS in all possible locations in the network, we will have a matrix of total energy consumptions E_{ij} which is denoted by E.

$$E = [E_{ij}]_{nn} \quad 4.4$$

Let BS_{ij}^{0} denote the initial optimum position of the BS, and let $\mathcal{W}$ be the set of alive nodes in the network. Using (4.2), BS_{ij}^{0} is obtained as:

$$BS_{ij}^{0} = arg \min_{BS_{ij}^{*}} \{ E , \mathcal{W} \} \quad 4.5$$

Our results show that the algorithm finds an optimum location for the BS, and not surprisingly this is close to the area of interest. Therefore, data originated by the nodes inside the area of interest reaches the BS quickly and reliably while causing minimum energy consumption as they transit the network. As the transmission rate of the nodes in the area of interest increases (in other words, as the importance of nodes inside the area of interest increases) the algorithm tends to choose positions for the BS towards the centre of the area of interest. This trend is beneficial in decreasing the total energy consumption in the network.

However, placing the BS statically in one position will cause nodes nearby the BS to run out of energy quickly as they are the most heavily utilized nodes in the network. In this case, the BS will be isolated from the network. In some cases, the BS's nearest neighbors are located in the area of interest. These nodes need even more long-term support in terms of energy because they are both originating and forwarding data. To reflect this, each node in the area of interest is assigned a threshold energy value $\mathcal{T}_{hs}$ assumed equal for all nodes located inside the area of interest. Here, "hs" denotes the area of interest, or "hot spot". The value of the threshold can be defined according to node physical resources such as battery capacity.

We set $\mathcal{T}_{hs}$ as the average energy required for a node in the area of interest to communicate with the BS in its initial position:

$$\mathcal{T}_{hs} = \frac{\sum_{xy \in hs} e_{xy}^{0}}{n_{hs}} \quad 4.6$$

where:

- $\mathcal{T}_{hs}$ is the threshold value for nodes located in the area of interest,
- e_{xy}^{0} is the energy consumption of nodes (x, y) for communicating with the BS in initial BS placement,
- hs is the set of the indices of the nodes in the area of interest,
- n_{hs} is the number of nodes in the area of interest.

In order to calculate $\mathcal{T}_{hs}$, we put the BS at its initial optimum position in the network without considering any threshold value, and compute the average of energy consumption of the nodes in the area of interest for sending data to the BS. Then, we use this value as $\mathcal{T}_{hs}$ and find an optimum position for the BS subject to the condition that every node in the area of interest can send a message to the BS using less energy than $\mathcal{T}_{hs}$.

If the features of the area of interest such as its location, size or transmission rate change, the algorithm calculates the new $\mathcal{T}_{hs}$ value. In order to calculate the new $\mathcal{T}_{hs}$ value, the algorithm locates the BS at the optimum position based on the new features of the area of interest, and computes the average energy which nodes in the area of interest use to communicate with the BS. This value is considered the new $\mathcal{T}_{hs}$ until any of the features of the area of interest changes again. The pseudo code of $\mathcal{T}_{hs}$ calculation is shown in Table 4.1.

Table 4.1. Area of interest threshold calculation

If *(Area of Interest's location is changed)* ***Or*** *(Area of Interest's size is changed)* ***Or*** *(Area of Interest's transmission rate is changed)* ***Then*** *Add the new features to the network status* *Run BS Placement algorithm (Equation 4.5)* $\mathcal{T}'_{hs} = \frac{\sum_{x,y \in hs} e_{xy}}{n_{hs}}$ $\mathcal{T}_{hs} = \mathcal{T}'_{hs}$

Using (4.6), we define a new optimal location for the BS, $BS^*_{\mathcal{T}}$:

$$BS^*_{\mathcal{T}} = \arg\min_{S^*_{ij}} \{ E \mid e_{ij \in hs} \leq \mathcal{T}_{hs}, \ \mathcal{W} \} \qquad 4.7$$

where,

- E is the matrix of total energy consumptions related to locating the BS in all positions,
- $BS^*_{\mathcal{T}}$ is an optimum position of the BS which satisfies the threshold.

(4.7) selects the position for the BS which minimizes the total energy consumption for each node to send a message to the BS. The selected position must meet the threshold condition of the nodes in the area of interest. It is not surprising to see slightly higher total energy consumption in the network after adding $\mathcal{T}_{hs}$ as a parameter of the optimization. Setting the threshold value is necessary to keep nodes in the area of interest safe from rapid energy depletion.

4.3 BS RELOCATION

Once the BS has been in place for a while at the chosen optimal position, the energy levels in neighboring sensor nodes will be reduced. We propose to relocate the BS from time to time to prevent this pattern of energy depletion from partitioning the network. We assume that the BS can move to any location in the area covered by the network.

Relocating the BS is complicated by the following factors. First, there exist an infinite number of locations in the network where the BS can be placed. Second, in every search step all the energy-aware routes that become possible must be considered. We also need to decide exactly when to move the BS.

We consider two different cases. First, we recall that the BS is being moved to avoid energy depletion in its neighbors. Therefore, we define a threshold value equal to a specific number of depleted nodes around the BS. We move the BS before this threshold is exceeded. Figure 4.2 shows the relocation of the BS in order to meet the threshold value. Leaving the BS where it is first placed will result in longer paths from other nodes that are communicating with the BS due to presence of some depleted nodes around the BS. We find that our algorithm avoids this undesirable situation by relocating the BS and keeps the total energy consumption low.

The following notation is used in deriving the condition for BS relocation:

- $\mathcal{D}$: the set of depleted nodes nearby the BS
- $\mathcal{W}$: the set of alive nodes in the network
- $BS_{\mathcal{T}}^{*(i)}$: new optimal location for BS

The BS relocation can be defined in (4.8) as:

$$BS_{\mathcal{T}}^{*(i)} = arg \min_{BS_{ij}^{*}} \{ E \mid e_{ij\in hs} \leq \mathcal{T}_{hs}, \mathcal{W} - \mathcal{D} \} \tag{4.8}$$

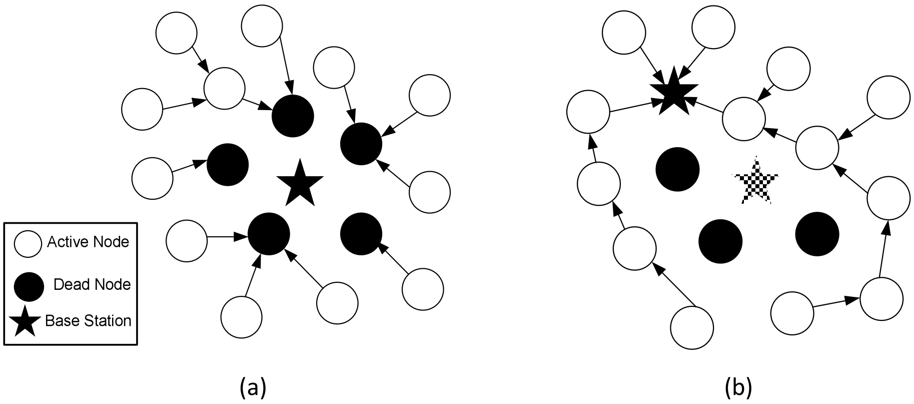


Figure 4.2. (a) Depletion of all nodes nearby BS resulted in isolating the BS from network. (b) BS is relocated to a new position. Other nodes' messages can reach the BS while keeping total energy consumption low.

Another reason to relocate the BS is that in practical situations, the area of interest may move from one place in the network to another. However, if the BS stays in its previous location regardless of changes in the location of the area of interest, then after a while the end-user is likely to lose contact with some of the nodes in the area of interest.

Therefore, we developed another algorithm in which the BS tracks the location of the area of interest. This reduces the total energy consumption while maintaining a high rate of successful data transmission. If either or both of the two relocation conditions are met, the algorithm for BS placement is called with the input of updated network conditions and the output as a new coordinate BS_{ij} for the BS. Pseudo code for the BS relocation algorithm is given in Table 4.2.

Table 4.2. BS relocation pseudo code

```
If (Area of Interest has moved)
else
If (too many BS's nearby nodes depleted)
Then remove depleted nodes from consideration
Run BS Placement algorithm (Equation 4.8)
Relocate BS_ij
```

4.4 SIMULATION RESULTS

We implemented a simulator in Matlab and evaluated the performance of our proposed algorithm. Then we compared the results of different scenarios. In our experiments, the sensor network consisted of 100 nodes deployed in a 10×10 square meter grid-shaped area.

The communication range of the sensor nodes was such that each node could communicate with its one-hop horizontal and vertical neighbors. We assumed that the energy used for transmitting one bit is twice the energy needed to receive a bit [57]. Every sensor consumed one unit of energy for each data transmission and reception.

The BS is assumed to know its own location and the location of the area of interest. The BS is assumed to have enough energy to broadcast a message containing its location to all the sensor nodes in the network. We used Dijkstra's algorithm to find a shortest path from each node to the BS. The threshold value for BS relocation was defined as 75% depleted nodes, and the energy threshold $\mathcal{T}_{hs}$ for nodes inside the area of interest was calculated by taking the average value of consumed energy for the nodes inside the area.

We ran the simulations under different network conditions while considering various characteristics for the nodes and the area of interest. These included the transmission rates, which we set at two, five and ten data transmissions per second for nodes inside the area of interest while considering one data transmission per second for all other nodes. We located the area of interest at the centre, corner and side of the network, and tried one hope and two hop lengths for the area of interest.

Figure 4.3 illustrates the optimal BS placements found by the proposed algorithm. Figure 4.3 (a) and (b) show the placements of the BS when the area of interest is located at the side of the network while increasing the data transmission rate and size of the area of interest respectively.

Figure 4.3 (c) shows the case when the area of interest is placed at the corner of network. It is interesting to note that the BS position at the centre of the network is never changed in Figure 4.3 (d). Obviously, this is caused by the symmetric shape of the network in this case.

Comparing the energy consumption of the network when using our proposed algorithm to the case of placing the BS without considering the area of interest, we find a significant reduction.

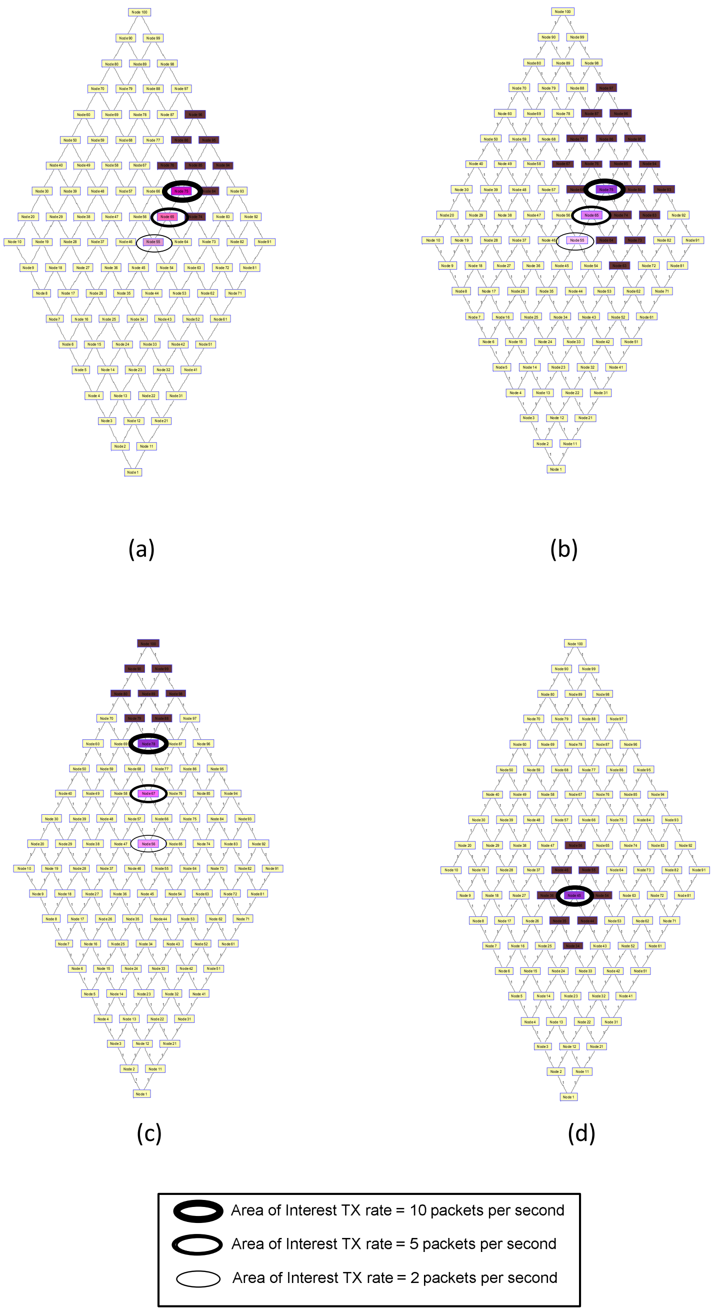


Figure 4.3. Effect of area of interest on BS position

Recall that setting the threshold for nodes in the area of interest, $\mathcal{T}_{hs}$, avoids depleting those nodes. Figure 4.4 shows the situation when the area of interest is placed at the corner of the network while we set $\mathcal{T}_{hs}$ equal to 50 units of energy and transmission rate for nodes inside the interesting area is set to 5. The BS tends to move away from the area of interest.

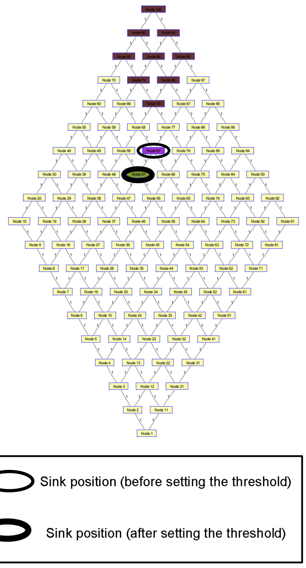
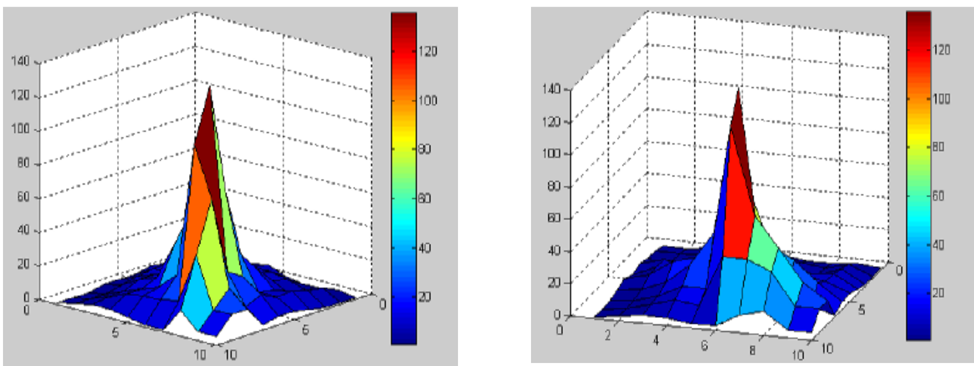


Figure 4.4. Effect of nodes' threshold on BS position

Figure 4.5 presents the results without and then with taking into account the threshold, $\mathcal{T}_{\mathrm{hs}}$. The results of BS placement simulation show that energy consumption before setting the threshold was 1644 units of energy while after having threshold for nodes in the area of interest the energy consumption increases slightly to 1800 units of energy. As can be seen from the results, the value for the case of considering threshold is higher than placement of the BS regardless of threshold. This is because the BS is positioned further away in contrast to situations without any threshold. Setting the threshold, results in data transiting longer paths to reach the BS. The goal is to respect the threshold $\mathcal{T}_{\mathrm{hs}}$ of the nodes in the area of interest. The algorithm tries to keep the consumed energy as low as possible. Other experiments with different conditions give similar results.



(a) (b)

Figure 4.5. (a) Before threshold, total energy consumption=1644 units of energy, (b) After threshold, total energy consumption=1800 units of energy

Moreover, the algorithm relocates the BS if the number of depleted nodes around the BS exceeds a threshold value. This value is set to 75% of all nearby nodes in our experiments. These sensor nodes are not necessarily nodes in the area of interest - they could be any node in the network. It is reasonable to move the BS after depletion of ¾ nearby nodes because we assumed each sensor node can communicate directly with its four horizontal and vertical neighbors. First the algorithm finds the optimal BS position. This yields a total energy consumption of 1800 units of energy. However, BS optimum static placement allows depletion of ¾ of neighbors and leads to 1830 units of energy.

Therefore, we do dynamic BS placement to avoid neighbor depletion. The new position for the BS is selected by running our relocation algorithm while we do not take into account the depleted nodes in this decision. The relocation algorithm finds a new position for the BS after reevaluating the overall network traffic flow. The result is to locate the BS in a position which leads to a lower total energy consumption. The new value for the total energy consumption is even less than the static placement of the BS because the new position of the BS in this case is closer to the area of interest. We achieved reduction in total energy consumption to 1755 units of energy.

Another condition which makes the algorithm relocate the BS to a new position is when the location of the area of interest changes. In order to evaluate our algorithm, first we placed the area of interest at the west corner of the network. We used the algorithm to find the optimal position for the BS, and this resulted in total energy consumption of 1800 units of energy.

Then, we moved the area of interest to the east corner of the network while keeping the BS's location unchanged. Total energy consumption increased to 2124 units of energy. By relocating the BS to a new optimum location with respect to the new location of the area of interest we obtained 7% reduction in total energy consumption from 2124 to 1971 units of energy. Therefore, careful BS relocation can prevent the loss of connectivity to the BS and also significantly reduce energy consumption compared to the case where the position of BS is static.

These results confirm that our algorithm enhances the network performance by repositioning the BS. However, BS repositioning must be controlled carefully as it can result in slightly higher energy consumption in if we set too high a value for the threshold $\mathcal{T}_{hs}$.

4.5 Conclusion

In this Chapter, we proposed a new approach for BS placement and relocation relative to a known area of interest. The BS is placed to minimize the total energy consumption while considering different features of the area of interest, such as its size, location and data transmission rate. Our algorithm considers the features of the area of interest as well as the importance of this area in order to position the BS in a place where the network consumes the least energy. As discussed, placing the BS statically in a position once and for all will result in depleting the energy of the BS's neighbors. Our algorithm takes into account the problem of early depletion of these nodes by relocating the BS to a new position whenever the nodes around the BS pass below a threshold value for remaining energy. Furthermore, the algorithm relocates the BS whenever the location of the area of interest changes.

It worth noting that the our solution based on the exhaustive search algorithm is guaranteed to give an optimum solution in obtaining the least consumed total energy in the network, and thus it is useful for comparison, however it is impractical on examples with large number of sensor nodes and multiple BSs in a WSN.

Chapter 5

5 Distributed optimal base station positioning and relocation in wireless sensor networks

As mentioned previously, none of the previous papers in the literature aims at finding the best position for the BS by deploying a metric-aware solution that pays attention to node characteristics such as data rate or remaining energy resources. In this Chapter, we propose a metric-aware solution to find an optimal position for the BS in a WSN. We consider node data rates, remaining energy reserves at each node and distances between nodes and the BS as the metrics that affect the decision-making process.

Centralized solutions are not efficient due to dynamic environment of WSNs; hence, the idea in this work is to request and process data locally at each node, while collecting required information from neighbors on a demand basis. We not only consider the network topology, but we also let every sensor node contribute to BS positioning calculations with regards to the conditions that it is experiencing at the time. Therefore, we implemented a distributed algorithm that uses only local information available at each node. We will describe our proposed distributed algorithm in depth in section 5.2.

5.1 Energy minimization: linear optimization

As illustrated in [14], the energy of transmitting a message via multihop communication is proportional to the distance between the transmitter node and the BS. Therefore, minimizing (3.6) is equivalent to minimizing the weighted sum of,

$$min \sum_{i=1}^{n} m_i d_i^{\alpha} \qquad 5.1$$

wher $d_i = \|v_i - v_s\| = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$, and $v_s = [x_s \quad y_s]^T$ stands for the optimal BS position. m_i is the weight of each node i, as below:

$$m_i = R_i + e_i \qquad 5.2$$

R_i and e_i denote the normalized values of data rate and residual energy at each node i respectively. Note that $\|\cdot\|$ is the usual Euclidean norm. As we are considering multihop communication, moving the BS closer to the nodes with low energy reserves increases the relay burden for those nodes. Therefore, we set a threshold value so that when a node's energy reserve drops below this threshold, that node will put its weight to a very low value so that it will be pushed away from the BS and not have to act as a relay.

We aim to position the BS such that (5.1) is minimized. We formulate the problem of the BS positioning as a curve-fitting process. If the path loss exponent value is equal to 2 or greater than 2, then the energy optimization problem turns into a linear or nonlinear least squares minimization respectively. The linear least squares problem can usually be solved by data fitting and has a closed form solution. The BS positioning method based on nonlinear least squares minimization will be explained later in Chapter 6. Figure 5.1 gives the flowchart of the BS placement and relocation method. L_{max} and t_{max} are the pre-specified thresholds for network lifetime and network operation time, respectively.

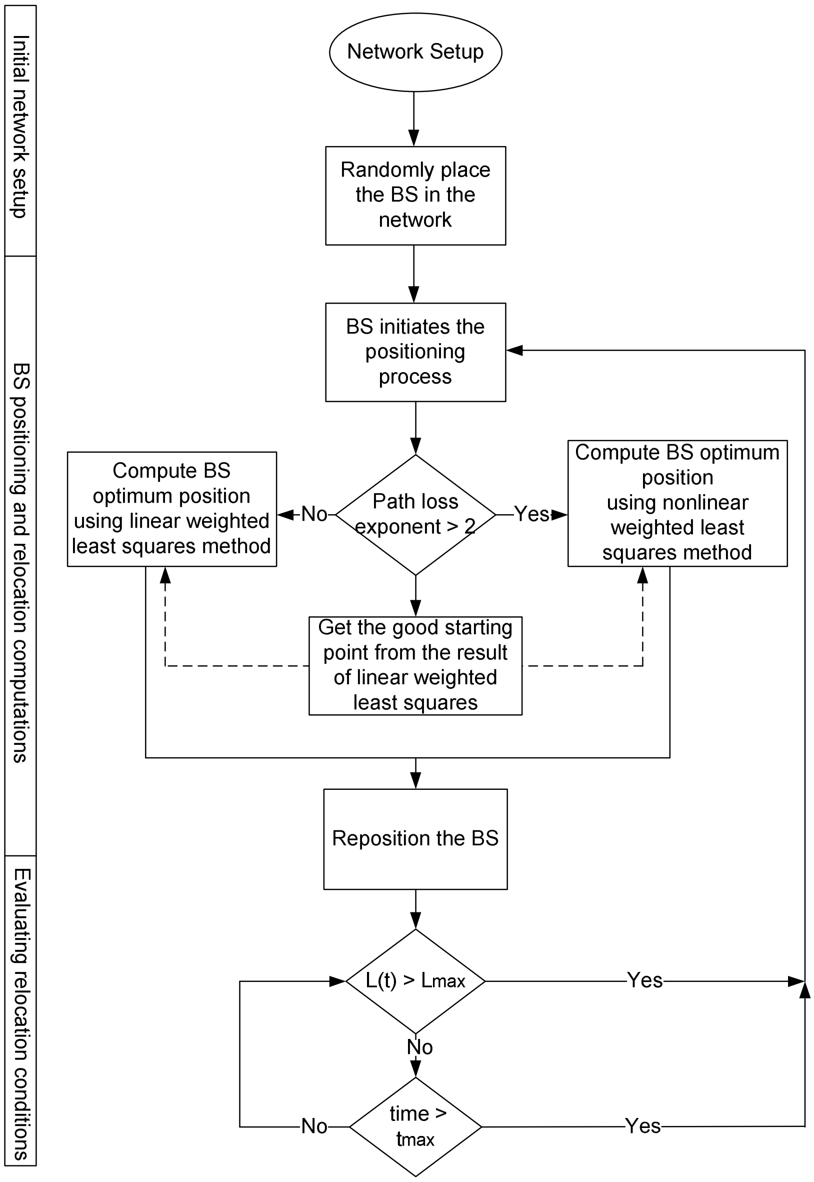


Figure 5.1. Flowchart of the BS positioning and relocation procedure used in our method

We can satisfy the minimization problem in (5.2) when $\alpha = 2$ by solving a weighted linear least squares problem:

$$F(v_s) = \min_{v_s} \sum_{i=1}^{n} m_i d_i^2 \tag{5.3}$$

In problem (5.3) the objective is to adjust the vector $v_s = [x_s \quad y_s]^T$ in order to best fit a regression model consisting of d_i and m_i. In fact, our data set includes n vectors $v_i = [x_i \quad y_i]^T$, i = 1,..., n, where x_i and y_i are independent variables. Moreover, the weighting matrix $\mathcal{M} = diag\ \{m_1, \dots, m_n\}$ gives different relative emphasis to different components of the residual vector $d = [d_1, \dots, d_n]^T$. The optimization problem can be expressed as follows:

$$\min_{v_s} F(v_s) = \min_{v_s} \sum_{i=1}^{n} m_i (v_i - v_s)^T (v_i - v_s) \qquad 5.4$$

The minimum is obtained by setting the gradient of F in (5.4) to zero:

$$\nabla F = \begin{bmatrix} \frac{\partial F}{\partial x_s} & \frac{\partial F}{\partial y_s} \end{bmatrix} = 0 \qquad 5.5$$

Knowing that $\nabla[(v_i - v_s)^T (v_i - v_s)] = -2(v_i - v_s)^T$, the solution can be written as:

$$v_s = \frac{\sum_{i=1}^{n} m_i v_i}{\sum_{i=1}^{n} m_i} \qquad 5.6$$

Remark 5.1: It can be inferred that the optimal solution in (5.6) is indeed the centre of mass of the network. The centre of mass is often called the centre of gravity because any uniform gravitational field g acts on a system as if the mass of the system were concentrated at the centre of mass [58]. We justified how this selection minimizes the total communication energy in (3.6) when $\alpha = 2$. Indeed, we position the BS at the centre of gravity of all the masses in the network, i.e. the distances between the BS and sensor nodes in the network are minimized according to each node's weight at that time. Furthermore, this method assures us that the new BS location is always a point within the network boundaries, which avoids isolating the BS from the network. It is worth noting that this technique is different from finding the centroid of the network as deployed in [12], where the focus is explicitly on minimizing the distances.

Remark 5.2: In the above proposed solution (5.6), the origin of the coordinate system is selected as the current position of the BS, *O*(x_s, y_s).

Remark 5.3: Approaches in [8, 12, 35] present a solution where the initial BS positioning is important; however, in our work the the solution obtained from (5.6) is independent of the selected origin of the framework (initial BS position). We support this statement as follows:

Let us assume v_{c1} and v_{c2} are the two vectors representing the centre of masses in the planes defined by origins v_s and $\bar{v}_s$ respectively, where $v_s \neq \bar{v}_s$. They can be defined as:

$$v_{c1} = \frac{\sum_{i=1}^{n} m_i (v_i - v_s)}{\sum_{i=1}^{n} m_i} \quad , \quad v_{c2} = \frac{\sum_{i=1}^{n} m_i (v_i - \bar{v}_s)}{\sum_{i=1}^{n} m_i} \qquad 5.7$$

By coordinate transformation of v_{c1} and v_{c2} to the coordinate system with $O(0,0)$ as the origin, we will have identical results for both cases as:

$$v_{c1} + v_s = v_{c2} + \bar{v}_s = \frac{\sum_{i=1}^{n} m_i\, v_i}{\sum_{i=1}^{n} m_i} \qquad 5.8$$

Remark 5.4: If $\alpha = 2$, then the BS placement solution obtained via our solution is optimal and offers provably minimum energy consumption in the network. However, if α is greater than two (which would result, for example, by considering path loss exponents greater than 2) then the solution given by (5.6) is not optimal anymore. In this thesis, we solve the nonlinear optimization using search from a good initial starting point (see Chapter 6).

5.2 DISTRIBUTED BS POSITIONING AND RELOCATION ALGORITHM

In this section, we present our algorithm which works in a distributed manner to find the BS optimum position. A level j is defined as an area that consists of a node i and the unvisited nodes in its neighborhood. Two nodes are considered as neighbors if the communication link between them is bidirectional. Let $v_i = [x_i \quad y_i]^T$ be a vector representing the coordinates of the node i in the network.

$$v_c^j = \begin{cases} \dfrac{\sum_{i=1}^{n^j} m_i^j \left(v_i^j - v_s\right)}{M^j} & j = 1 \\ \dfrac{\sum_{i=1}^{n^j} m_i^j \left(v_i^j - v_s\right) + \sum_{k=1}^{j-1} M^k \left(v_c^{j-1}\right)}{\sum_{k=1}^{j} M^k} & j \neq 1 \end{cases} \qquad 5.9$$

v_c^j is a vector of the BS position coordinates related to j^{th} level of the network, with the assumption of $v_c^0 = v_s = [x_s \quad y_s]^T$, where x_s and y_s are the coordinates of the BS initial position. n^j is the number of nodes in j^{th} level, m_i^j is the weight of a node i in j^{th} level and $M^k = \sum_{i=1}^{n^j} m_i^j$.

5.9(5.9) is formulated based on our distributed BS positioning algorithm. Theorem 5.1 demonstrates that propagating (5.9) through the entire network will compute the BS optimum position described by (5.6).

Theorem 5.1: Our proposed BS positioning method given by (5.6) minimizes the total energy cost function in (3.6) when $\alpha = 2$ based on our distributed algorithm in (5.9).

Proof: It can be inferred that (5.6) is indeed the proposed BS positioning given by (5.9) computed across the entire network as below:

The BS position in the first layer can be computed as:

$$v_c^1 = \frac{\sum_{i=1}^{n^1} m_i^1 (v_i^1 - v_s)}{M^1} \qquad 5.10$$

Similarly for the second layer:

$$v_c^2 = \frac{\sum_{i=1}^{n^2} m_i^2 (v_i^2 - v_s) + M^1 (v_c^1)}{\sum_{k=1}^{2} M^k} \qquad 5.11$$

Substituting v_c^1 in v_c^2 leads to a new BS position:

$$v_c^2 = v_s^{new} = \frac{\sum_{i=1}^{n^2} m_i^2 (v_i^2 - v_s) + \sum_{i=1}^{n^1} m_i^1 (v_i^1 - v_s)}{\sum_{k=1}^{2} M^k} \qquad 5.12$$

This is equivalent to (5.6) for a two level network. By induction, we deduce that (5.9) will result in (5.6) for a network with n levels, and therefore minimizes (3.6).

This concludes the proof. ■

Figure 5.2 illustrates a scenario where the WSN is partitioned into different levels while running the distributed BS positioning algorithm. Moreover, only the integrated information of each level which is the optimum BS coordinates needs to be sent to the next level in the network. It should be noted that the BS positioning algorithm will be initiated by the BS periodically, or if an unacceptable situation is observed as described in the next section.

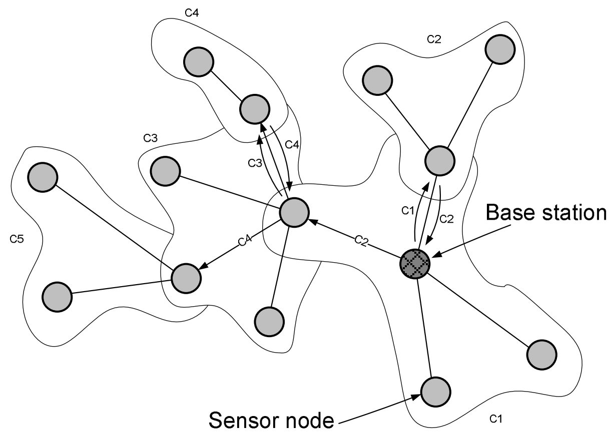


Figure 5.2. Nodes calculate the centre of mass of each level and send it to the next level, while information integrated as it traverses through the network.

5.2.1 BASE STATION POSITIONING

Our proposed distributed algorithm for BS positioning is shown in Table 5.1. The calculation is initiated by the BS. In line 2, $Node_i$ (initially the BS) creates a list containing the nodes located in its communication range. Then the parent node information is stored by $Node_i$, in lines 3-4. The parent of a $Node_i$ is defined as the first node that sends the BS positioning information to the $Node_i$ (line 24). In the initial step where $Node_i$ is the BS, the parent information is set to null. In the next step, line 5, $Node_i$ creates a list of nodes in L_{dif}, by removing the nodes from L_{new} which also exist in L_{old} (initially empty). L_{old} contains the list of the visited nodes from the beginning, thus we avoid considering a node more than once.

In lines 7-9, if L_{dif} of $Node_i$ contains one or more nodes, then $Node_i$ calculates the BS optimum position based on the list L_{dif} which contains the nodes that have not been yet considered for the calculation; moreover the computation takes into account the latest value of the BS position, COM_{old}, as shown by v_c^{j-1} in (5.9). Here, M_{old} contains sum of the nodes' weights up to the current level and M_{new} includes sum of the weights related to the nodes in the current level. The list of the nodes that are considered up to this level in the computation is updated in line 10. Then, $Node_i$ randomly selects one of the nodes from its list L_{dif}, while removing it from this list, and sends the required information (COM_{old}, L_{old}, Pa, M_{old}) to the chosen node (lines 20-24). The above steps continue until no more nodes are left in the L_{dif} of $Node_i$, which results in backward flow of information in the network (line 12). In line 12, $Node_i$ sends the values of COM_{old} , L_{old} and M_{old} to its parent node, which was previously stored in line 4. The above steps repeat until the parent node is the BS (line 14), which happens only when all the nodes in the network have contributed to the calculation. At that point the value of COM_{old} is the BS optimum position of the entire network, which is the centre of mass of the network when path loss exponent value is 2. The BS is repositioned accordingly, line 15. Clearly, our algorithm is distributed and independent of the network topology whether it is a tree or not, since a node in each level eliminates repeated received information. Therefore, the information is pruned as it flows through the network. Our method handles the dynamic infrastructure of a WSN where sensor nodes are added and removed during the network operation.

Table 5.1. Distributed BS positioning pseudo code

BS_Positioning()

1 $Node_i$=L_{old}=BS; Pa=M_{old}=∅; COM_{old}=0;

2 $Node_i$ creates the list of nodes in its communication range $Node_i.L_{new}$

3 **if** ($Node_i$.PI is empty) /* $Node_i$.PI contains parent information of $Node_i$ */

4 $Node_i$.PI = Pa /* $Node_i$ stores its parent information */

5 $Node_i.L_{dif}$ = $Node_i.L_{new}$ – L_{old}

/* $Node_i$ removes the repetitive nodes from L_{new} */

6 **end**

7 **if** ($Node_i.L_{dif}$ is not empty)

8 $Node_i$ creates M_{new} /* from nodes in $Node_i.L_{dif}$ */

9 COM_{old} = BS_Computation ($Node_i.L_{dif}$, COM_{old},M_{old},M_{new})

/* Using the computation discussed in Section 4 */

10 L_{old} = $Node_i.L_{new}$ ∪ L_{old} /* Update the list of visited nodes */

11 **else**

12 Send (COM_{old} , L_{old}, M_{old}) → $Node_i$.PI

13 $Node_i$= $Node_i$.PI

14 **if** ($Node_i$ is BS) /*At this step, COM_{old} is BS optimum position */

15 BS repositions according to COM_{old}

16 **EXIT**

17 **end**

18 **end**

19 **if** ($Node_i.L_{dif}$ is not empty)

20 Pick a $Node_j$ from $Node_i.L_{dif}$ randomly

21 Remove $Node_j$ from $Node_i.L_{dif}$

22 M_{old}=M_{new} ∪ M_{old}

23 Pa=$Node_i$

24 Send (COM_{old} , L_{old}, Pa,M_{old}) → $Node_j$

25 $Node_i$ = $Node_j$

26 Go to line 2

27 **else**

28 Go to line 12

29 **end**

5.2.2 Base station relocation

Leaving the BS where it is first placed will result in longer paths from other nodes that are communicating with the BS due emergence of depleted nodes around the BS; thus increasing total energy consumption. We propose a BS relocation scheme to prevent this pattern of energy depletion that may result in partitioning the network. We assume that the BS can move to any location in the area covered by the network. We define a maximum time period and a threshold value equals to a specific number of depleted nodes that are one hop away from the BS. The BS is moved before the thresholds are exceeded. We find that our algorithm keeps the total energy consumption low during network operation by relocating the BS. The pseudo code for this algorithm is shown in Table 5.2.

Table 5.2. BS relocation pseudo code

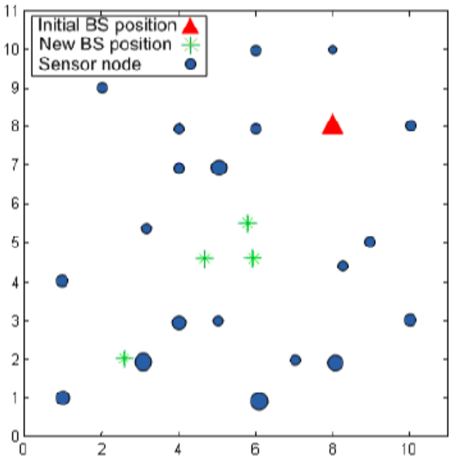
```
BS_Relocation( )
1 if (number of BS's neighbor nodes drops the threshold value) or (Maximum time duration is
reached)
2 Then
3 Run BS_Positioning ( )
4 Relocate BS
5 end
```

5.3 Analysis and proof of optimality

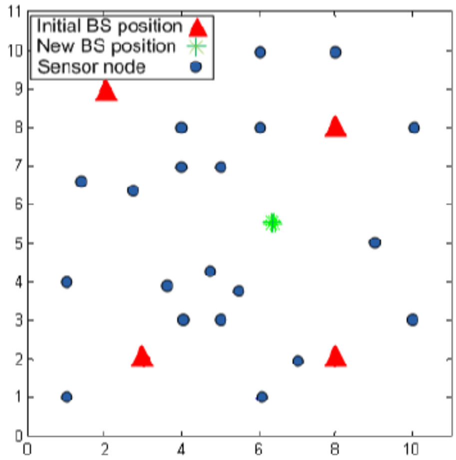
In this section, we investigate the effectiveness of our BS positioning technique when $\alpha = 2$, using the linear optimization method discussed.

All nodes are assumed to have identical communication capabilities; hence the maximum communication range is the same for all nodes. As mentioned earlier, nodes are assumed to have weights that correspond to each node's characteristics including data rate and remaining energy reserves. In our model, these values are normally distributed random numbers. We consider 20 nodes that are uniformly randomly distributed in a 10×10 square field. We also randomly place the initial BS within the network boundaries. Moreover, sensor nodes are assumed to be able to adjust their transmission power. Thus, each sensor node consumes only the amount of energy that will suffice to reach the destination sensor node. We examine two scenarios. In the first, sensor nodes generate Constant Bit Rate (CBR) data, which is commonly employed in various wireless sensor network applications. In the second, we use variable data rates where the packet generation process is assumed to be Poisson with rate $\gamma = 3$. It is assumed that each node knows its own position in the network without having full or partial knowledge of the rest of the network. We set the path loss exponent $\alpha = 2$, $K = 4.16 \times 10^{-7}$ Joules/bit and Z = 1.66×10^{-9} Joules/bit. These values are chosen because they are very close to the Berkeley/Crossbow Mica Mote specifications [15].

Figure 5.3 (a) illustrates how different node weights affect the algorithm decision for finding the optimum position for the BS. Different weights (represented with different node sizes in Figure 5.3 (a)) are assigned to the nodes in different simulation rounds, which directly affect the computed BS location. In the second approach (see Figure 5.3 (b)), the effect of different initial BS positions on the BS optimum solution is investigated while keeping the node weights constant in all rounds. The solution for BS position is identical in all cases regardless of the initial placements of the BS. This is because the algorithm solution is independent of the chosen origin of the framework (viz. Remark 5.3).



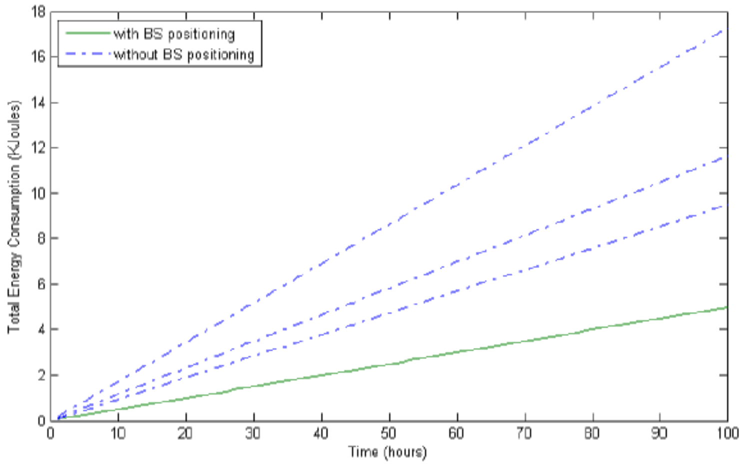
(a)



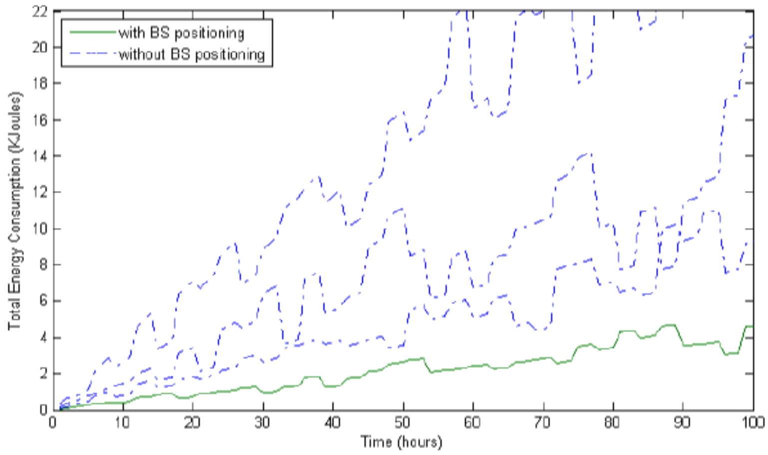
(b)

Figure 5.3. (a) Effect of nodes' weights on BS new position, (b) Effect of initial BS positions on BS new position

Figure 5.4 (a) and (b) demonstrate the effect of our BS linear optimization positioning method on total energy consumption in the network based on two scenarios of packet generation, namely constant data rates and variable data rates respectively. Each dotted line denotes a different random initial BS deployment in the network. We observe that our BS positioning scheme (solid line) leads to a significant reduction in total energy consumption in the network for both data rate models.



(a)



(b)

Figure 5.4. Energy conservation (a) constant data rate, (b) variable data rates

Figure 5.5 shows that our technique keeps the total energy consumption low for different path loss exponent values during the network operation with variable data rates, as stated in Remark 5.4. We repeated the experiment with different conditions in the network, while we observed the same trend for keeping the energy consumption low.

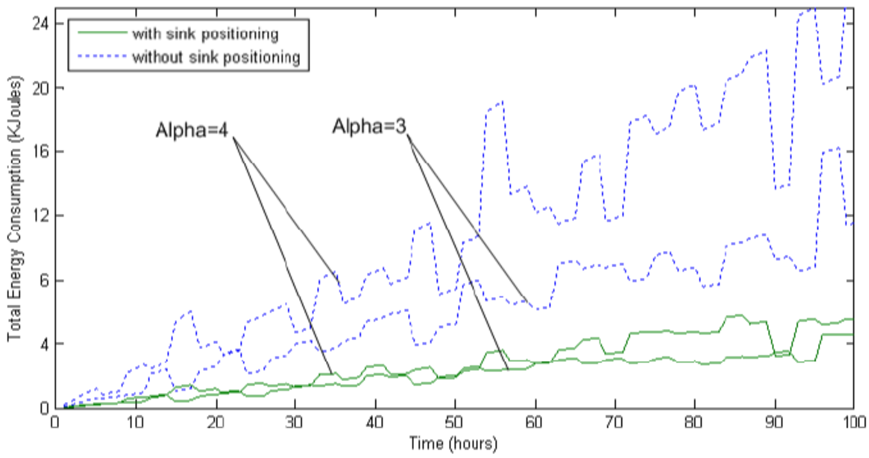


Figure 5.5. Varying path loss exponent (α)

Figure 5.6 shows that the energy consumption decreases when BS relocation method is deployed. The two curves diverge at hour 23. The reason for this behavior is that the nodes close to the BS will be heavily involved in data forwarding and thus their energy resources will be drained rather quickly. This will result in longer paths from other nodes to the BS due to some unreachable nodes around the BS, and increase the total energy consumption. Our method avoids this situation by relocating the BS, hence conserving energy.

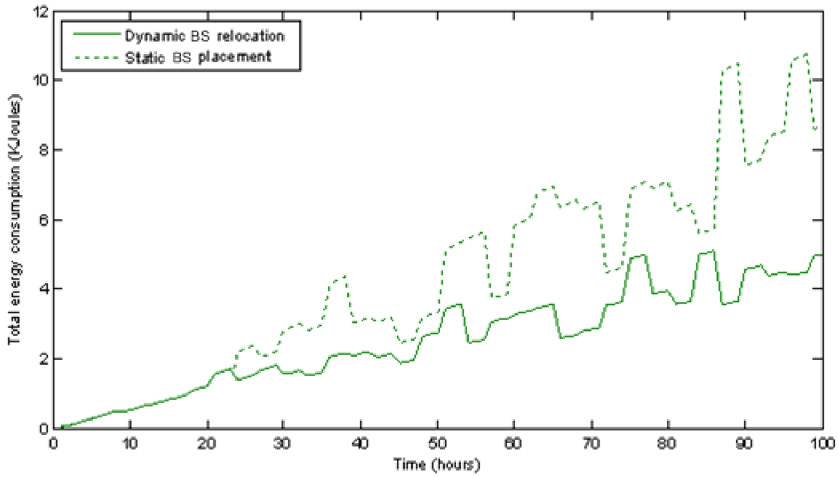


Figure 5.6. Effect of BS relocation on total energy consumption

Figure 5.7 presents the number of unreachable nodes over time in two cases of a fixed BS and a moveable BS relocated via our method. Clearly, the number of unreachable nodes increases more quickly when the BS is fixed. However, the growth is noticeably slower when our BS relocation technique is deployed. Figure 5.8 illustrates the effect of our approach on network lifetime with different threshold values. Our simulations show a 40% improvement in network lifetime over the case when no relocation method is deployed.

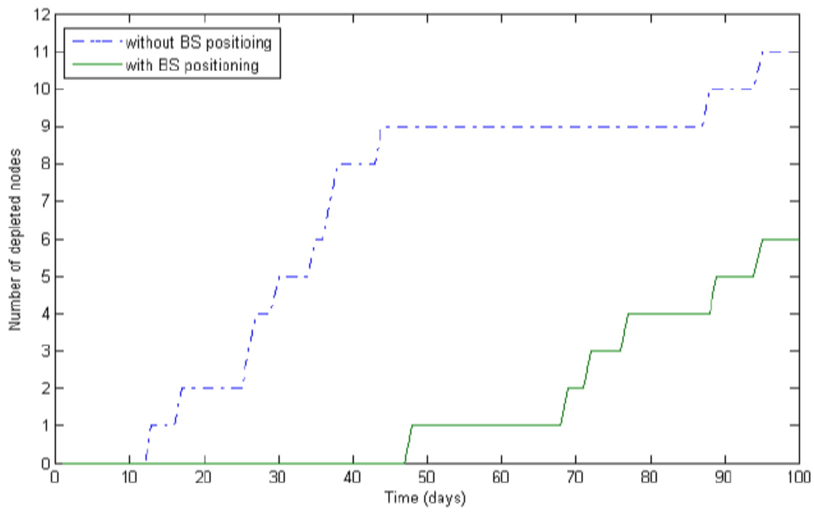


Figure 5.7. Unreachable nodes versus time

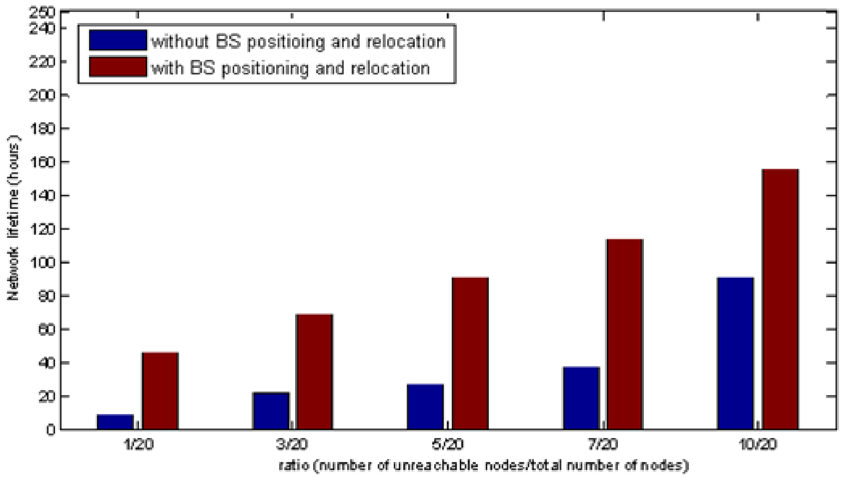


Figure 5.8. Network life time for different values of reliability ratio

Figure 5.9 compares our proposed BS placement and relocation method with the proposed solution in [12], presented in solid and dotted lines respectively. The result confirms that our approach, at all times, keeps the consumed total energy of the network lower than the BS positioning technique in [12]. The reason is that our method is a metric-aware approach and also has a broader view of the network since a larger set of nodes in the network has been considered. Comparing the two curves, we observe higher fluctuation of energy consumption in the scheme proposed by [12], which is not desirable for network status. However, due to considering various metrics for BS positioning in our method, our technique avoids such instability by dynamically adapting the BS position to the current network condition over time.

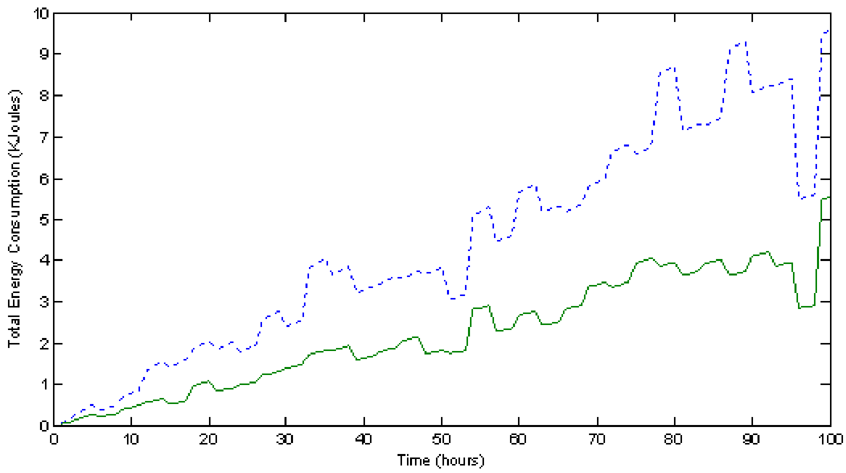


Figure 5.9. Comparison of the two approaches

5.4 Conclusion

In this Chapter, we addressed the BS positioning problem in WSNs, where the best location for the BS should be calculated according to several design criteria. Our approach is based on weighted linear least squares optimization. We proposed a distributed algorithm in order to find an optimal position for the BS in the network. Our proposed distributed algorithm makes a decision based on node characteristics at the time such as data rates, energy reserves at nodes and distances from the BS, in order to minimize the total energy consumption in the network and extend the network lifetime. We tested our solution for both constant and variable data rates, where the source bit-rate can be time-varying. Our simulation results show a significant reduction in total energy consumption of the network during network operation. Moreover, since the BS has to be relocated in order to avoid energy depletion in its neighbors, we presented an algorithm to relocate the BS. The simulation results showed that we achieve 40% higher network lifetime by relocating the BS compared to fixed BS deployment.

Chapter 6[2]

6 NONLINEAR BASE STATION POSITIONING IN WIRELESS SENSOR NETWORKS BASED ON BOUNDARY CONSTRAINTS

As discussed, if the path loss exponent value is greater than 2, then the energy optimization problem turns into a nonlinear least squares minimization. In order to find a minimum solution for a nonlinear least squares function, an iterative algorithm starts by picking an initial value of the argument in the cost function. Subsequent solutions are repeatedly calculated until an approximate optimum solution is reached.

6.1 ENERGY MINIMIZATION: NONLINEAR OPTIMIZATION

As illustrated, the BS position obtained when $\alpha = 2$ is optimal and offers minimum energy consumption in the network. However, if α is greater than 2, then the problem described by (5.1) forms a nonlinear least squares curve fitting problem. A weighted nonlinear least squares method is used to determine the vector v_s in order to minimize the sum of residuals squared as follows:

$$F(v_s) = \frac{1}{2}\sum_{i=1}^{n}\left(f_i(v_s)\right)^2 = \frac{1}{2}\|f(v_s)\|_2^2 = \frac{1}{2}f^T(v_s)f(v_s) \qquad 6.1$$

where $f_i: \mathbb{R}^n \longrightarrow \mathbb{R}$, *i=1,…,n*. We want to find v_s^* such that:

$$v_s^* = arg\min_{v_s} \{F(v_s)\} \qquad 6.2$$

where $f(v_s)$ is an n-dimensional vector function given by:

$$f(v_s) = \begin{bmatrix} f_1(v_s) \\ f_2(v_s) \\ \vdots \\ f_n(v_s) \end{bmatrix} = \begin{bmatrix} \sqrt{m_1}[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{4}} \\ \sqrt{m_2}[(x_2 - x_s)^2 + (y_2 - y_s)^2]^{\frac{\alpha}{4}} \\ \vdots \\ \sqrt{m_n}[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{4}} \end{bmatrix} = \begin{bmatrix} \sqrt{m_1}\|v_1 - v_s\|^{\frac{\alpha}{2}} \\ \sqrt{m_2}\|v_2 - v_s\|^{\frac{\alpha}{2}} \\ \vdots \\ \sqrt{m_n}\|v_n - v_s\|^{\frac{\alpha}{2}} \end{bmatrix} \qquad 6.3$$

Our objective is to establish the vector v_s such that sum of squares $f_i(v_s)$ is minimized. There exist a number of efficient algorithms for solving a nonlinear least squares problem such as the Gauss-Newton [53] and the Levenberg-Marquardt [59, 60] methods. It should be noted that the optimization problem in (6.2) needs to be solved under specific constraints over v_s as determined by (6.4). In practice, the network has known lower and upper bounds from its physical nature. Since the Gauss-Newton method solves unconstrained problems, it is not sufficient to be used in this situation and has to be combined with another method. Few approaches exist for least squares problems with constraints including ASTRAL [56, 61], and Boundary-Constraint Linear Least Square (BCLS) [62]. In this thesis, we use the Boundary-Constraint Nonlinear Least Square (BCNLS) algorithm to solve the nonlinear least squares problem in (6.2). Basically, the BCNLS technique is a combination of the Gauss-Newton and the

[2] A version of this Chapter has been submitted for publication for Journals of Computer Networks

BCLS methods, and finds a solution subject to simple constraints on the variable. Each iteration solves a linear least squares problem subject to the original constraints.

Thus, we aim to minimize $F(v_s)$ subject to:

$$\ell \leq v_s \leq u \tag{6.4}$$

ℓ and u are lower and upper bounds on the variable v_s, where they are the boundaries of the network. If the network bounds are unknown, they can be set as $-\infty$ and $+\infty$. These bounds can be used for deploying the BS in a specific sub-region of the network, e.g. in networks where the BS safety is threatened.

Based on the classical Gauss-Newton method, minimizing (6.2) leads to solving the following equations:

$$\begin{gathered}(\mathcal{J}^T\mathcal{J})\ h_k = -\mathcal{J}^T f \\ v_{s_{k+1}} = v_{s_k} + h_k\end{gathered} \tag{6.5}$$

where h_k is a direction of descent. The parameters of v_s are calibrated for each subproblem at step k by the value of h_k. $\mathcal{J}$ is the Jacobian matrix of the vector f and can be obtained as:

$$\mathcal{J} = \begin{bmatrix} \frac{-\alpha\sqrt{m_1}}{2}(x_1 - x_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{4}-1} & \frac{-\alpha\sqrt{m_1}}{2}(y_1 - y_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{4}-1} \\ \vdots & \vdots \\ \frac{-\alpha\sqrt{m_n}}{2}(x_n - x_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{4}-1} & \frac{-\alpha\sqrt{m_n}}{2}(y_n - y_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{4}-1} \end{bmatrix} \tag{6.6}$$

It follows that $\mathcal{J}^T\mathcal{J}$ is a 2×2 matrix, and its elements are given as:

$$\begin{aligned}
\mathcal{J}^T\mathcal{J}_{(11)} &= \frac{\alpha^2 m_1}{4}(x_1 - x_s)^2[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-2} + \cdots \\
&\quad + \frac{\alpha^2 m_n}{4}(x_n - x_s)^2[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-2} \\
\mathcal{J}^T\mathcal{J}_{(12)} &= \frac{\alpha^2 m_1}{4}(x_1 - x_s)(y_1 - y_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-2} + \cdots \\
&\quad + \frac{\alpha^2 m_n}{4}(x_n - x_s)(y_n - y_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-2} \\
\mathcal{J}^T\mathcal{J}_{(21)} &= \frac{\alpha^2 m_1}{4}(x_1 - x_s)(y_1 - y_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-2} + \cdots \\
&\quad + \frac{\alpha^2 m_n}{4}(x_n - x_s)(y_n - y_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-2} \\
\mathcal{J}^T\mathcal{J}_{(22)} &= \frac{\alpha^2 m_1}{4}(y_1 - y_s)^2[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-2} + \cdots \\
&\quad + \frac{\alpha^2 m_n}{4}(y_n - y_s)^2[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-2}
\end{aligned} \tag{6.7}$$

Consequently, we can derive $\mathcal{J}^T f$ as:

$$
\mathcal{J}^T f = \begin{bmatrix} -\frac{\alpha m_1}{2}(x_1 - x_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-1} - \cdots - \frac{\alpha m_n}{2}(x_n - x_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-1} \\ -\frac{\alpha m_1}{2}(y_1 - y_s)[(x_1 - x_s)^2 + (y_1 - y_s)^2]^{\frac{\alpha}{2}-1} - \cdots - \frac{\alpha m_n}{2}(y_n - y_s)[(x_n - x_s)^2 + (y_n - y_s)^2]^{\frac{\alpha}{2}-1} \end{bmatrix} \quad 6.8
$$

Remark 6.1: The above method provides a guaranteed convergence with the condition that $\mathcal{J}(x)$ has full rank in all steps. In our problem, matrix $\mathcal{J}$ encounters rank deficiency only if:

$$
\frac{x_1 - x_s}{y_1 - y_s} = \cdots = \frac{x_n - x_s}{y_n - y_s} = c \quad 6.9
$$

for c ∈ ℝ. Note that the above condition will be met when all the sensor nodes are located on a virtual single line. Normally, this situation does not happen in a WSN where the distribution of sensor nodes follows a random process. However, we will discuss a solution to this problem later in this section.

Now, we can proceed to solve our boundary constraint optimization problem (6.2)-(6.4). Using the Taylor expansion:

$$
f(v_{s_k} + h_k) \approx f_k + \mathcal{J}_k h_k \quad 6.10
$$

Recall that we assumed a boundary (6.4) for the solution, the bounds for each subproblem can be written as:

$$
\begin{gathered} \ell \le v_{s_k} + h_k \le \mathcal{u} \\ \ell_k \le h_k \le \mathcal{u}_k \end{gathered} \quad 6.11
$$

Hence, the upper and lower bounds of h_k at each iteration k are:

$$
\begin{cases} \ell_k = \ell - v_{s_k} \\ \mathcal{u}_k = \mathcal{u} - v_{s_k} \end{cases} \quad 6.12
$$

Thus, our problem can be converted to a boundary constraint linear least squares (BCLS) problem as:

$$
\frac{1}{2}\left\|f(v_{s_k} + h_k)\right\|_2^2 \approx \frac{1}{2}\|f_k + \mathcal{J}_k h_k\|_2^2 \quad 6.13
$$

subject to: $\ell_k \le h_k \le \mathcal{u}_k$

In order to remedy the numerical difficulties of the Gauss-Newton method (as stated in Remark 6.1), we may take advantage of the two-norm regularization method as follows:

$$
\frac{1}{2}\|f_k + \mathcal{J}_k h_k\|_2^2 + \frac{1}{2}\delta_k^2\|h_k\|_2^2 \quad 6.14
$$

where $\delta_k \ge 0$ is a design parameter.

Note that (6.15) can also be written as:

$$
\frac{1}{2}\left\|\begin{bmatrix} \mathcal{J}_k \\ \delta_k I \end{bmatrix} h_k - \begin{bmatrix} f_k \\ 0 \end{bmatrix}\right\|_2^2 \quad 6.15
$$

Now, the matrix $\begin{bmatrix} \mathcal{J}_k \\ \delta_k I \end{bmatrix}$ is always full-rank.

Selection of δ_k as a damping parameter protects $\|h_k\|$ from becoming large when $\mathcal{J}_k$ is not full-rank. There exist different strategies for choosing this value; in our approach selection of the appropriate value of δ_k is based on [63]. For further discussion on the choice of δ_k parameter, see [64]. The problem in (6.15) can now be solved directly through the BCLS algorithm [62].

Remark 6.2: For simplicity, our proposed solution is based on a two-dimensional space. However, it can be easily adopted for a three-dimensional space where the sensor nodes are deployed over a complex three-dimensional area.

6.2 SIMULATION RESULTS AND COMPARISON

Here, we present our simulation results obtained from nonlinear optimization method for BS positioning given in section 6.1. For this purpose, the path loss exponent value is assumed to be greater than 2 in all scenarios.

In this section, we evaluate energy consumption and network lifetime associated with our proposed BS positioning. We consider 20 nodes that are uniformly randomly distributed in a 10×10 square field. The BS is initially placed randomly within the network boundaries. It is assumed that all nodes have identical communication capabilities and are able to adjust their transmission power. Thus, each sensor node consumes only the amount of energy that will suffice to reach the destination sensor node. Nodes are assumed to have weights that correspond to each node's characteristics including data rate and remaining energy reserves. In our model, these values are normally distributed random numbers. We evaluated two scenarios with different path loss exponents. In each scenario, two models for traffic generation are examined. In the first, sensor nodes generate Constant Bit Rate (CBR) data, which is commonly employed in various WSN applications. In the second, we use variable rate data where the packet generation process is assumed to be Poisson with rate $\gamma = 3$. It is assumed that each node knows its own position in the network without having full or partial knowledge of the rest of the network. The values of the model parameters are listed in Table 6.1.

Table 6.1. Model parameters

Parameter	Meaning	Value
γ	Traffic generation rate	3
p	Packet size	1024 bits (fixed)
α	Path loss exponent	2,3,4
K	Energy cost of transmitter electronics	4.16×10^{-7} Joules per bit[3]
Z	Transmission overhead energy	1.66×10^{-9} Joules per bit[1]
W	Energy cost of receiver electronics	1.66×10^{-9} Joules per bit[1]
δ	Regularization factor	0.1
h_0	Initial step size parameter	0.25

Table 6.2 illustrates how initial BS positions affect the convergence speed of the algorithm for finding the optimal BS position. It is reasonable to choose the solution of the linear optimization as a good starting point since it significantly reduces the number of iterations of the algorithm, as shown in row 5 of Table 6.2. Recalling Remark 5.3, initial BS position does not affect the final BS position.

[3] These values are chosen because they are very close to the Berkeley/Crossbow Mica Mote specifications [65].

Table 6.3 shows the impact of node weights. It is seen that the BS positions itself closer to the nodes with higher weights. It should be noted that the initial BS position is kept the same in all rounds.

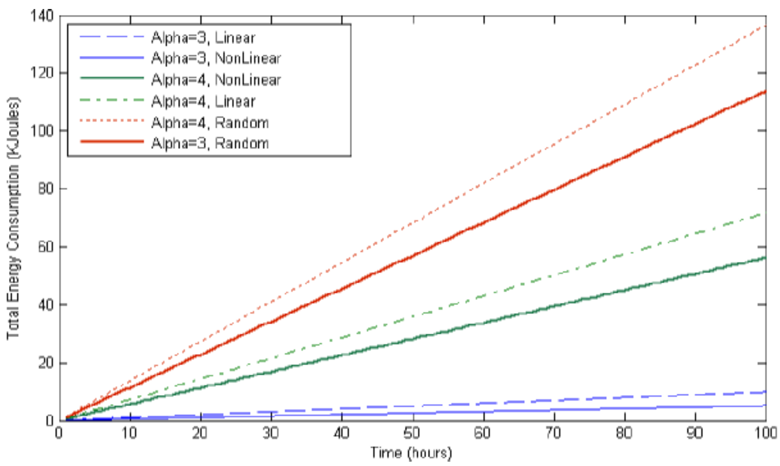
Table 6.2. Effect of initial BS positions on new BS position, **α** = 3

#	Method for initial BS placement	Initial BS position	No. of iterations	Norm-2 of the residual *f(x)*	Optimal BS position
1	Random	(6,9)	14	8592.26	(5.7,6.2)
2	Random	(1,3)	13	8592.26	(5.7,6.2)
3	Random	(8,1)	18	8592.26	(5.7,6.2)
4	Random	(9,6)	14	8592.26	(5.7,6.2)
5	Linear ans.	(5.1,5.7)	8	8592.26	(5.7,6.2)

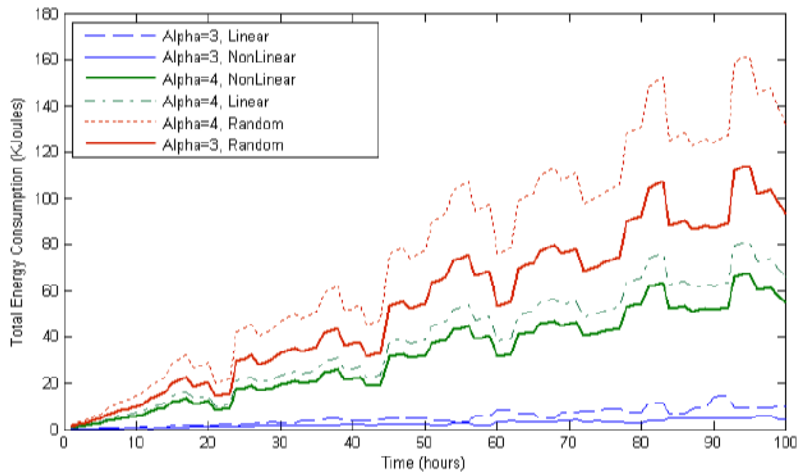
Table 6.3. Effect of nodes' weights on new BS position, **α** = 3

#	Norm-2 of nodes' weights	Norm-Infinity of nodes' weights	Position of the dominant weight	No. of iterations	Norm-2 of the residual *f(x)*	Optimal BS position
1	41.81	18.77	(5,4)	15	11170.5	(7.2,3.5)
2	39.25	25.99	(7,3)	17	7934.17	(6.6,3.4)
3	52.25	21.36	(8,1)	16	10620.1	(7.5,2.8)
4	1.0005e+003	1000	(9,2)	16	19845.2	(9.1,2.3)

Figure 6.1 depicts the comparison of the BS positioning based on random, linear and nonlinear minimization methods for environments with $\alpha > 2$. In Figure 6.1 (a) a constant data rate for all nodes is considered. We observe BS positioning based on the nonlinear method leads to a further reduction in total energy consumption compared to the linear optimization method alone. The linear method still gives an acceptable result at the price of a small performance loss compared to the nonlinear method. This is because the BS position found by the linear optimization technique is sub-optimal yet close to the optimal solution given by the nonlinear optimization method. Figure 6.1 (b) shows a similar experiment when nodes are generating variable data rates. It can be inferred that random BS positioning causes the worst performance at all times.



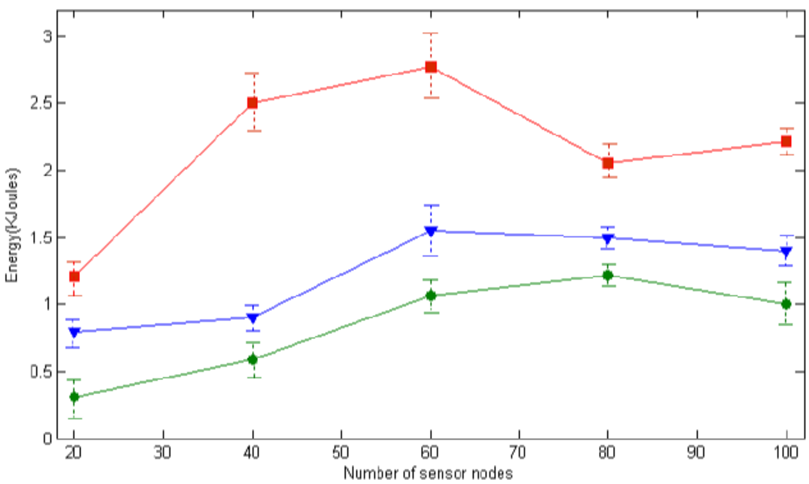
(a)



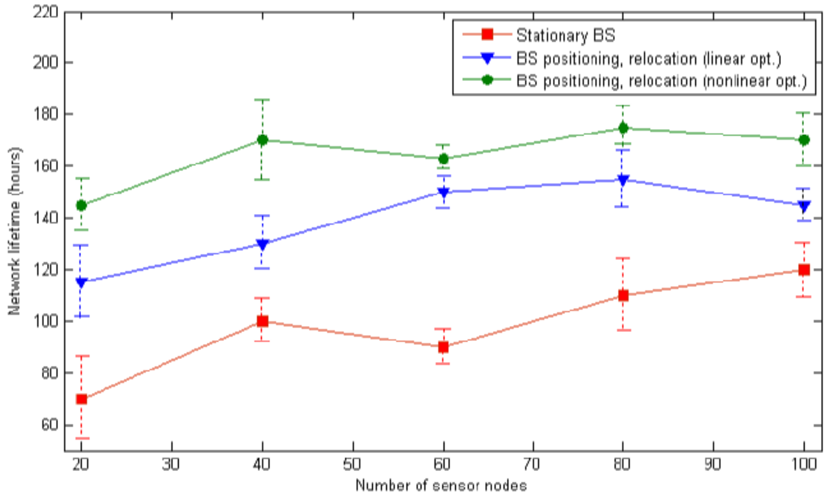
(b)

Figure 6.1. Comparison of random, linear and nonlinear least squares optimization techniques for BS positioning in networks given $\alpha > 2$: (a) Constant data rate, and (b) Variable data rate.

Figure 6.2 (a) demonstrates the effect of increasing the number of sensor nodes on total energy consumed at hour 1 in a network when $\alpha = 3$. The results indicate that the BS placement according to the nonlinear minimization technique achieves the best performance regardless of the number of sensor nodes. According to Figure 6.2 (b), BS positioning and relocation derived from the nonlinear optimization leads to the longest lifetime independent of the number of sensor nodes. It should be mentioned that the network lifetime is defined with the reliability ratio of 60%. In order to verify the reliability of our results, we tested our method on 20 experiments with different node weights. The confidence intervals in Figure 6.2 are obtained based on the term $\mu \pm 2\sigma$, where μ and σ are the mean value and variance of the experiments respectively.



(a)



(b)

Figure 6.2. Effect of number of sensor nodes for $\alpha = 3$ on (a) the consumed energy (b) on network lifetime

6.3 Conclusion

In this Chapter, we proposed a solution for BS positioning problem in WSNs when the path loss exponent value is greater than 2 based on weighted nonlinear least squares optimization. Our solution is resource-aware by taking into account several parameters. Also the distributed algorithm proposed in Chapter 5 can effectively handle the required computation related to our BS positioning method. We investigated the network performance for different snapshots in time on random networks. Analytical and simulation results demonstrate that our BS positioning and relocation technique significantly reduces the energy consumption of the network. We also demonstrate that BS relocation based on our method can extend network lifetime w.r.t. a static BS deployment.

Chapter 7

7 Conclusion and future work

This Chapter summarizes the contributions of this dissertation. Moreover, we will introduce some potential research topics for future studies.

In this dissertation, we studied the BS positioning problem in WSNs and its impact on energy consumption and network lifetime. Different parameters affecting the energy consumption and network lifetime are considered in our analysis. The outcome of our BS positioning study can be utilized in WSN design step and also during the network operation.

Initially, we studied the BS positioning for WSNs, where the sensor nodes are uniformly distributed in the area. In fact, the proposed algorithm was evaluating the required energy consumption for communication between all sensor nodes and the BS for all possible BS positions in the network through an exhaustive search algorithm. Based on the result, the BS is located in a position where the least consumed energy is achieved. Moreover, through simulations the improvement made by applying the BS relocation was verified. The result from this initial algorithm was an encouragement to develop more efficient strategies for realistic network models, which are explained in the following.

We argued that BS positioning needs to be metric-aware. Thus, we proposed a technique that makes a decision based on the sensor nodes' characteristics such as data rates, energy reserves at the nodes, and distances from the BS. Then, we proposed an optimization technique based on weighted linear least squares minimization when the path loss exponent value - a major characteristic in wireless communication - is 2. We analytically showed that the solution given by our method is identical to the centre of mass of the network. The accuracy of the algorithm solution is verified by knowing the fact that in physics, centre of mass is defined as an equidistant point from network borders regarding the weights throughout the network. It should be noted that weights were considered as the sensor nodes' characteristics, which have a strong influence on the network performance criteria. We tested the improvement by our proposed algorithm through computer simulations.

In addition, we extended the analysis to WSNs that operate in a nonlinear environment where the path loss exponent value is greater than 2. Notably, our analysis on the energy minimization relies on a realistic network model assumption. We formulated this problem into a weighted nonlinear optimization with the goal of minimizing the energy consumption. Similar to the study of the BS positioning in environments with path loss of 2, we have included nodes' characteristics as the metrics. We also proposed a solution for BS relocation when specific thresholds are met. The results showed that our method for BS positioning and relocation significantly reduces the total energy consumption and enhances the network lifetime. We also provided a BS safety strategy by locating the BS in a specific sub-region. This way, BS can be protected from dangerous events within the network.

Furthermore, we proposed a distributed algorithm to find the BS position in the network based on the distributed collaboration of the nodes. Therefore, our technique is scalable to large WSNs, where the calculations are carried out on smaller sub-networks. We showed that our distributed algorithm is independent of the network topology, and the information passing between the sensor nodes is reduced.

There exist interesting questions related to the proposed techniques. In our study, we assumed that each node knows its location information, while it participates in the calculation. The challenge in this direction is to evaluate the accuracy of our proposed algorithm as a function of the level of uncertainty in the knowledge of node coordinates.

Our BS positioning methodology can be further extended to the case when multiple BSs exist in a WSN. This way, not even the position of the BS within the network has to be determined, but also even more energy can be saved by considering relative positions of BSs to each other. Similar to the case of a single BS, we anticipate that strategic positioning of multiple BSs can help increase the network lifetime. Moreover, in the WSNs that the number of BSs is unknown in advance, the BS positioning problem is combined with finding an optimum number of BSs in the network.

Another potential area to study is to perform the BS relocation through predictive modeling, which we call it "Predictive decision for BS position detection in WSNs". For this purpose, a model is created to predict the direction that the BS is travelling based on the previous observations. The concept is based on the fact that most of the BS's next positions show a significant correlation between the successive locations. Deploying this method for BS relocation is anticipated to reduce the required computation and consequently decrease the consumed processing energy in the network, compared to recalculating the BS position every time.

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