A Study on Energy Efficient Data Gathering for Mobile-Sink-based WSNs

モバイルシンクを用いた無線センサネットワークにおける省電力データ収集に関する研究

A dissertation presented

by

Ahmed E.A.A. Abdulla

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To my family and dear friends for their endless love and support.

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Abstract

Recent developments of wireless communications and nanotechnology coupled with their low costs have accelerated the spread of Wireless Sensor Networks (WSNs), in which wireless-transmission capable sensor-equipped nodes are deployed in great numbers to collect information concerning areas of interest. The primary role of sensor nodes is to gather data of importance from its surroundings. Also, owing to the infrastructureless operation of WSNs, the sensor nodes assume the packet-forwarding role by relaying transmissions from other sensor nodes. The sink node assumes the role of a network gateway, through which data are gathered from sensor nodes, and where from users can extract the data from the WSN. WSNs are ideal for a variety of applications, ranging from environmental (e.g., temperature readings) to military uses (e.g., adversary movement).

Sensor nodes rely heavily on battery power to drive their functionality. When the energy of a battery is depleted, the sensor node loses its functionality. Replacing/charging the batteries of a large number of sensor

nodes is an insurmountable task in terms of time and cost; the task becomes infeasible in potentially dangerous terrain. Hence, severely limited energy capacities of wireless sensor networks render energy-efficient technologies indispensable for deploying wireless sensor networks. The main concern in this research direction is low-energy communications for data gathering. This is attributed to the large share of energy consumed for communications. Practically, sending a bit over 10 or 100 meters can consume as much energy as millions of computational operations conducted in the processing unit of the sensor node, this phenomenon is referred to as R4 signal energy drop-off. Improving the transmission circuits and/or devising a better transmission strategy can decrease energy consumed for data gathering. In this thesis, we consider how to devise a better transmission strategy in order to result in better energy efficiency.

We plan to propose data gathering method from sensor nodes in a manner that is energy efficient and leads to a longer lifetime of battery powered sensor nodes. Towards this end, focus on two aspects, namely, data gathering from clusters and data gathering within clusters, detailed as follows:

Data Gathering from clusters to the mobile sink: This happens between the cluster head and the mobile sink node. For data gathering from clusters, we aim to propose a method to gather data in a manner that maximizes energy efficiency (throughput per energy consumption) of clusters while maintaining a predefined level of fairness among clusters. We performed an in depth investigation energy efficient methods for data gathering from clusters in WSNs. Furthermore, we considered what are the drawbacks of contemporary methods. In particular, we were interested in energy inefficiencies. We devise a method based on game-theory to overcome the drawbacks of contemporary methods, namely, a method to maximize energy efficiency (throughput per energy) while maintaining fairness of resource allocation among cluster heads. We propose a game theoretic analytical model to analyze the performance of the proposed method and explore several important properties. Especially, the properties of optimality in terms of energy efficiency and convergence (the ability to reach an optimal solution). To evaluate the performance of the proposed method more thoroughly, we developed a simulator. Through using the simulator, we were able to evaluate energy efficiency, throughput, fairness, the effect of different environmental parameter on the performance of the proposed method.

Data Gathering within clusters: This happens among sensor node to transmit data to the cluster head. For this data gathering we aim to devise a method that minimizes energy consumption of the sensor nodes that are participating in the relay of data to the cluster head. We performed an in depth investigation energy efficient methods for data gathering within clusters of a WSNs. Furthermore, we considered what are the drawbacks of contemporary methods. In particular, we were interested in energy inefficiencies. We devise a method to overcome the drawbacks of contemporary methods, namely, a method to minimize energy consumption. We propose an analytical model based on Markov chain to analyze the performance of the proposed method in terms of energy consumption and derive the transmission distance that results in the minimum energy consumption. Through our numerical analysis, we were able to evaluate the energy consumption, and the effect of different environmental parameter on the optimal settings to achieve minimal energy consumption.

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Chapter 1

Introduction

Recent developments of wireless communications and nanotechnology coupled with their low costs have accelerated the spread of Wireless Sensor Networks (WSNs) [1–3], in which wireless-transmission capable sensor-equipped nodes are deployed in great numbers to collect information concerning areas of interest. The primary role of sensor nodes is to gather data of importance from its surroundings. Also, owing to the infrastructureless operation of WSNs, the sensor nodes assume the packet-forwarding role by relaying transmissions from other sensor nodes. The sink node assumes the role of a network gateway, through which data are gathered from sensor nodes, and where from users can extract the data from the WSN. WSNs are ideal for a variety of applications, which include the following:

1. **Environmental monitoring:** A WSN can be deployed in a forest to collect information about temperature, air pressure, and/or acoustic information.

2. **Health care:** A WSN can be deployed to collect information about patients' life signs including, heart beat, blood pressure, and/or, sugar level.

3. **Military:** In military combat WSNs can be deployed to collect information about adversary movement, mine detection, and/or combat situation.

1.1 Background

Sensor nodes rely heavily on battery power to drive their functionality. When the energy of a battery is depleted, the sensor node loses its functionality. Replacing/charging the batteries of a large number of sensor nodes is an insurmountable task in terms of time and cost; the task becomes infeasible in potentially dangerous terrain. Hence, severely limited energy capacities of wireless sensor networks render energy-efficient technologies indispensable for deploying wireless sensor networks. The energy consumption of a wireless senor node can be attributed to the following major activities [4]:

1. **Information gathering:** Energy consumed by the sensors onboard the sensor nodes for gathering information.

2. **Computation:** Energy consumed for processing purposes, predominantly attributed to the basic system operation.

3. **Data Gathering:** Energy consumed to transmit data from sensor nodes to their neighbors. This usually takes up the largest share of energy consumption of a wireless sensor network.

The main concern in this research direction is low-energy communications for data gathering. This is attributed to the large share of energy consumed for communications. Practically, sending a bit over 10 or 100 meters can consume as much energy as millions of computational operations conducted in the processing unit of the sensor node, this phenomenon is referred to as R4 signal energy drop-off [5]. Improving the transmission circuits and/or devising a better transmission strategy can decrease energy consumed for data gathering. In this thesis, we consider how to devise a better transmission strategy in order to result in better energy efficiency.

1.2 Objectives

We plan to propose data gathering method from sensor nodes in a manner that is energy efficient and leads to a longer lifetime of battery powered sensor nodes. Towards this end, focus on two aspects, namely, data gathering from clusters and data gathering within clusters, detailed as follows:

1. Data Gathering from clusters to the mobile sink: This happens between the cluster head and the mobile sink node. For data gathering from clusters, we aim to propose a method to gather data in a manner that maximizes energy efficiency (throughput per energy consumption) of clusters while maintaining a predefined level of fairness among clusters. Comparable methods do not consider energy efficiency in the link between the mobile-sink and cluster heads.

2. Data Gathering within clusters: This happens among sensor node to transmit data to the cluster head. For this data gathering we aim

to devise a method that minimizes energy consumption of the sensor nodes that are participating in the relay of data to the cluster head. Our method considers energy consumed due to collisions in deciding the transmission strategy.

1.3 Thesis Structure

The remainder of this thesis is structured as follows:

- **Chapter 2: Literature Review.** In this chapter, we conduct a literature review on data gathering methods for WSNs. A key design parameter is the mobility of the sink node. we classify immobile sink node energy-aware data gathering methods into five categories according to their network architecture: flat data gathering that finds paths to minimize energy consumption or increase sensor network lifetime, hierarchical data gathering that creates a hierarchy and applies *data-aggregation* to reduce energy consumption, hybrid data gathering that is a combination of the former two and mitigates the energy hole problem, *data-centric* data gathering that performs in-network *data-aggregation* to eliminate wasteful transmissions, and location-based data gathering that uses location information to reduce the energy consumption of the wireless sensor network. Furthermore, we present a cross-cutting discussion which addresses *data-aggregation*, network lifetime definition, routing overhead, the energy hole phenomenon, and collisions/interferences. Moreover, we examine methods for data gathering with mobile sinks.

- **Chapter 3: Mobile-sink-based WSN Architecture.** In this chapter, we give an overview of the architecture of the mobile-sink-based WSN examined in this thesis, along with justification for the design decision. Furthermore, we give a detailed description of the composite parts, namely, that of data gathering from clusters to the mobile sink, in addition to that of data gathering within clusters to the cluster head.

- **Chapter 4: Energy Efficient Data Gathering from Clusters.** In this chapter, we address a fundamental research challenge stunting data gathering for mobile-sink-based WSNs, which is how to fairly maximize the energy efficiency (throughput per energy) in networks comprising adaptive modulation-capable cluster heads. For the mobility pattern of mobile sinks, we demonstrate how adaptive modulation is affected. Furthermore, we formulate the problem of maximizing fair energy efficiency as a potential game that is played between the multiple cluster heads, and substantiate its stability, optimality, and convergence. Based on the formulated potential game, a data collection method is proposed to maximize the energy efficiency with a fairness constraint. Additionally, we analyze the Price of Anarchy (PoA) of our proposed game-theoretic data collection method. Extensive simulations exhibit the effectiveness of our proposal under varying environments.

- **Chapter 5: Energy Efficient Data Gathering within Clusters.** In this chapter, we address the problem of how to collect data within a cluster. This problem is crucial to insure the longevity of such networks. Most contemporary research that attempts to minimize the energy consumption does so via short distance transmissions. However, this transmission strategy leads to an increase in the number of network operations, and thus increases the probability of collision, which results in extra energy consumption for retransmissions. We show that the minimum transmission distance does not result in the minimum energy consumption, and find the optimal transmission distance such that the energy consumption of the ad hoc network is minimal.

- **Chapter 6: Conclusion.** This chapter concludes this thesis.

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1.5 Contribution

The contribution of this thesis is three-fold, namely, 1) to conduct an investigation of energy efficiency issues in wireless sensor networks, 2) to propose a data gathering scheme form clusters to a mobile sink, and 3) to propose a energy efficient method for gathering data within the cluster to the cluster head. The details are as follows:

1. **Investigation of energy efficiency issues in wireless sensor networks:**

   (a) Categorize data gathering methods according to network architecture.

   (b) Compare the performance of each category of data gathering method.

2. **Data gathering from clusters to the mobile sink:**

   (a) Show how energy efficiency is affected by the mobile sinks trajectory and how adaptive modulation can be utilized to improve the energy efficiency of the data gathering from clusters within a WSN.

   (b) Formulate the problem of maximizing energy efficiency while satisfying fairness among CHs as a game.

   (c) For the formulated game, we prove the properties of stability, optimality, and convergence.

   (d) By using the formulated game, we propose a game-theoretic data gathering method that improves the energy efficiency while considering fairness in mobile-sink-based WSNs.

   (e) We analyze the Price of Anarchy (PoA) of our proposed data gathering method.

3. **Data gathering from sensor to cluster heads:**

   (a) Show how energy efficiency is affected by the transmission distance.

   (b) Formulate the problem of minimizing energy consumption as a function of transmission distance.

   (c) Show that minimal transmission distance does not result in minimal energy consumption and show the transmission distance that does result in minimal energy consumption.

Chapter 2

Literature Review

2.1 Introduction

Advances in wireless communications and nanotechnology have facilitated the widespread use of wireless sensor networks [2, 6–8]. Wireless sensor networks rely heavily on battery power to drive their functionality. When the energy of a battery is depleted, the sensor loses its functionality. Replacing/charging the batteries of a large number of sensors is an insurmountable task in terms of time and cost; the task becomes infeasible in potentially dangerous terrain. Hence, severely limited energy capacities of wireless sensor networks render energy-efficient technologies indispensable for deploying wireless sensor networks. The energy consumption of a wireless sensor node can be attributed to the following major activities:

(a) Information gathering: energy consumed by the sensors onboard the nodes for gathering information.

(b) Computation: energy consumed for processing purposes, predominantly attributed to the basic system operation.

(c) Communications: energy consumed to transmit data from sensors to their neighbors. This usually takes up the largest share of energy consumption of a wireless sensor network.

In this chapter, we focus our attention on the energy consumption associated with communications; in particular, we consider energy-aware routing for wireless sensor networks. This kind of routing algorithms has a very different objective from traditional routing algorithms; traditionally, routing has been designed to maximize throughput and/or scalability. Although the aforementioned objectives are important, communications is the major energy guzzler, and thus considering the energy consumption of routing is of significant importance. Therefore, this chapter addresses energy-aware routing for wireless sensor networks.

A wireless sensor network is usually deployed without the aid of infrastructure such that sensors cooperate to facilitate communications in the wireless sensor network. A wireless sensor network consists of two basic building blocks, namely, a sink and a number of sensors, all of which are capable of communicating with each other over a common wireless channel. The sink acts as the final point of collection, and from which data can be extracted for further processing and transmission. The sink assumes the role of a gateway because it is where all packets are routed, thus enabling connection to other networks such as the Internet. In a practical implementation, the sink has access to a virtually unlimited energy source. Although we have limited our discussion to a wireless sensor network with a single sink, the wireless sensor network can, in general, have more than one sink. With each sink responsible for collecting data from a sub-group of sensors, all the data collected from nodes of all sub-groups are gathered into a single node for processing. As a result, this mode of data gathering can be thought of as an integration of multiple wireless sensor networks, each with a single sink. The second component of the sensor network is a collection (hundreds or thousands) of sensors, which are responsible for collecting data from their surroundings; to enable communications in an infructureless network, they consume their limited energy reserves to relay data from other sensors, and thus decreasing the energy consumption of the sensors is the key objective of energy-aware routing for wireless sensor networks. Energy-aware routing algorithms can be classified into five categories according to their network architecture.

The first category is flat multi-hop routing, where routes from the source node to the destination node are selected with low energy consumption in mind. The second category is hierarchical multi-hop routing, where sensors take different roles and form hierarchies. Hierarchical multi-hop routing reduce energy consumption by decreasing the volume of data flowing within the wireless sensor network. The third is hybrid multi-hop routing, which is a combination of the first and second categories, and aims to mitigate the energy hole problem inherent to the many-to-one (convergecast) traffic patterns in wireless sensor networks. The forth category is *data-centric* routing that performs in-network *data-aggregation* in intermediate sensors to reduce the energy consumption inefficiencies in classical routing algorithms. The fifth is location-based routing, where location information is used to decrease the energy consumption of the wireless sensor network. In this chapter, we examine the landmark algorithms of each category that have largely shaped the roadmap for innovation in this area. Moreover, we examine recently proposed state-of-the-art routing schemes of each category.

The remainder of this chapter is organized as follows. Section 2.2 provides background materials of energy-aware routing in wireless sensor networks. Sections 2.3-2.7 examine various categories of energy-aware routing algorithms proposed for wireless sensor networks. We further discuss and compare these routing algorithms from different perspectives in Section 2.8, and finalize this chapter with a conclusion in Section 2.9.

2.2 Single-hop vs multi-hop energy consumption

Owing to the lack of infrastructure support in wireless sensor networks, sensors need to take the responsibility of transmitting the data they collected to the sink. In a relatively small-scale wireless sensor network deployment, it may be possible for all the nodes to transmit their collected data to the sink directly. For the majority of wireless sensor networks applications, where nodes are far away from the sink, the simple strategy of directly sending data to the sink does not work for a number of reasons. We mention the most relevant of them. Firstly, the sensors have a limited transmission range and cannot transmit data over this hardware-specific range. Secondly, long transmission distances are considered to be energy inefficient. Given a sending and receiving node, the following equations quantify the energy consumption of the sender and receiver [9–11],

$$e_s(i) = \epsilon_1 d_{i,j}^{\phi} + \epsilon_2 \tag{2.1}$$

$$e_r(j) = \epsilon_3. \tag{2.2}$$

Here, $e_s(i)$ is the energy consumed for sending a unit of data by the sensor i to the sensor j. ϕ is the path loss exponent dependent on the wireless fading environment, and its value is usually from two to four, two for short distances and four for long distances. The term ϵ_1 is a constant specific to the specific wireless system. ϵ_2 is the electronics energy, characterized by factors such as digital coding, modulation, filtering, and spreading of the signal. $e_r(j)$ is the energy consumed by the receiving node, which is a constant, ϵ_3. Given that $\epsilon_1 \gg \epsilon_2$ and $\epsilon_1 \gg \epsilon_3$, Eq. (2.1) shows that the energy consumption has a growth rate of order $O(d_{i,j}^{\phi})$. In other words, the energy consumption efficiency degrades with the length of transmission distance, $d_{i,j}$.

Multi-hop transmission strategies are considered to be advantageous due to their energy-efficient transmission distances. In a multi-hop transmission strategy, rather than transmitting the data directly from the sending sensor to the receiving sensor, one long transmission is divided into multiple shorter transmissions with each having energy consumption according to Eq. (2.1). Evidently, transmitting at shorter distances is more energy efficient. Therefore for the above-mentioned reasons, multi-hop routing is suitable for wireless sensor networks, where sensors cooperate with each other to facilitate low-energy communications in wireless sensor networks.

2.3 Flat multi-hop routing algorithms

Flat multi-hop routing algorithms are based on concepts inherent from contemporary networks [12]. In traditional wired networks, if a set of nodes are directly connected together via a common medium, point-to-point communications between two neighboring nodes can be easily executed via a data-link layer algorithm. If the two nodes do not share a common wired link, the concept of routing, which is applying the point-to-point data-link algorithm iteratively, applies to a packet as it passes from one node to another till it reaches its destination. Since there are many possible paths, choosing the best possible path defined by a specific criterion is dictated by the routing algorithm.

The above-mentioned techniques are applicable to networks that are wireless and lack infrastructure support, i.e., wireless sensor networks. The set of nodes that are within the maximum transmission distance of each other are thought of as neighbors, and can directly be connected via the wireless medium. Since many paths exist between a source and destination pair, there must be criteria to select the most appropriate path. In traditional wired networks, an emphasis has been placed on choosing the path which maximizes the end-to-end throughput and minimizes the delay (by selecting the path with the minimum number of hops, or the path with the fastest links). These criteria are usually derived from the user requirements (users want to have a fast connection). In wireless sensor networks, although the end-to-end delay is important, the amount of energy consumed by the network is even more critical as exhausted nodes will greatly affect the lifetime of the network. Specifically, the routing algorithm can evaluate a path from the viewpoint of energy consumption of a single link according to Eqs. (2.1)-(2.2).

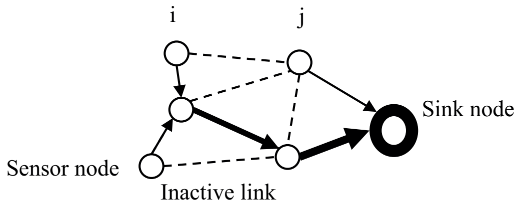


Figure 2.1: An example of flat multi-hop routing. Each sensor can communicate with other sensors within its maximum transmission range. The arrow's width represents the amount of data that should flow through its associated link. Other links are not utilized.

2.3.1 Minimizing energy consumption

C.-K Toh [11] described a method to select paths that allow minimum energy consumption as shown in Fig. 2.1. In the illustration, the flat energy-aware routing algorithm utilizes the links indicated by arrows that minimize the energy consumed in the wireless sensor network, while the rest of the links are inactive. The energy calculation method is as follows. The energy-aware *link cost* is defined in terms of the amount of energy consumed by each wireless link. More precisely, the energy burden on the two end nodes, i.e., the sending and receiving nodes, can be quantified as

$$linkcost(i, j) = e_s(i) + e_r(j). \tag{2.3}$$

Thus, the total energy consumed by the wireless sensor network for using path l, P_l, can be quantified as

$$P_l = \sum linkcost(i, j) \quad \forall i, j \in l. \tag{2.4}$$

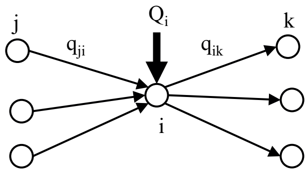


Figure 2.2: Flow conservation at sensor i. The summation of all incoming flows to sensor i, $\sum_{j \in S_i} q_{ji}$, subtracting the summation of all outgoing flows from sensor i, $\sum_{k \in S_i} q_{ik}$, equals the information generated in sensor i, Q_i.

The desired route, which can minimize the energy consumption for sending data between any sensor, i, and the sink, $P^{min}_{(i,sink)}$, can be obtained from the following equation

$$P^{min}_{(i,sink)} = \min_{l \in L} P_l. \tag{2.5}$$

Here, L is the set of all possible paths from sensor i to the sink. Thus, by routing traffic through $P^{min}_{(i,sink)}$, the energy consumed by the wireless sensor network can be minimized, hence ultimately increasing the lifetime of the wireless sensor network.

2.3.2 Maximizing network lifetime

J.-H. Chang and L. Tassiulas [13,14] adopted concepts from *linear programming* to design a routing algorithm that maximizes the lifetime of the wireless sensor network. We first present their proposed model, followed by the theory and their proposed heuristic algorithm that spreads the data flow equally among sensors to increase the lifetime of the sensor network.

Linear programming model

Given a directed graph, $G(N, L)$, in which a set of sensors, N, exist and are connected together via a set of directed links (i, j), L. Here, i and $j \in N$, are the two sensors that communicate via this link. Each sensor i has a set of sensors, S_i, which can be reached within its maximum transmission range. A link (i, j) exists in L if $j \in S_i$. Denote E_i as the initial battery energy reserve of sensor i. The energy consumed for transmitting a message by sensor i to destination sensor j can be evaluated from Eq. (2.1) and is denoted as e_{ij}. Sensor i transmits to sensor j at the rate of q_{ij}. Data being transmitted from a source sensor to a destination sensor over a path is referred to as a flow. It has quantity and direction. If it is from the source to the destination, then it is referred to as a positive flow; otherwise, it is called a negative flow. Denote O as the set of origin sensors, from which data are originated, and D as the set of possible destination sensors.

We shall next present properties and the associated equations to model network behavior. Firstly, the conservation of flow (the summation of all incoming flows subtracting the sum of all outgoing flows in each node must be equal to the amount of data generated from the node itself), as illustrated in Fig. 2.2, can be expressed in form of a linear equation as

$$\sum_{j \in S_i} q_{ji} - \sum_{k \in S_i} q_{ik} = Q_i, \forall i \in (N - D). \tag{2.6}$$

Here, Q_i is the information generation rate of sensor i. The time period till the energy of the sensor i is depleted, $T_i(\mathbf{q})$, is inversely proportional to the amount of data flowing through it, $\mathbf{q} = q_{ij} : \forall j \in S_i$, that is,

$$T_i(\mathbf{q}) = \frac{E_i}{\sum_{j \in S_i} e_{ij} q_{ij}}. \tag{2.7}$$

Network lifetime: The lifetime of the system is defined as the minimum lifetime of a sensor in a wireless sensor network, i.e.,

$$T_{WSN}(\mathbf{q}) = \min_{i \in N} T_i(\mathbf{q}). \tag{2.8}$$

A network designer would like to maximize the lifetime of the wireless sensor network, and thus the objective function can be formulated as follows,

$$\max_{\mathbf{q}} T_{WSN}(\mathbf{q}). \tag{2.9}$$

Furthermore, this can be expressed as

$$\max_{\mathbf{q}} \min_{i \in N} \frac{E_i}{\sum_{j \in S_i} e_{ij} q_{ij}}. \tag{2.10}$$

The above optimization problem also serves as a model for understanding how energy-aware routing algorithms can operate to maximize the lifetime of the wireless sensor network. The basic observation is that if a sensor would have to transmit more data than other sensors, it would live for a shorter time. Thus, the network lifetime would decrease according to Eq. (2.8). Ultimately, to achieve the maximum lifetime, a routing algorithm should equally spread the load among all sensors.

Theorem 1 (Necessary optimality condition [13])**.** *Given that paths are of positive flow to the destination. The minimum lifetime over all nodes is maximized* $\rightarrow$ *The lifetime of all paths from the source node to the destination node are equal.*

Proof. We prove the above theorem by contradiction. Let the lifetime of a path be determined by the minimum lifetime over all the nodes in the path. Also, define a path with positive flow as one with flows originating from the source to the destination. Assume that the minimum lifetime over all nodes is maximized. Here, assume that the lifetime of all paths with positive flow to the destination are not equal (contrary to the conclusion of the above theorem). Then, there exists a path with positive flow that has a shorter lifetime as compared to all other paths. This path's lifetime, which is also the minimum lifetime over all nodes, can be increased by moving a small amount of positive flow from it to any of the other paths, thereby making its lifetime longer than the minimum lifetime over all nodes before moving the flow. Thus, this contradicts the first assumption that the minimum lifetime over all sensors is maximized. □ □

Algorithm

Chang and Tassiulas [13] proposed two algorithms that spread flows equally among all the paths. Both of them follow the same structure, as will be explained next; their differences will be described afterwards.

For each node $i \in (N - D)$ in the wireless sensor network,

(a) Determine from which path to which path the flows should be redirected.

(b) Determine the fraction of flows that should be diverted.

(c) Redirect the fraction of flows as determined in Step 1 and Step 2

The two algorithms differ in the way they implement Step 1. It may be implemented based on the lifetime, calculated by Eq. (2.7), of the sending node and the nodes along the path to the destination node. Additionally, it can be based on the residual energy of the sending node and the intermediate nodes along the path to the destination. The cost function is defined as:

$$linkcost(i, j) = \frac{1}{E_i - e_{ij} n_{ij}}, \tag{2.11}$$

where E_i is the residual energy of the sensor i, and n_{ij} is the number of message units transmitted from node i to node j (i.e., the size of flow traversing the link).

2.3.3 Recent innovations

The seminal work of Chang and Tassiulas [13, 14] has paved the way for many innovations for flat multi-hop routing algorithms. Indeed, many new routing algorithms have been proposed to tackle the short comings of the foundation laid out by them. We shall next highlight how these latest works advance the state of art in flat multi-hop routing for wireless sensor networks.

The linear programming model presented in [13, 14] models the lifetime of the wireless sensor network as the time when the first sensor dies. This definition of network lifetime is not an accurate one because the network can still be functional after the first sensor's death. Many researchers have tried to improve this definition. For example, Karkvandi *et al.* [15] proposed a novel network lifetime criterion based on Sensing Spatial Coverage (SSC), which refers to the ability of a sensor to monitor a phenomenon of interest in an area. By using the SSC based lifetime definition, the network is able to improve the monitoring of the area of interest. Liu and Cao [16] pointed out that in a wireless sensor network with low density, the spacial temporal coverage requirements cannot be satisfied while satisfying the lifetime constraints. Therefore, they proposed to schedule sensors to sleep in order to increase their coverage while meeting network lifetime requirements. Furthermore, Naddafzadeh-Shirazi and Lampe [17] defined lifetime as the time till the network is unable to achieve given detection requirements (DRs), which are defined in terms of probabilities of detection and false alarm as dictated by application requirements.

Liu *et al.* [18] considered maximization of network lifetime by scheduling sensors to sleep during idle listening periods. They observed that the traffic is light most of the time in many sensor network applications and the idle sensors are wasting valuable energy during this period. Therefore, they proposed to include sleep cycle scheduling in the routing problem to eliminate the energy wasted in idle periods and thus improve the longevity of the wireless sensor network.

2.3.4 Summary

Flat multi-hop routing algorithms are based on classic concepts for traditional wired networks. The basic idea is to modify the link cost to reflect the energy consumption attributed to utilizing the wireless link between two sensors. After assigning link costs to each link, a shortest-path algorithm such as Dijkstra's algorithm [19] can be utilized to find the least energy consuming path among a set of available paths between a source node and a destination node. Generally, this category of routing algorithms fails to capitalize on the redundancy that is inherent in wireless sensor networks to reduce their energy consumption.

2.4 Hierarchical routing algorithms

Hierarchical routing assigns different roles to sensors. The hierarchy is formed when some nodes are chosen to act as gateways (an intermediary) for other nodes.

The concept of hierarchical routing has been readily applied in traditional wired networks [19]. The complexity of the routing process increases with the network size. The number of interactions among sensors increases owing to the increased interaction of the routing protocol initialization, thus leading to huge waste of computation resources. Based on a clever insight that there is no need for every node to know information about every other node, a hierarchy can be established. Following the divide-and-conquer concept, the network can be divided into smaller areas, sometimes referred to as *regions*, and then each region internally creates paths among individual nodes. At the *inter-region* level, each *region* establishes the routes to other *regions*, and individual nodes can communicate outside their *regions* through a special node, often referred to as a *gateway*. Consequently, the computation cost can be substantially decreased. The example presented here is a two-level hierarchy. Two levels are definitely not sufficient for huge networks. In general, the number of levels is dependent on the size of the network.

In the context of wireless sensor networks, *regions* are refereed to as

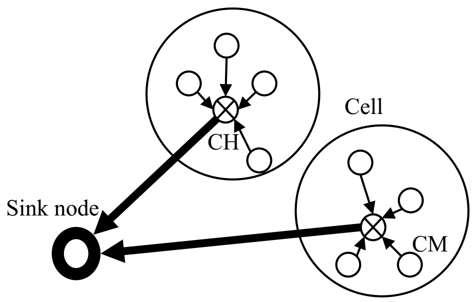


Figure 2.3: An example of LEACH, where each CH collects data from its CMs to aggregate and send them to the sink.

clusters and gateways as cluster heads. Adopting hierarchical network architectures allows special operations to be assigned to the gateway of each cluster, viz, *data-aggregation*, where redundancy is capitalized as well as can be reduced, therefore reducing the volume of data flows in the wireless sensor network. This eliminates many unneeded network operations, and greatly reduces the energy consumption of the wireless sensor network.

2.4.1 LEACH

Low Energy Adaptive Clustering Hierarchy (LEACH) [20] is the most popular form of hierarchical routing for wireless sensor networks. LEACH as depicted in Fig. 2.3 is a two-level hierarchy, with the sink acting at the top of the hierarchy. Time is divided into time periods called rounds. In the beginning of each round, the sensors divide themselves into two groups, a group of Cluster Heads (CHs) and a group of Cluster Members (CMs).

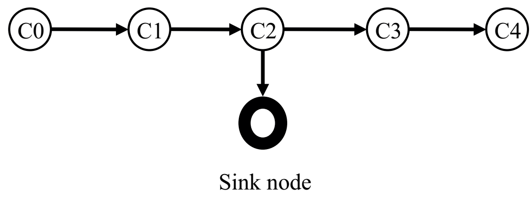


Figure 2.4: An example of chain-structured clusters of PEGASIS, where nodes apply a greedy algorithm to find the closest node to them to form a cluster.

The first group of sensors serve the role of CHs, and the remaining nodes assume the role of CMs. The number of CHs is generally less than the number of CMs. The wireless sensor network is divided into clusters. The distributed selection of cluster shapes results in their resemblance to Voronoi diagrams centered on each CH.

According to the location of each CM, it will choose to join its closest CH. Each CH, along with a number of CMs, forms a cluster. CMs act as normal sensors by collecting data from their surroundings. The CHs also function as normal sensors but, additionally, they act as gateways for their respective clusters. After each CM collects data from its surrounding, it transmits the data to its respective CH. After the CH collects data from its CMs, it aggregates them along with its own data, and sends them to the sink.

Subsequently, the volume of data flowing within the network is substantially reduced due to *data-aggregation*, thus significantly decreasing the energy consumption in the wireless sensor network.

2.4.2 PEGASIS

Power-Efficient Gathering in Sensor Information Systems (PEGASIS) [21] clusters nodes in a chain-based shape, differing from the cluster shapes adopted in LEACH. Fig. 2.4, redrawn from [21], illustrates PEGASIS.

The basic idea is that each sensor forwards its data to its neighbor; the neighbor adds its own data and aggregates both of them and sends a single packet to its neighbor. This process is repeated till the data is delivered to the leader (the sensor that is responsible for sending the data to the sink). The choice of neighbors follows a greedy method, in which each node finds the closest neighbor to itself. Each node in a chain takes turn to become a leader.

In PEGASIS, nodes only need to communicate with their closest neighbors, so that the transmission distance is short, thus decreasing the energy consumed for communication per unit of data. The advantage of using a chain-based design is to avoid cluster formation found in LEACH.

2.4.3 Recent innovations

The cluster-based design of hierarchical routing pioneered in LEACH [20] is an effective solution to decrease the energy consumption of wireless sensor networks. LEACH, however, presents several drawbacks, and thus many researchers have proposed important improvements to

LEACH. One major drawback is the distributed nature of cluster formation in LEACH that can result in uneven distribution of CHs, thus leading to variated transmission distances among CHs and their CMs. Consequently, energy consumption among CHs and CMs vary greatly, i.e., imbalanced energy consumption. Grid-based cluster design [22] mitigates this drawback. In a grid-based cluster wireless sensor network, the network is divided into grids of equal size. Sensors are aware of the grid they belong to by relating grid dimensions to their positions. Zhang *et al.* [22] proposed to optimize the grid size by using probabilistic distance models to achieve more efficient energy consumption.

Although clustering significantly reduces the energy consumption of individual sensors, it increases the communication burden on CHs. As illustrated in Fig. 2.5, once the CH has gathered information, it needs to transmit it to the sink either via direct transmission or via multi-hop transmissions through intermediate nodes. Shu and Krunz [23] proposed to optimize the balance between the aforementioned CH transmission schemes to extend the lifetime of CHs.

CH selection has a great influence on the energy consumption of the wireless sensor network. Various CH selection schemes have been proposed [24], in which a sensor is elected to become a CH based on several criteria such as residual energy and node degree. Recently, Wei *et al.* [25] considered the case where sensors produce differing amounts of traffic load, and proposed to increase the probability of nodes with

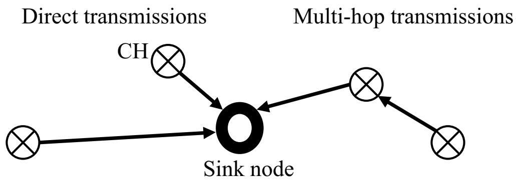


Figure 2.5: An illustration of the two transmission schemes used for communication between CHs and the sink.

higher power and lower traffic generation rates to become a CH.

In most wireless sensor network scenarios, the correlation of sensor data makes collecting all the sensor data unnecessary. Also, collecting all sensor data is energy consuming. One technique to eliminate the transmission of unnecessary data is to employ data predictors. Data predictors use sensors' past inputs to estimate their future data. If the error bound (difference between the predicted value and actual value) is acceptable, the sensors need not transmit their sensed data. Thus, data predictors alleviate the traffic burden and subsequently reduce the energy consumption of the wireless sensor network. Jiang *et al.* [26] proposed to implement data predictors in CHs found in hierarchical routing, such as the one illustrated in Fig. 2.3. However, the energy consumption for training the data predictor (computation) is non-negligible, and therefore they have investigated which conditions render using data predictors in CHs energy efficient. They showed that energy efficiency is a function of both the correlation of sensors' collected data and the desired error bound.

2.4.4 Summary

Hierarchical multi-hop routing is a technique adapted from existing networks, where it has been employed for its superior scalability and low complexity. In wireless sensor networks, hierarchical multi-hop routing exhibits its merit in the form of *data-aggregation*, which reduces the volume of data transmissions, and in turn reduces the energy consumption of the wireless sensor network. The *data-aggregation* [27] scheme itself is dependent on the nature of data collected within the wireless sensor network. For examples, *data compression* is applicable when the data are correlated to a certain extent in environmental monitoring applications, *beamforming* when various signals are combined to produce a signal with a better signal-to-noise ratio in acoustic data, and *data fusion* when several messages contain the exact content in moving/migrating objects.

Some wireless sensor network environments only allow *data-aggregation* to reduce the volume of data by a small amount. For example, when data compression is employed and the correlation between the collected data is low, then the compression rate defined as

$$Compression\,rate = \frac{SIZE[Compressed\,Data]}{SIZE[Original\,Data]} \tag{2.12}$$

will be close to one, and hence the energy savings gained by transmitting a lower volume of data will be outweighed by the energy consumed by forming clusters. In summary, hierarchical multi-hop routing should only be employed in applications where the volume of data can be substantially reduced with *data-aggregation*.

2.5 Hybrid routing algorithms

The concept of hybrid routing for wireless sensor networks was first proposed in [28]. The motivation behind this strategy is to address the energy hole problem, which is also refereed to as the hotspot problem. This problem is inherent to the design of sink-based wireless sensor networks. Since all traffic originating from the sensors is destined to the sink, the nodes that are close to the sink consume more energy and exhaust their battery energy in a much more rapid manner than other sensors. If the sensors close to the sink die, the sink will be isolated. Thus, the wireless sensor network will loose its functionality, despite the fact that the rest of the wireless sensor network is left intact.

2.5.1 HYMN

Table 2.1: A comparison among three types of energy-aware routing algorithms.

Type	Data-aggregation	Transmission distance
Flat multi-hop routing	No	Short
Hierarchical routing	Yes	Long
HYMN	Yes	Short (in the SCA)

HYbrid Multi-hop routiNg (HYMN) [28, 29], depicted in Fig. 2.6, is a hybrid of two categories of routing algorithms, namely, flat multi-hop

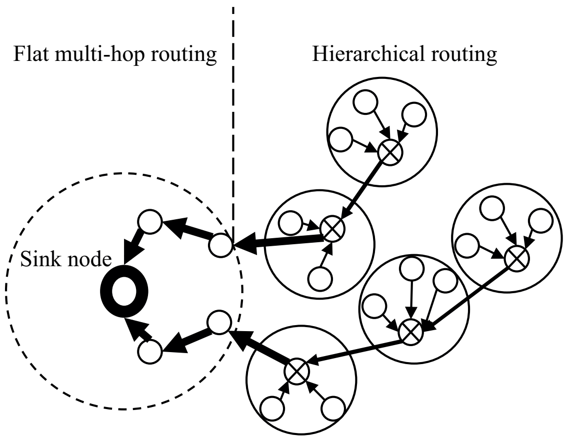


Figure 2.6: An illustration of HYbrid Multi-hop routinNg (HYMN). HYMN combines two categories of routing algorithms.

routing, introduced in Sec. 2.3, and hierarchical routing, introduced in Sec. 2.4. A comparison among these three categories is shown in Table. 2.1.

The area within the maximum transmission range of the sink is referred to as the Sink Connectivity Area (SCA). The sensors in this area allow the sink to connect to the sensors beyond its maximum transmission range. Generally, the number of sensors in the SCA is relatively much less than the remaining sensors in the wireless sensor network. Rationally, the largest part of energy consumption in the SCA is attributed to relaying traffic that originates from outside the SCA. On the other hand, the share of energy consumption attributed to transmitting data originating from the SCA itself is relatively much less.

From the above discussion, to decrease the energy consumption of the SCA, the energy consumption per unit of data transmission must be decreased, and/or the volume of data flowing through the network must be limited. HYMN achieves the effect of both solutions. Outside the SCA, a hierarchical routing algorithm can be adopted to reduce the volume of influx going into the SCA, so that *data-aggregation* decreases the flow of data into the SCA, and flat multi-hop routing is used inside the SCA to achieve energy-efficient transmissions (short distances).

Consequently, by focusing on mitigating the energy hole problem, HYMN successfully decreases the energy consumption in the SCA, and increases the longevity of the wireless sensor network.

2.5.2 Summary

Hybrid multi-hop routing adopts two strategies of routing, namely, flat multi-hop routing and hierarchical routing. Although it has been shown that HYMN improves the longevity of wireless sensor networks, selecting the two respective routing algorithms still remains an open research issue.

2.6 Data-centric routing algorithms

Owing to the large number of deployed sensors in a typical wireless sensor network, it is difficult to assign a global identification scheme such as an IP identifier. Additionally, although disseminating information from a source to a possible destination can be handled by applying the classical flooding method [30], this technique is energy inefficient. Thus, researchers [30, 31] have proposed a new addressing scheme, referred to as *data-centric* routing. In contrast with *address-centric*, in which each sensor independently transmits its data along a path towards a destination, *data-centric* routing algorithms scrutinize data-types, give each datum an identifier/name, and instead of identifying individual sensors, data are identified. Furthermore, these methods allow efficient energy consumption by eliminating redundant data transmissions. In the remainder of this section, we describe how basic schemes for information dissemination work, followed by prominent examples of *data-centric* routing algorithms.

2.6.1 Basic schemes and issues

A routing algorithm needs to find paths between a source node and a destination node; the intermediate sensors operate independently from other sensors with no prior knowledge to determine the path between the source sensor and the destination sensor. *Flooding* and *gossiping* [32, 33] are classical local techniques used for disseminating data throughout the network.

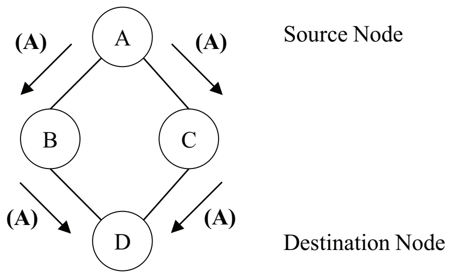


Figure 2.7: The implosion problem in classical *flooding*. The destination node, D, gets the same data twice. The wireless sensor network wastes energy by the sending the same data twice.

Flooding

Flooding [32] starts from the sensor that is the origin of the data; the origin broadcasts its message to its neighboring nodes. Each of these neighbors progresses by re-broadcasting the same message to all their neighbors. In effect, the message gets propagated throughout the entire network. *Flooding* clearly generates a large number of packets; furthermore, the algorithm can go on infinitely and ceases to stop unless a mechanism is used to halt it. The mechanism to halt the message from propagating forever can be provisioned by a *Time To Live (TTL)* mechanism. A TTL mechanism is a counter that is decremented every time a message is relayed; upon reaching zero, the message is no longer propagated and is discarded, thus resulting in the termination of the propagation. Generally, the TTL field should be approximately set equal to the number of hops, i.e., *hop-count*.

Gossiping

Gossiping [32, 33] is another dissemination algorithm that is based on local interactions. Generally, *gossiping* transmits a smaller number of packets as compared to *flooding*. In a gossip algorithm, each sensor, which has a message to share, periodically chooses one sensor from its neighbors as its peer. Then, the sensor transmits the message to its chosen neighbor. The receiving sensor re-transmits the message to one of its neighbors with probability p or drops the message with probability $1 - p$. Consequently, the message reaches its destination. The choice of which neighbor sensor to send to and p are design dependent parameters. The choice of which neighbor to send to can be random. p can be fixed or a function of network parameters such as the number of received duplicates, which can be determined by a unique ID for each message.

Energy consumption issues

The disadvantages from the viewpoint of energy consumption is the large amount of redundant transmissions that needlessly consume the energy of the wireless sensor network. Figs. 2.7 and 2.8, redrawn from [30], illustrate the wasted energy in the wireless sensor network. Fig. 2.7 shows the *implosion* problem. It is clear that only the transmissions on either of the right or left path are sufficient, and all other transmissions are extra transmissions that unnecessarily consume the

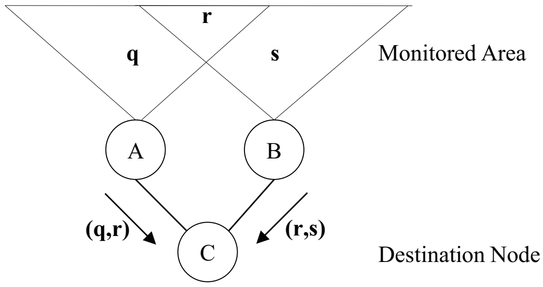


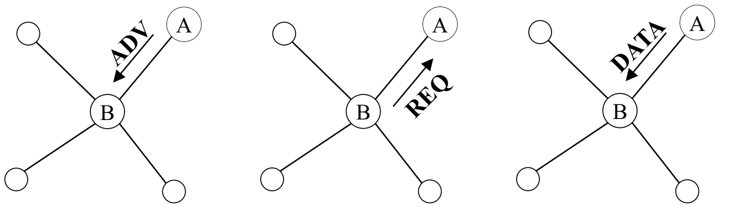
Figure 2.8: The overlap problem in classical *flooding*. The destination node, C, receives two copies of the data r.

energy of the wireless sensor network. Also, as illustrated in Fig. 2.8, the same data that was collected from the same area, i.e., area r, is delivered multiple times to the destination, i.e., sensor C, needlessly wasting the energy of the wireless sensor network. This phenomenon is referred to as *overlap*.

Energy-aware *data-centric* routing algorithms eliminate the energy consumed by the *implosion* problem by eliminating needless forwarding and the *overlap* problem by eliminating the transmission of duplicated data.

2.6.2 SPIN

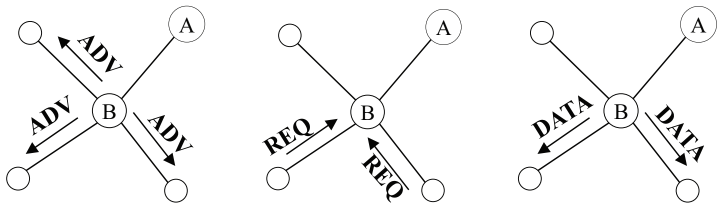
The main idea behind Sensor Protocols for Information via Negotiation (SPIN) [30] is to give high-level data descriptors to identify each kind of data, referred to as *metadata*. Utilizing the *metadata*, the SPIN nodes negotiate with each other and insure that only required data are transferred, thus eliminating excess energy consumption caused by both the *overlap* and *implosion* phenomena. There is no standard definition for *metadata*, and they differ from applications to applications as well as vary from the types of data collected.



(a) **ADV stage:** Sensor A starts by sending an advertisement message indicating that it has new data to its neighbor, sensor B.

(b) **REQ stage:** Sensor B responds by requesting the data through a REQ message sent to sensor A.

(c) **DATA stage:** After receiving the REQ message, sensor A sends the requested data to sensor B in a DATA message.



(d) **ADV stage:** Upon obtaining the data, sensor B advertises its new data through a REQ message sent to all its neighbors.

(e) **REQ stage:** The process in Fig. 2.9(b) is repeated.

(f) **DATA stage:** The process in Fig. 2.9(c) is repeated.

Figure 2.9: The operation of the *data-centric* routing algorithm SPIN.

The negotiation process in the basic SPIN protocol, named SPIN-1, is conducted via a three hand-shake procedure, as illustrated in Fig. 2.9, which is redrawn from [30]. Each stage of the hand-shake has a defined message, as described below.

(a) **ADV**: new data advertisement. This message begins the three-state handshake, and it is sent when a sensor has new information it would like to share. The sensor could have acquired the new information via monitoring its surroundings or from one of its neighbors. The ADV message contains *metadata*, which are sent to the sensor's one-hop neighbors.

(b) **REQ**: request data. The second stage of the three-stage handshake is triggered when a node that has received an ADV message is interested in the data defined in the *metadata*. An interested node sends the REQ message to the ADV message sender.

(c) **DATA:** data message. The third and final stage of the SPIN handshake. The DATA message contains the information defined by the *metadata*, and is sent by the ADV message sender.

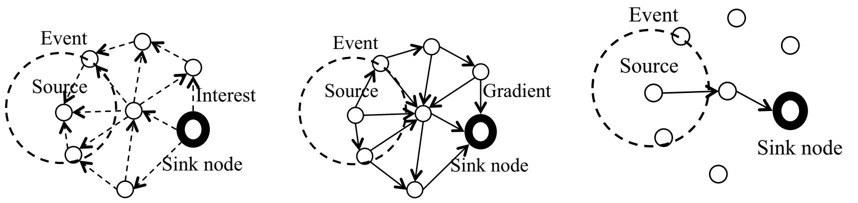
After the DATA message is sent, the three-stage handshake is completed. Upon acquiring the DATA message, the receiver initiates the above-mentioned three-stage handshake; by iteratively applying the three-stage handshake mechanism, all the data are efficiently disseminated throughout the network. The above described mechanism avoids energy consumption attributed to unneeded transmissions, i.e., the *implosion* problem, since it eliminates redundant transmissions. Additionally, the *metadata* enable a sensor to request only the data it requires and avoids wasting the energy of the wireless sensor network by receiving data that it already has, i.e., the *overlap* problem.

2.6.3 Directed diffusion

Directed diffusion [31] is a great innovation over basic *data-centric* routing algorithms because it decreases the flow of data in the wireless sensor network by incorporating *data-aggregation.* In directed diffusion, the sink creates tree like routes throughout the wireless sensor network to eliminate the energy consumption associated with the *implosion* problem. Also, the *data-aggregation* scheme mitigates the excessive energy consumption associated with the *ovelap* problem.

The above mentioned tree structure is created by the sink when it advertises its *interests.* Upon receiving these *interests*, the sensors know what kind of information the sink requests. When the sensors reply, in-network *data-aggregation* is performed. In-network *data-aggregation* aggregates messages from different sources to decrease the amount of network operations. This form of aggregation utilizes knowledge of application requirements, and is conducted via local-interactions.
The algorithm, as illustrated in Fig. 2.10 redrawn from [31], is first trigged by the sink.

(a) The sink broadcasts a message describing the information that it has interest in, and the message is intuitively referred to as



(a) Interest propagation from the sink throughout the network.

(b) Gradient setup from the source to the sink.

(c) Sending data to the sink and path reinforcement.

Figure 2.10: The operation of the *data-centric* routing algorithm, directed diffusion.

an *interest* message. The sink's *interests* are propagated through the network. An *interest* may contain the following information

Type : The type of object to be monitored.

Interval : How often information should be reported back.

Duration : How long the sink is still interested in acquiring this information.

Location : The location of sensors where information is of interest.

(b) Sensors within the one-hop range of the sink, i.e., within its maximum transmission range, receive the sink's interests directly. These one-hop neighbor sensors relay the *interests* to their neighboring sensors. Via relaying, the sink's *interests* get propagated throughout the wireless sensor network, and all sensors get to know about the *interests* of the sink. *Gradients* are created in each sensor, and indicate the source of the *interests*.

(c) Data reporting is triggered when a sensor located within the field of interest receives an interest message. The sensor sends the data back to the neighboring sensor that is indicated in the gradient. An intermediate sensor which receives multiple reports corresponding to earlier interests it relayed can play an active role in decreasing the energy consumption of the wireless sensor network. Intermediate sensors are able to apply *data-aggregation* (e.g, looking into multiple reports and combining them, or forwarding reports with better confidence intervals).

As described above, the *gradients* are created after the *interests* propagate in the wireless sensor network. As there could be many paths from the source sensor to the sink, transmitting the messages from the source sensor through all the paths to the sink would lead to needless energy consumption associated to the *implosion* problem. Directed diffusion reinforces one path, thus eliminating the excessive energy consumption attributed to the *implosion* problem. Furthermore, as described above, the *interest* and *gradient* mechanisms allow intermediate sensors between the source sensor and the sink to apply *data-aggregation* to decrease the number of network operations needed to transmit messages in the wireless sensor network, thus reducing the energy consumption caused by the *overlap* problem. In summary, directed diffusion utilizes the *data-centric* communication paradigm and in-network *data-aggregation* to reduce energy consumption.

2.6.4 Recent innovations

Since the groundbreaking work of directed diffusion [31], various advances within the realm of *data-centric* routing have emerged, and have made inroads in new applications. For example, Jiang *et al.* [34] have investigated the top-k problem, which aims to acquire the top most (or least) k-values from the data collected in a wireless sensor network (e.g., the top ten highest temperature readings). Since only the top k-values are needed (i.e., essential), collecting all data from the sensors is wasteful, and thus Jiang *et al.* [34] proposed to enable intermediate nodes along the path from the source node to the sink to filter/discard less significant data, viz. those having values less than the required top-k values. As a result, redundant transmissions of insignificant data that unnecessarily consume energy of the wireless sensor network are avoided.

Directed diffusion enforces a path from many available paths for data delivery. Yahya and Ben-Othman [35] pointed out that if the current drawn from a battery is decreased or halted, the battery can regain some of its energy back; this is called the relaxation phenomenon. RELAX [35] routes traffic through multiple paths so as to capitalize on the battery relaxation phenomenon to increase the lifetime of the wireless sensor network.

As illustrated in Fig. 2.10(b), gradients in data-centric routing allow sensors to route their collected data to the sink via sink-bound paths. Since their formation is determined by the location of the phenomena under surveillance (e.g., object tracking or event monitoring) and the sink location, these gradients are far from optimal in terms of the energy consumption of the created path. Ren *et al.* [36] proposed to construct the gradients such that packets flow through the area with high residual energy density, i.e., an area with a large number of nodes and large residual energy. Furthermore, Wu *et al.* [37] proposed to construct the gradients so as to maximize the lifetime of the sensors. Lifetime is defined as the time until the first sensor has died. Chatzimilioudis *et al.* [38] investigated the energy loss associated with collisions. The occurrence of collisions causes more energy consumption for retransmission. They pointed out that the probability of collision increases with node degree, i.e., the number of links each node is connected. Also, as illustrated in Fig. 2.1, since all the data ends in the sink, the node degree of a sensor increases as the node's position gets closer to the sink. Therefore, they have proposed to construct gradients so as to minimize collisions by balancing the node degrees.

In directed diffusion, data can be opportunistically aggregated when they meet at any intermediate node. The formation of the aggregation tree is based on the chronological order of occurred events. However, the resulting tree structure produces non-optimal aggregation. Villas *et al.* [39,40] proposed a method to increase the overlap between routes to enhance the quality of aggregation, thus leading to more energy savings.

2.6.5 Summary

Data-centric routing modeled after directed diffusion is one of the most popular routing algorithms with *data-aggregation* for wireless sensor networks. This class of routing algorithms are particularly suitable for query-based data collection. In contrast, LEACH-like routing algorithms are intended to be used for uniform reporting purposes.

Data-centric routing algorithms require data to be clearly defined by using *metadata*. By using the *metadata* field, sensors can do in-network *data-aggregation* to decrease the amount of network operations conducted in the network. There is no standard definition for the *metadata* field, and it is application specific. Thus, defining an efficient format for the *metadata* field to allow *data-aggregation* for complex schemes is a very important issue in *data-centric* routing algorithms.

2.7 Location-based routing algorithms

Location information is essential to the functionality of most energy-aware routing algorithms for wireless sensor networks. It is used to calculate energy consumption of transmissions to be used to make

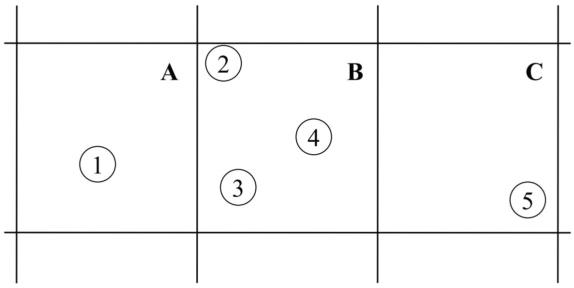


Figure 2.11: An example of virtual grid in GAF.

path selection decisions as in flat multi-hop routing algorithms, discussed in Sec 2.3. Location information can be obtained based on small low-power Global Positioning System (GPS)-enabled devices built into the sensors, from the relative signal strength of the received signals, and other methods. Location information can play a central role in the absence of IP-like addresses, and help reduce energy consumption. Location-based routing algorithms have been previously proposed for general ad-hoc networks, but those that are energy-aware can be applied to wireless sensor networks.

2.7.1 GAF

Geographic Adaptive Fidelity (GAF) proposed by Y. Xu *et al.* [41] is a *location-based* routing algorithm implemented for general ad hoc networks, but is suitable for use in wireless sensor networks. GAF capitalizes on the spatial redundancy of sensors and reduces the number of unnecessary active sensors by setting some of them to sleep while insuring sufficient active sensors to achieve a constant level of routing *fidelity*. In general, deactivating redundant sensors substantially decreases the energy consumption of the wireless sensor network. This dividend is particularly distinctive in densely deployed networks, such as wireless sensor networks. This is attributed to the high correlation between node density and node redundancy. It is worth noting that GAF can integrate with other routing algorithms.

GAF starts by dividing the wireless sensor network into virtual grids, as shown in Fig. 2.11. Each sensor in a virtual grid cell is able to directly communicate with all the sensors in the neighboring adjacent cells. As shown in Fig. 2.11, each cell contains several wireless sensors, and all sensors that are within the same cell are considered to be equivalent in terms of packet routing. It is worth noting that the maximum transmission distance of the sensors dictates the size of a block.

In the illustration, sensors 1 and 5 can relay data between each other by transmitting their packets to any of the sensors in the intermediate cell, i.e., sensors 2, 3, and 4. In other words, only one of these intermediate sensors is essential for inter-cell communications, and thus the remaining sensors can be put to sleep. This consequentially reduces the energy consumption of the wireless sensor network.

Sensors employing GAF enter a three-state process. As depicted in Fig. 2.12, the states of this process include discovery, active, and sleeping. The discovery state is when a sensor turns on its radio, waits for

T_d seconds, and exchanges messages with other sensors to find out its neighbors within the virtual grid cell. Once a single active sensor is selected, this sensor becomes fully functional by participating in routing activities for a period of T_a seconds. The remaining nodes enter the sleep state, in which the sensors turn off their radio and save substantial energy for a period of T_s. The time spent in each state is application dependent and can be tuned by adjusting the values of T_a, T_d, and T_s. A node in the active or discovery states goes into the sleep state if it determines that some other high ranking node will take over the role of routing. A high ranking node is chosen by a ranking procedure, which is dependent on applications and is done via node negotiation. For example, ranking can be an arbitrary ordering of nodes or can be performed to optimize wireless sensor network lifetime.

Consequently by reducing the number of active sensors to only the essential number required to sustain routing fidelity, GAF is able to successfully reduce the energy consumption of the wireless sensor network.

2.7.2 GEAR

Geographic and Energy-Aware Routing (GEAR) was proposed in [42, 43], also independently in [44], as a wireless sensor network specific *location-based* routing algorithm. GEAR is based on the observation that usually queries include location information indicating the target

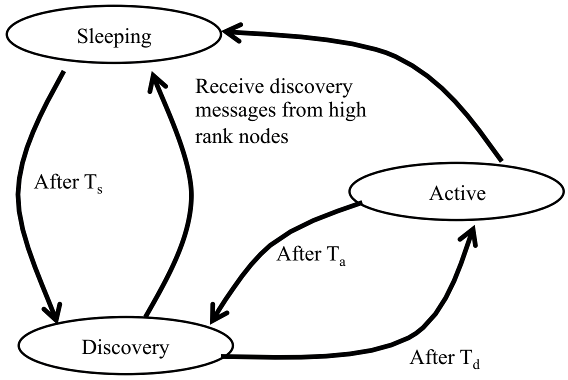


Figure 2.12: The three states of GAF.

area of the sensors. Intuitively, to be efficient, every query should only be propagated towards its targeted area, not to the entire network because doing so is aimless. This approach is in stark contrast with flooding in which data propagates throughout the entire network.

Each individual node maintains two values that quantify the energy consumption of each path. The first is a speculative cost, which is a function of the energy consumption of the sensor itself and the distance between the sensor and the destination. The second is an acquired cost that is the actual cost, and is learned from messages once they reach their destinations. The differences between the speculated cost and the acquired cost arise from holes in the topology. A hole in the topology is generated when a sensor does not have a next hop, which is closer to the destination, thereby forcing the sensor to divert the traffic around the hole.

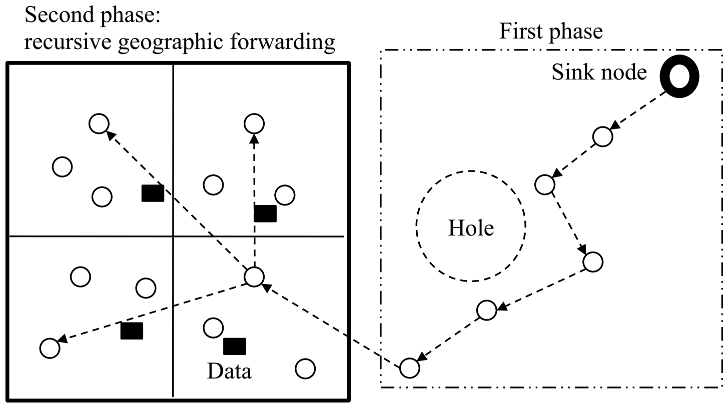


Figure 2.13: An illustration of GEAR's two stages of routing. The first phase delivers the query message to the intended area. The second phase uses recursive geographic forwarding to distribute the query message to the intended area.

The algorithm has two phases. The first phase delivers the packet to the target region, and the second distributes the packet within the region itself.

(a) The first phase starts when a query is disseminated. Upon receiving a packet, the sensor reads its destination information and checks whether it has a neighboring node, which is closer to the destined region. If a sensor, which satisfies this criterion, exists, the packet is forwarded to that node. In the case where there is more than one sensor, the closest among them is chosen. On the other hand, if there are no neighboring nodes, then this implies the existence of a hole. When a hole exists, a sensor is chosen based on the speculated cost to detour the packet around the hole.

(b) The second phase starts when the packet reaches its intended region. It can be diffused in the region by following one of two methods, restricted flooding or recursive geographic forwarding. Restricted flooding requires each sensor to broadcast once, and is not a wise choice when the sensor density is high. Recursive geographic forwarding, illustrated in Fig. 2.13, works by using a divide-and-conquer approach; first, the area to which the message is to be disseminated is divided into four regions, and a copy of this message is transmitted to one of the sub-regions. This procedure is repeated until each region has one sensor, and consequently the message is disseminated to all sensors in the targeted area.

In conclusion, GEAR efficiently reduces the amount of wasteful transmissions by limiting the query propagation towards its intended region only. Therefore, it decreases the wasteful energy consumption.

2.7.3 Recent innovations

Geographic routing is a class of location-based routing algorithms that uses a greedy algorithm to forward its data to the sink through intermediate sensors closer to the sink. However, the existence of holes (dead ends) in topologies requires geographic routing to maintain extra non-local state information or employ other auxiliary techniques. Kermarrec and Tan [45] proposed to decompose a given network into Greedily Routable Components (GRC). GRC are paths where greedy routing is guaranteed to work. By routing packets through GRC, the overhead associated with non-local state information is removed, and energy consumption due to routing around holes is eliminated. Furthermore, Chang *et al.* [46] proposed an innovative scheme that to get around these holes. Sensors bordering around holes in their approach actively establish a forbidden region to enable packets to be guided around holes and move along a short path from the hole to the sink, and thus incurring less energy consumption. It has been shown that contemporary geometric algorithms that are designed to function in 2D environments perform poorly in practical 3D environments [47]. Zhou *et al.* [47] proposed a scheme that first forwards packets greedily as in [43] as long as it can find a node closer to the destination than itself. If a hole is reached and greedy forwarding fails, packets are routed deterministically using hull trees around the hole. A hull tree is a spanning tree where each node has an associated 2D convex hull that contains the positions from all its child nodes in the subtree rooted at the sink. A 2D convex hull is a geometric object that for any line drawn from two end points in it, the line will be in the 2D convex hull.

In an environment where there are multiple sinks that generate queries to nodes in an overlapped area, as shown in Fig. 2.14, the sensors in the overlapped area have to report the same data multiple times, thus incurring wasteful energy consumption. Zhang *et al.* [48] proposed to group nodes into zones according to their locations. In the event that

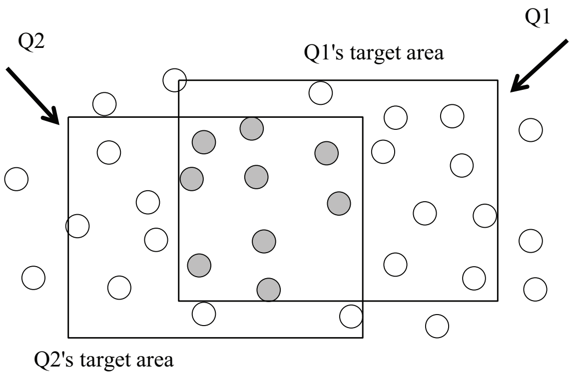


Figure 2.14: An illustration of a wireless sensor network under two queries, Q1 and Q2. The sensors that are overlapping between the two queries are colored in gray.

there exists queries that overlap in an area, the sensors in the area only respond once, thereby eliminating the energy wasted from redundant transmissions.

2.7.4 Summary

Location-based routing algorithms are a class of routing algorithms that enhance energy consumption efficiency by capitalizing on location information. The GPS system might not function in some applications, such as ocean-bottom wireless sensor networks that place the sensors at the bottom of the sea, or applications where large obstacles hinder GPS's functionality. Thus, localization techniques to take the role of GPSs are of prime importance.

Table 2.2: A general comparison among various classes of energy-aware routing for wireless sensor networks.

Name	Class	Data-aggregation	Local-interactions	Mobility	Network lifetime
C.-K. Toh [11]	Flat	No	No	Unsupported	ANL[1]
Chang *et al.* [14]	Flat	No	No	Unsupported	FNL[2]
LEACH [20]	Hierarchical	Yes	Yes	Unsupported	ANL
PEGASIS [21]	Hierarchical	Yes	Yes	Unsupported	ANL
HYMN [28]	Hybrid	Yes	No	Unsupported	SNI[3]
SPIN [30]	Data-centric	No	Yes	Limited	ANL
DD[4] [31]	Data-centric	Yes	Yes	Unsupported	ANL
GAF [41]	Location-based	No	No	Unsupported	ANL
GEAR [43]	Location-based	Yes	No	Unsupported	ANL

[1] Average node lifetime. [2] First node lifetime. [3] Sink node isolation. [4] Directed Diffusion.

2.8 Discussion

Energy-aware routing is a challenging issue, which has attracted substantial research efforts. Research in this area has adopted many techniques from similar networks. Specifically, since some wireless sensor networks possess features similar to those of a wireless ad hoc network, many routing techniques employed in ad hoc networks can be adopted for wireless sensor networks.

The main concern in this research direction is low-energy communications. This is attributed to the large share of energy consumed for communications. Practically, sending a bit over 10 or 100 meters can consume as much energy as millions of computational operations conducted in the processing unit of the sensor, referred to as the R4 signal energy drop-off [5].

Wireless sensor networks can capitalize on the application scope in their real world implementations to reduce energy consumption by taking into account of redundancy of their locations and collected data.

Radio operation schemes also play a major role in the energy consumed in a wireless sensor network. The amount of time a radio is on has a direct relationship with the energy it consumes. The longer it is on, the more energy it consumes. Generally, the radio can operate in always-on, synchronized radio [18,20], or low-duty cycle [49,50] operation modes. In always-on operation mode, the radio is always on. This consumes the maximum amount of energy. In the synchronized radio operation, the radio is on only when it is needed. This allows more efficient energy consumption as compared with always-on operation. In low-duty cycle radio operation, the radio is off most of the time and is only on for a relatively small amount of time. This operation mode is the least energy consuming.

Table 2.2 summaries the characteristics of the routing categories examined in this chapter, along with notable representative algorithms of each routing category. They are also characterized in terms of *data-aggregation*, location awareness, mobility, and network lifetime.

Location-interactions refers to the ability of a routing algorithm to function via local interactions executed in individual sensors without the need for global information about the wireless sensor network. Gathering global information about the entire wireless sensor network consumes a large amount of energy for information exchange. It is worth noting that although hybrid routing algorithms require global information for the flat multi-hop routing part to function, the area of the flat multi-hop routing part is relatively small in size.

Early research in wireless sensor networks mostly envisioned and considered inexpensive sensors with limited or no mobility. Consequently, as can be seen from Table 2.2, very limited support for mobility was considered in early wireless sensor network routing algorithms. Recent advances in this field have investigated many scenarios with mobility of sinks [51–54]. In addition, wireless sensor and actuator networks [55, 56] have recently drawn much research attention, where the sensors are mobile and self-healing.

2.8.1 Data-aggregation

The larger the volume of data to transmit, the larger the energy consumption of the network. Hence, *data-aggregation* is of paramount importance to achieve low-energy communications in wireless sensor networks. Four routing categories, namely, hierarchical, hybrid, *data-centric*, and location-aware routing algorithms, facilitate *data-aggregation*. Hybrid routing utilizes the *data-aggregation* function of hierarchical routing algorithms. Also, GEAR adopts the *data-aggregation* method of *data-centric* routing. Thus, it is worthwhile to elaborate on *data-aggregation* methods employed in both *data-centric* and hierarchical routing algorithms. As will be discussed later, the *data-aggregation* method methodology is rather application specific/dependent.

Data-aggregation in hierarchical routing algorithms is conducted in the CHs of each cluster. The reporting model is aimed at constant uniform reporting, in which sensors transmit data in each time interval; once the CH receives the sensed data from its CMs, it can utilize *data-aggregation*. As compared with the *data-aggregation* in *data-centric* routing, the *data-aggregation* method utilized in hierarchical routing can work in conditions where the sensors produce a low amount of data collected from overlapping areas. It can reduce the energy consumption in scenarios with high data correlation. This reporting model is particularly suited for applications such as environmental monitoring, where periodic information is required about the environment.

Data-aggregation in *data-centric* routing, viz, in-network *data-aggregation*, eliminates the overhead of cluster formation found in hierarchical routing algorithms. In in-network *data-aggregation*, sensors along the path to the destination do *data-aggregation* to reduce the flow of data in the wireless sensor network.

Generally, the in-network *data-aggregation* method considers overlapping data collected from different sensors and merges redundant reports to decrease the number of transmissions conducted in the wireless sensor network. The performance of this *data-aggregation* mechanism will degrade when the overlap between data collected from different sensors is small. The overlap between the data collected from different sensors decreases when the sensing area of sensors is small relative to their density (the ratio between the number of deployed sensors to the size of area they are deployed in). In such cases, the reduction of energy consumption gained by using the *data-aggregation* function of *data-centric* routing will become insignificant.

On the other hand, the query model adopted in *data-centric* routing is well suited for applications where need-based data reporting is conducted. For example, the sensor node observing a desired event only reports to the sink when the event occurs. It produces a low amount of transmissions and will consume a small amount of energy as compared to the uniform data reporting model.

2.8.2 Network lifetime definition

The objective of all the energy-aware routing algorithms for wireless sensor networks is to decrease the energy consumption, and therefore to prolong operation periods of the network. Furthermore, these routing algorithms can be evaluated under different metrics. Particularly, network lifetime is a widely accepted metric for evaluating the energy-aware routing algorithms. Network lifetime can have differing definitions, and some of these definitions can be misleading. It is important to understand how the wireless sensor network functions, and carefully define the network lifetime to accurately evaluate a given routing algorithm. Many researchers have defined network lifetime as the time that the first sensor dies, i.e., first node life [14]. However, in many scenarios, a wireless sensor network can still function even after the first sensor has died. Alternatively, defining network lifetime as the time when all sensors die does not give much insight on the functionality of the wireless sensor network since an isolated node collecting data and unable to transmit its collected data to the sink is of no use. Therefore, defining network lifetime as the time when the sink cannot collect data from the wireless sensor network, i.e., Sink Node Isolation (SNI), is more appropriate and accurate. Moreover, designing energy-aware routing algorithms to improve the average lifetime over all sensors is rather popular.

Table 2.2 shows various definitions of network lifetime that each routing algorithm has adopted. It can be seen that the most popular definition is average network lifetime, which does not necessarily result in longer lifetime. Note that only hybrid multi-hop routing is designed with the motivation to mitigate the energy hole problem, thus resulting in improved lifetime of the wireless sensor network.

2.8.3 Routing overhead

Routing overhead is a major energy consumer in wireless sensor networks. Decreasing frequency of information updates necessary for routing can decrease the energy consumed by the routing overhead. However, decreasing their frequency leads to degradation of the energy-aware routing algorithm's performance due to inaccurate information or outdated information about the wireless sensor network.

In flat multi-hop routing algorithms, deciding which path to route traffic in order to achieve minimum energy consumption or maximum lifetime requires information about the energy consumed per unit in each link, which can be calculated from Eq. (2.1), and the residual energy of each sensor. This information needs to be regularly updated to achieve minimum energy consumption when some nodes along a path die and the path no longer produces the minimum energy consumption and/or a sensor is overly energy exhausted and traffic must be directed from it to allow it live longer. The frequency of route information updates affects the accuracy of paths with the minimum energy consumption and the maximum lifetime. Obviously, requiring frequent updates is an energy intensive operation, and hence could pose a great drawback to these methods.

Hierarchical routing algorithms form clusters wherein a single sensor acts as a CH. To form a cluster, an election process needs to take pace where sensors present themselves as CHs, and then each CH manages a collection of CMs, and this process consumes energy of the wireless sensor network. Furthermore, since the role of CH is an energy consuming role with *data-aggregation* and inter-cluster communications, the sensors take turns in becoming a CH, thus reinitiating the energy consuming CH election process. Decreasing the frequency of CH election puts the elected CHs in risk of energy exhaustion (dying) and lost coverage before other sensors can take on the CH role. Alternatively, increasing the CH election process frequency would put a high energy burden on the wireless sensor network.

In *data-centric* routing, the sink sends queries to the wireless sensor network advertising its *interests*; such queries consume energy. Therefore, a relationship between the sink and sensors is created that can satisfy its *interests*, and afterwords data transfer occurs between sensors and the sink. Generally, this relationship has a predetermined time limit, and upon expiration a new relationship needs to be established. Thus, continuous relationship establishment is required, thereby consuming energy of the wireless sensor network. On the other hand, limiting relationship establishment results in failures of the wireless sensor network to fulfill its objective.

Location-aware routing algorithms are generally incorporated with other routing energy-aware routing algorithms, and thus inherit the energy consumption attributed to the routing overhead of the adopted energy-aware routing algorithm. Furthermore, this category employs additional schemes for energy savings such as allowing some sensors to sleep. These schemes require information exchange, and thus consume additional energy.

2.8.4 Energy hole phenomenon

The energy hole phenomenon is defined as the energy consumption imbalance among sensors. This inevitably leads to rapid energy exhaustion of sensors in the high-energy consuming areas, thus resulting in holes in these areas, and subsequently network partition. This phenomenon is attributed to the traffic patterns in wireless sensor networks, namely, the many-to-one (convergecast) traffic directed towards the sink.

In flat multi-hop routing, all nodes, except the sink, assume the same role and responsibility. If all the sensors transmit their data towards a central point, i.e., the sink, nodes closer to the sink will inevitably end up draining their energy faster. Along with the lack of *data-aggregation* that decreases the volume of data flowing in the wireless sensor network, the sink is consequentially disconnected from the surviving sensors.

The application scope of hierarchical routing algorithms considers applications with uniform reporting directed to the sink that subsequently causes the energy hole phenomenon. Furthermore, CHs in hierarchical routing algorithms conduct inter-cluster communications, and their relatively smaller number leads to inefficient long-distance transmissions that in turn augments the severity of the energy hole phenomenon.

HYMN synergies two categories of wireless sensor network routing algorithms to mitigate the energy hole phenomenon by using energy efficient transmission distances and *data-aggregation*. Thus, HYMN surpasses the contemporary categories of energy-aware routing algorithms.

Data-centric routing algorithms adopt the query-based reporting model. In this model, the sink queries a specific area. As a direct result, the flow of traffic depends on the scenario under consideration. For example, if an application demands reporting of a certain object's movements, the areas where this object moves will incur higher energy consumption rate than other areas. This phenomenon is referred to as the query hotspot.

Location-based routing algorithms are typically coupled with other routing algorithms, and thereby inherit the energy hole phenomenon characteristics of the latter algorithm.

2.8.5 Collisions and interferences

Wireless sensor networks can be categorized as a special case of ad hoc networks, and face the same issues of collisions and interference, which occur when two nodes within sufficiently close distance from each other try to communicate on the same channel; thus, energy is consumed for retransmitting the same message again. The higher the number of collisions, the larger the amount of energy is consumed in the wireless sensor network. Owing to the ad hoc nature of wireless sensor networks, adopting a centralized management schemes for Medium Access Control (MAC) is not feasible; it is practical to deploy a distributed MAC scheme. All the routing techniques, except hierarchical routing, introduced here employ such MAC schemes. In the case where distributed MAC schemes are implemented, a high amount of energy is consumed for MAC operations due to collisions. This is also applicable to HYMN as it is also partly composed of hierarchical routing.

In hierarchical routing, the CH takes a leading role by aggregating data and sending them to the sink. Furthermore, a CH is normally enabled with a centralized MAC scheme to manage the collision and interference issues. LEACH [20] adopts the Time Division Multiple Access (TDMA) MAC scheme for channel access. Upon cluster formation, the CH organizes a TDMA schedule and transmits this schedule to the CMs in its cluster. Applying TDMA ensures that there are no collisions when the CMs transmit their data to the CH, and thus avoids the energy consumed due to collisions. Moreover, the transmission circuitry of each CM can be turned off at most of the time except when it is its turn for transmission, thus reducing the energy consumed by the individual sensors. However, this scheme cannot avoid interferences or collisions caused by neighboring clusters.

2.9 Summary

In this chapter, we have investigated the crucial problem of energy-aware routing for wireless sensor networks. The limited energy capacity along with the difficulty of changing batteries of deployed sensors makes energy-efficient technologies essential for the longevity of wireless sensor networks. We classify energy-aware routing algorithms into five categories according to their network architecture; flat multi-hop routing that finds paths to minimize energy consumption or increase sensor network lifetime, hierarchical routing that creates a hierarchy and applies *data-aggregation* to reduce energy consumption, hybrid multi-hop routing that is a combination of the former two routing algorithms and mitigates the energy hole problem, *data-centric* routing where in-network *data-aggregation* is performed to eliminate wasteful transmissions, and location-based routing that uses location information to reduce the energy consumption of the wireless sensor network.

Moreover, we have discussed how the various energy-aware routing algorithms perform from many different perspectives such as *data-aggregation*, network lifetime definition, routing overhead, the energy hole phenomenon, and collisions/interferences.

Chapter 3

Mobile-sink-based WSN Architecture

3.1 Introduction

In this chapter we present the assumed WSN architecture of this thesis, as well as data gathering in this architecture. The WSN architecture is composed of two main parts, which are shown in Fig. 3.1. The two parts are the mobile sink and the cluster. The sink node is described in more detail in section 3.2, and the cluster is described in more details in section 3.3.

Data gathering occurs in two stages, i.e., in the sink node and in the cluster heads. The process of collecting data from cluster heads to the sink node is one of the two stages of data gathering, it is referred to as the data gathering from clusters. Please see chapter 4 for further

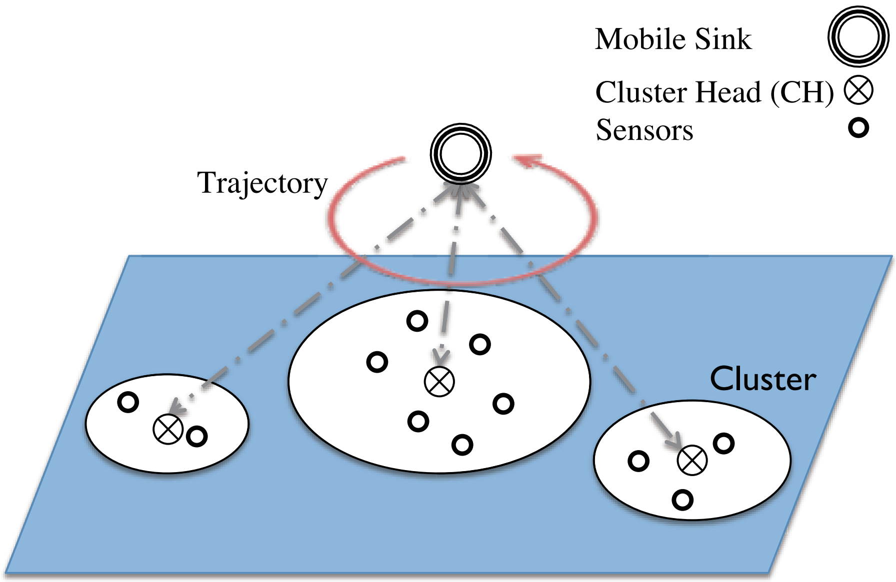


Figure 3.1: The considered mobile-sink-based wireless sensor network architecture .

details. Moreover, the process of collecting data from sensor nodes to cluster heads is the other stage of data gathering, referred to as data gathering within clusters, described in detail in chapter 5.

3.2 Mobile Sink

The sink node is the point where data is extracted from the WSN. Thus, all data needs to be transmitted to it. A sink node is considered to have access to plentiful energy resources. A key design issues is whether or not a sink node is mobile, i.e., the ability of the sink node to change its position. Follows is an explanation of the implications of this design choice on the performance of the WSN from the point of view of communications. Moreover, we give a discussion on the kinds of mobile sinks and their advantages.

A static sink node is such a node that is unable to change its position. For such a sink node, the following phenomena occur, imbalance of energy consumption, imbalance of lifetime, imbalance of delay, and the sink-node isolation problem. The imbalance of energy consumption occurs due to the fact that sensor nodes act as relay for other sensor nodes. Furthermore, the closer the sensor node is to the sink node the higher its energy consumption due to the larger amount of data it relays. The imbalance of sensor node life occurs due to two factors, namely, the limited energy reserves of a battery and the imbalance of energy consumption. Given that all sensor nodes have similar energy reserves, sensor nodes closer to the sink node deplete their energy reserves earlier than nodes farther from the sink node. The imbalance of delay occurs because data that originates far from the sink needs to travel through more hops, referred to as hop count, as compared with nodes that are closer to the sink node. The sink-node isolation problem is the state a WSN reaches to when all nodes that are within transmission range reach of the sink node consume their energy reserves. This renders the sink node unable to communicate with the other sensor nodes that have plentiful energy reserves.

If the sink node is mobile, i.e., able to change its location, the aforementioned problems associated with the immobile sink node can be largely eradicated. As the sink node flays according to its trajectory the distance between the sink node and any node in the WSN changes, and the average distance between any sensor node and the sink node becomes largely similar among all nodes. Thus, the imbalances of energy consumption, lifetime, and delay can be largely mitigated. Furthermore, since the sink node can change its location, sink-node isolation cannot occur. Due to the above advantageous, this thesis focuses on mobile sink node-based WSNs.

Its very important that kind of mobile sink be chosen in a correct manner to enable efficient data gathering in WSNs. Sinks can be categorized into airborne and nonairborne mobile sinks. In general, airborne mobile sinks have have the ability to reach areas that nonairborne cannot reach (e.g. mountains, hazardous terrain, or war zones). Furthermore, airborne sinks can further classified as small size and large size airborne sinks. Unmanned Arial Vehicles (UAVs), Unmanned Arial Systems (UASs), and drones fall under the category of small airborne sinks. Small airborne sinks have many advantages over their bigger counterparts. these advantages include, flexibility, flying at low altitudes, unnecessariness of pilots. Most important of these is the UAVs ability to fly close to ground nodes, i.e., sensor nodes, which allows the sensors to decrease the amount of energy they spend transmitting to the sink node [28]. Moreover, fixed-winged UAVs have higher speeds than rotor-propelled UAVs. These higher speeds allows for faster missions completion times. For the aforementioned reasons, we focus our thesis on fixed-winged UAVs.

3.3 Clusters

A cluster is a sensor node group that has a number of Cluster Members (CMs) and a single Cluster Head [20]. A CM is a sensor node that has two main responsibilities, namely, 1) to collect information from its surroundings using its sensors and 2) to transmit and relay other sensor nodes' transmissions. A CH may collect data in addition to three main responsibilities, which are 1) to act as a local data gathering point for all data originating from within the cluster, 2) to perform data aggregation and processing on the collected data, and 3) to transmit all the aggregated data to the sink node. The benefits of employing clusters are reduced routing overhead and reduced energy consumption, for details please see section 2.4.

3.4 Summary

In this chapter, we have introduced the WSN architecture adopted in this thesis. Furthermore, we have highlighted the need for this architecture. It is important to highlight that since there are two data gathering points, i.e., in the CHs and in the sink node, data gathering energy efficiency needs to be considered for these two points. The following chapters deal with these issues. Chapter 4 proposes an energy efficient data gathering scheme for collecting data from clusters to the sink node. Chapter 5 proposes an energy efficient data gathering scheme for collecting data within clusters to the CH.

Chapter 4

Energy Efficient Data Gathering from Clusters

4.1 Introduction

Advances in propulsion systems, energy storage, miniaturized payloads, communications systems, and autonomous control have rendered the development of Unmanned Aircraft Systems (UASs) feasible. UASs are small unmanned airborne vehicles equipped with wireless transceivers, Global Positioning Systems (GPS), and superior computational capabilities. UASs can be fixed-winged or rotor-propelled. The UASs with fixed-wings have higher speeds compared with the rotor-propelled ones. We subject our study to the fixed-winged UASs because of their superior speed that renders the ability to complete operations in shorter periods of time. Hereafter, we refer to a fixed-winged UAS as a UAS for brevity. UASs have a great potential to create a multitude of applications in many disciplines [57–64]. The applications include but are not limited to polar weather monitoring [65], provisioning communications in disaster devastated areas [61, 66], and wildfire management [67]. We aim to utilize the UAS' abilities to construct an autonomous UAS-aided network, where multiple UASs fly over the sensor field to collect ambient data from sensor nodes. These sensor nodes are deployed in various kinds of terrains including dangerous areas that are difficult to reach with conventional vehicles, which include helicopters.

We consider a network where multiple UASs collect data from sensor nodes as they fly according to annular trajectories. Given that it is expensive to equip all sensor nodes with functionality to communicate directly with a UAS, special sensor nodes, Cluster Heads (CHs), which have special communication capabilities, are distributed in the area. The remaining sensor nodes entail only capabilities to communicate with the CHs. The mobility pattern of UASs causes the distance between a CH and a UAS to vary. Furthermore, the distance between a CH and a UAS affects the Signal-to-Noise Ratio (SNR), which in turn affects the modulation scheme. This is because modulation schemes that have more bits per symbol necessitate higher values of SNR for a given BER requirement [68]. Moreover, if high levels of BER are tolerable, the attainable number of bits per symbol that a modulation scheme transmits can be further improved.

Sensor nodes and CHs, which are powered only by batteries, are coveted to be able to function for prolonged durations of time without battery replenishment [28, 69]. This renders energy efficiency to be a fundamental requirement to assure the longevity of CHs without the need for battery renewal, particularly if the target applications imply hazardous environments. For the majority of data collection applications with sensor nodes it is essential to make efficient utilization of the limited battery capacities. Therefore, given a fixed budget of energy reserves, the quantity of transmitted data should be increased to the utmost. We define this metric to be energy efficiency. Adaptive modulation is a key technology that can enable transceivers to transmit more data for the same transmission power under the condition that the channel conditions are favorable, i.e., SNR level is high.

For the considered UAS-aided network, the number of bits that can be transmitted per symbol, and consequently the energy efficiency, defer according to which time slots are assigned to which CH. Since increasing the energy efficiency is of interest, the network designer is inclined to opt to give priority of transmission to CHs with higher SNR to have a higher priority to transmit. This undoubtedly will result in the unfair allocation of time slots among CHs, where the CHs that are distant from the UAS transmit less compared to CHs that are in the proximity of the UAS. Thus, our goal is to devise a method to improve the network's energy efficiency given that a determined degree of fairness among CHs holds regardless of their distance from the UAS.

Contemporary data collection methods (similar to those that are designed for mobile sinks) do not consider the challenges associated with the aforementioned energy efficiency issues in UAS-aided networks [70–73]. In this chapter, we propose a data collection method based on game theory that improves network energy efficiency while satisfying fairness in the distribution of resource among CHs.

Contributions: The contributions of this chapter can be summarized as follows:

- We demonstrate how adaptive modulation is affected by the UAS' annular trajectory.
- We formulate the problem of maximizing the energy efficiency with fairness among CHs using the framework provided by Game Theory, where each CH i is interested in increasing its individual utility, U_i, by acting as per its Best Response (BR) correspondence, $BR(A_{-i})$.
- For the formulated game, we substantiate the properties of stability, optimality, and convergence. These properties yield performance guarantees for the formulated game.
- Based on the formulated game, we devise a game-theoretic data collection method for enhancing the energy efficiency while considering fairness in multiple UAS-aided Networks.
- The Price of Anarchy (PoA) of our proposed game-theoretic data collection method is analyzed.

The remainder of the chapter is as follows. Section 4.2 commences with a related work section. Section 4.3 details the system assump-

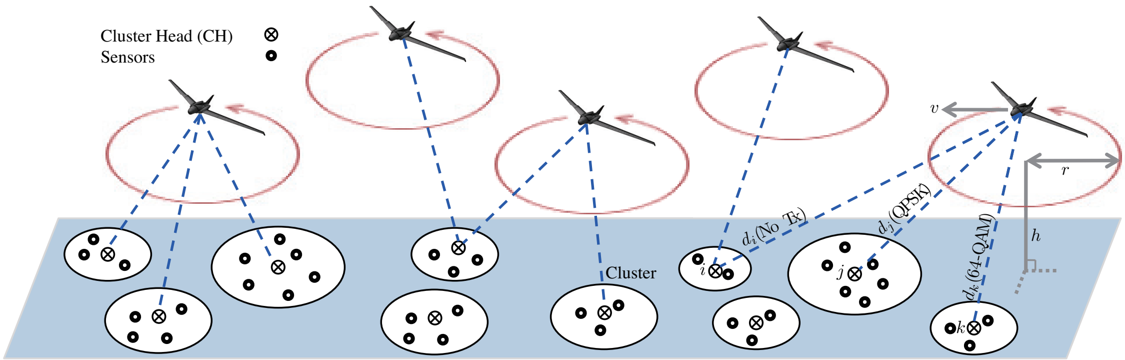


Figure 4.1: Considered UAS-network topology. The M UASs travel around the sensor field according to an annular trajectory, which is characterized by altitude (h), speed (v), and radius (r). The UASs communicate with N CHs. The CHs use a low power communication standard to communicate with sensor nodes. © 2014 IEEE.

tions and definitions. Section 4.4 gives our envisioned data collection method for multiple UAS-aided networks. In Section 4.5, we analyze the PoA of our proposed game-theoretic method. Section 4.6 presents the performance evaluation of our proposed data collection technique. We conclude this chapter in Section 4.7.

4.2 Research Direction

In this section, we investigate the works relevant to the UAS-aided networks research direction. These works include the investigations of UAS-aided networks, mobile sink-based Wireless Sensor Networks (WSNs), network segmentation know as hierarchical routing, channel adaptive modulation techniques, and wireless network optimization based on Game Theory.

UASs have been integrated into many applications across many domains that span those of civilian and military [57–62]. The UAS has been employed to application that include polar weather monitoring [65] and wildfire management [67]. Namuduri *et al.* [63] discussed the opportunities and challenges for using UASs in civilian applications. Daniel *et al.* [58] explored how to use multiple UASs provisioned with sensing capabilities that enable the sensing of data from hostile environments. Using the UAS' abilities for communications purposes has attracted the attention of many researchers. Bekmezci *et al.* [57] outlined communication related issues of ad hoc networks comprising multiple UASs referred to as Flying Ad-Hoc Networks (FANETs). Freitas *et al.* [59] proposed using UASs as relays to link partitioned ad hoc networks. The research in [74] explored medium access control for UASs. Varakliotis *et al.* [61] envisioned providing communications in disaster struck areas with UASs equipped with cognitive radio technology. Asadpour *et al.* [75] designed an ad hoc network composed of UASs for high traffic data application. Goddemeier *et al.* [62] proposed communication-aware steering algorithms for UAS swarms in exploration applications. The considered communication-aware positioning algorithms maximize exploration coverage with the simultaneous ability to self-optimize the communication links among UASs and the ground base station by exploiting controlled mobility.

In comparison with the existing works on UAS-aided networks, our research aims at using the UAS' abilities to construct an autonomous UAS-aided network, where the M UAS fly over the sensor field to collect ambient data from ground nodes, which are in various kinds of terrains including dangerous areas that are difficult to reach with conventional means like helicopters. Among all the existing works on UAS-aided networks, to the best of our knowledge, there have not been any research that taps onto the UAS' unique abilities to collect data from nodes on the ground. Indeed, we aim to devise a method on how to collect data from ground nodes while considering the unique characteristics of the UAS, of which we consider the UAS' inability to be stationary in the air. Additionally, the UAS quintessentially wheels in a trajectory. This constantly changes the communication distance and the SNR of the transmissions between a UAS and a ground nodes. Since the SNR of transmissions is of varying levels, adaptive modulation [68, 76] can be incorporated to capitalize on favorable SNR levels to increase energy efficiency and throughput.

The closest proposals to the research direction of this chapter are data collection techniques for mobile sink nodes in WSNs [70–73]. However, they do not consider the ecliptic trajectory akin to the UAS' mobility pattern and the inability of UAS to remain stationary in air. Additionally, they do not exploit favorable channel conditions by capitalizing on adaptive modulation. Most notable of which is the work of Shah *et al.* [70], where the mobile sinks go to sensor nodes to collect data of interest.

Equipping all nodes with the ability to communicate with the UAS limits the deployability of data collection applications because of hardware and energy consumption issues. Network hierarchy is a suitable solution. Many studies have been carried out that segment the network layer into smaller components, known as clusters, most notably is Low-Energy Adaptive Clustering Hierarchy (LEACH) and its many variants [25,28]. Clusters decrease the deployment cost of sensor nodes, since only a special subset of nodes, referred to as CHs, need to be able to communicate with the UAS while the remaining nodes only need to have basic communication functionalities to communicate with the CHs.

Many research works have been conducted to explore adaptive M-ary Quadrature Amplitude Modulation (M-QAM) [68, 76]. Adaptive transmission techniques can harness the number of degrees available for communications to enhance the capacity of the network by adapting the modulation scheme according to channel conditions, i.e., SNR levels. Without such a technology the transceivers on the CHs can only transmit at a constant number of bits per symbol despite the favorable SNR conditions.

Our proposal aims to maximize the energy efficiency of the UAS-aided network, where CHs located around the sensor field exist with time varying SNR levels. Thus, an optimization method is required so that the allocation of time slots of the M UASs to the CHs is done in a manner that maximizes network's energy efficiency while maintaining a predetermined degree of fairness. Game Theory is a suitable solution for such a problem. Game Theory has been applied to a wide range of research areas, most notably of which are economic problems [77, 78]. Using the framework provided by Game Theory to solve complex issues has attracted the attention of many researchers in the last decade and their has been a plethora of applications ever since. In particular, Game Theory has been applied to many research issues in the context of wireless network communications, which include channel assignment in wireless mesh networks [79], quality of service in wireless networks [80], power control in cellular radio systems [81], and cognitive radio networks [82]. Readers unfamiliar with Game Theory concepts and its applications in wireless communications are encouraged to refer to the works in [77,83], which contain fundamental results in wireless communications research area. In this work, we employ the framework of potential games, which have been utilized in the context of objective maximization problems such as the problem investigated in this chapter.

4.3 Preliminaries and System Model

Fig. 4.1 shows the envisioned UAS-aided network. CHs are provisioned with superior hardware that enable communication with the M UASs. On the other hand, a normal sensor node is equipped with basic communication facilities, and has to transmit the data that it collects to the closest CH to it. This configuration lowers the deployment cost of the UAS-aided network because only CHs need to be equipped with expensive hardware.

Sensor field: Similar to many data collection applications of sensor nodes [15, 23, 37], the sensor nodes sense their surroundings to collect data and report the data that they have sensed to the CH in their proximity by using a low energy consuming communications standard, which include ZigBee or Bluetooth Low Energy [84, 85]. A CH communicates with the UAS by using specific time slots assigned to it by our proposed method.

Mobility model: The UASs are used to collect data from the sensor field. They glide around the sensor field in a circular trajectory innate to UASs [86]. The UAS have varying degrees of mobility, which enable the UASs to achieve its objective of data collection. The UAS' degrees of mobility (comprising altitude (h), speed (v), and radius (r)) are flexible [57, 87]. The degree of mobility changes to accommodate mission objectives, which are influenced by time limitation of mission completion, or the terrain that the sensors are deployed in and so on.

Adaptive modulation: The CHs in the UAS-aided network are provisioned with transceivers that are capable of adaptive modulation. The adaptive modulation scheme can change its modulation level to one of five modes, which include no transmit, Phase-Shift Keying (PSK), Quadrature Phase-Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (QAM), and 64-QAM. For these possible K-modes ($n = 0, 1, ..., K-1$), the modulation scheme is able to transmit a different number of bits per symbol, b_n, and have M_n possible constellations.

4.3.1 System Model

The network is composed of a set of sensor nodes, N CHs, and M UAS. According to [88, 89], the path-loss factor, which reflects the extent of attenuation that the signal transmitted from CH i to the UAS suffers from can be given by

$$G_i = \xi d_i^{-\varphi}, \tag{4.1}$$

where d_i is the displacement between CH i and a given UAS. φ is the path-loss exponent (it takes values between 2 and 4), and ξ is a constant dependent on the factors that are mainly determined by receiver gain, transmitter gain, and wavelength. The received signal is distorted by Additive White Gaussian Noise (AWGN) with a normalized one-sided power spectral density N_0. We assume that transmission devices onboard the CHs transmit with a constant symbol-wise average transmission power P. Moreover, CHs are not able to control the transmission power, which is constant. Also, the network has a limited bandwidth B, which is measured in Hertz. Hence, the network SNR can be defined according to the following equation [88, 89]:

$$\rho = \frac{P}{N_0 B}. \tag{4.2}$$

Table 4.1: SNR switching levels for five-mode adaptive M-QAM. © 2014 IEEE.

SNR	n	M_n	b_n	mode
$\gamma_0 \leq \gamma < \gamma_1$	0	0	0	No Tx
$\gamma_1 \leq \gamma < \gamma_2$	1	2	1	BPSK
$\gamma_2 \leq \gamma < \gamma_3$	2	4	2	QPSK
$\gamma_3 \leq \gamma < \gamma_4$	3	16	4	16-QAM
$\gamma_4 \leq \gamma < \gamma_5$	4	64	6	64-QAM

The SNR for a transmission conducted by CH$_i$, ρ_{CH_i}, can be given as:

$$\rho_{CH_i} = \rho G_i. \tag{4.3}$$

4.3.2 Adaptive Modulation Switching Levels Model

Similar to [68, 76], we adopt the fixed switching scheme that determines the switching criterion based on fixed SNR levels. In the so-called fixed switching scheme, the assignment of the SNR boundaries is performed in a fashion that renders the SNR level at the boundary to satisfy the BER requirement with the modulation scheme used in an AWGN channel. According to [68,76] the criteria used to find the SNR switching levels are shown in Table 4.1. The switching levels, γ_n, can be derived from the formulas devised by Alouini and Goldsmith [76]:

$$
\begin{aligned}
\gamma_0 &= 0 \\
\gamma_1 &= [erfc^{-1}(2BER_0)]^2 \\
\gamma_n &= \frac{2}{3}K_0(M_n - 1); n = 2, 3, ..., K - 1 \\
\gamma_K &= +\infty,
\end{aligned}
\tag{4.4}
$$

where BER_0 is the BER requirement level for the wireless system, $erfc^{-1}$ is the inverse complementary error function, and $K_0 = -\ln(5BER_0)$. K in our wireless system has the value of five.

4.4 Data Collection Challenges and Proposed Solution

The sensor nodes and the CHs in the UAS-aided network power their operation by finite battery reserves. Energy efficiency (throughput per energy) is a critical issue since it is a measure of how much data can be transmitted with the limited battery capacities of CHs. Energy efficiency of a transmission is influenced by the UAS' mobility. The influence arises from the change of distances between the CHs and the UASs as the UAS traverses the sensor field according to its circular trajectory. Consequently, the SNR levels of the transmissions between the CHs and the UASs also change. When the SNR of the transmitted signal is high, the CHs' transmitters can adapt the modulation scheme to allow for more bits to be transmitted per symbol. Inversely, if the SNR of the transmitted signal is low, the CHs adapt the modulation scheme to decrease the number of bits transmitted per symbol. Such adaptation of the number of bits per symbol (b_n) controls the BER level such that it is within the BER requirement (BER_0) of the wireless system. The UAS' time slots should be assigned in a manner that allows for improved energy efficiency of the UAS-aided network. Assigning time slots for the maximization of energy efficiency results in the unfairness of the distribution of time slots among CHs. The fairness criterion (β), the extent of equality of distribution of a resource, should reflect on the fairness in both energy efficiency and throughput among the CHs in the UAS-aided network. Fairness among CHs can be expressed by using the fairness index, which is proposed by Jain *et al.* [90]:

$$Fairness = \frac{(\sum_{i\in(1,2,....,N)} m_i)^2}{N\sum_{i\in(1,2,....,N)} m_i^2}, \tag{4.5}$$

where m indicates either throughput or energy efficiency. Eq. (4.5) has been designed by Jain *et al.* [90] to increase as the difference between m values of CHs decreases. The maximum value of Eq. (4.5) is 1, which occurs when all CHs have the same value of m. The minimum value of Eq. (4.5) is $1/N$, which occurs when one CH has a nonzero m and the remaining CHs have a zero value m. The problem of allocating the M UAS' time slots among N CHs to maximize the networks energy efficiency such that the fairness criteria is satisfied cannot be solved in real time due to the inherent number of computations entailed in solving this problem. To illustrate this issue, consider a hypothetical UAS-aided network that consists of 20 CHs, where 1000 time slots need to be assigned. For such a slot assignment, finding a slot assignment for the aforementioned problem involves computations of enormous proportions (20^{1000}). Game Theory can be used to solve this optimization problem without the associated computational burden [91]. Thus, we aim to formulate this problem as a game, as shown in Section 4.4.1. Additionally, we substantiate the performance characteristics of our formulated game in Section 4.4.2. The results found in Section 4.4.2 are utilized to formulate a game-theoretic method in Section 4.4.3.

4.4.1 Game-based Interactions

We model the CHs as players in oder to optimize the slot assignment using the framework provided by Game Theory. Each CH is defined to be an intelligent decision maker of the game $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$. Here, $\mathbf{N}$, $\mathbf{A}$, $\mathbf{U}$ refer to the main components of $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, which are the $\mathbf{N}$ players, their actions, and their utility functions. The players in this game are N CHs defined as follows:

$$\mathbf{N} = \{CH_i; \forall i \in (1, 2, ..., N)\}, \tag{4.6}$$

where CH_i represents the CH with index i. U_i is the utility function of CH i, which reflects the energy efficiency that can be formulated as:

$$U_i = \frac{\delta_i}{\eta_i}; \forall i \in (1, 2, ..., N), \tag{4.7}$$

where δ_i is the amount of data that CH i has transmitted and η_i is the amount of energy CH i consumed for the δ_i consumed energy. U_i reflects the energy efficiency of CH i, defined as throughput per energy. The utility of the UAS-aided network is formulated as follows:

$$U_{Network} = \sum_{i \in (1,2,....,N)} U_i. \tag{4.8}$$

Each CH in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ controls a threshold, α_i, which is the farthest distance that the CH is willing to transmit to the UAS at. Hence, α_i indicates the lowest SNR that CH i is willing to transmit at. Thus, the actions of CH i, A_i, can be defined as:

$$A_i = \{\alpha_i; \forall i \in (1, 2, ..., N)\}. \tag{4.9}$$

The game profile of $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, Ψ, is derived from the Cartesian product of the players' actions, i.e.,

$$\begin{aligned} \Psi &= \times_{\forall i \in (1,2,....,N)} A_i \\ &= A_1 \times A_2 \times A_3 \times ... \times A_N. \end{aligned} \tag{4.10}$$

Let $a_i \in A_i$. Then, define a_{-i} as the set of actions chosen by all other players excluding player i. Thus, a_{-i} is defined as:

$$a_{-i} = \{a_1, ..., a_{i-1}, a_{i+1}, ..., a_N\}. \qquad (4.11)$$

It is desired that players negotiate their interdependent actions to arrive to an optimized slot assignment (S) such that the value of $U_{Network}$ is maximized and the fairness constraint is satisfied. The issues of convergence and efficiency surface. Convergence is whether the proposed game can converge to a steady state solution, a consensus between players that implies stability. Moreover, what is the efficiency of the stable solution in terms of $U_{Network}$. These issues will be addressed in Section 4.4.2. Thereafter, the results of Section 4.4.2 will be used to formulate a game-theoretic method in Section 4.4.3.

4.4.2 Stability, Optimality, and Convergence in the potential game $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$

Nash Equilibrium (NE) [77, 78] is a central principle in Game Theory that is used to define stability between negotiating players. NE is a stable state that can occur when players in a game act according to their Best Response (BR) correspondences. The BR correspondence of player i is defined as:

Definition 1. action $a_i^* \in BR(a_{-i})$ if

$$U_i(a_i^*, a_{-i}) \geq U_i(a_i, a_{-i}); \forall a_i \in \boldsymbol{A}_i. \tag{4.12}$$

As the above definition indicates, the BR correspondence of player i is its best response given other players actions, i.e., a_{-i}. Now, let $\hat{a}$ be defined as the action profile:

$$\hat{a} = (a_1, ..., a_N). \tag{4.13}$$

$\hat{a}$ is said to be a NE action profile if it satisfies the following definition:

Definition 2. $\hat{a}$ is a NE action profile if

$$a_i \in BR(a_{-i}); \forall i \in \{1, 2, ..., N\}. \tag{4.14}$$

The aforementioned definition indicates that no player has a motive to deviate from its action if other players do not deviate their actions. That is to say that the game has attained a stable state. However, this stable solution does not entail an implicit guarantee of optimal outcome. Nevertheless, potential games, which are a specific kind of game, have useful properties that address the convergence to a NE and the NE's efficiency issue. A potential game possesses the following useful properties:

- For any finite potential game, at least one pure action profile NE exists [92].

- All the NEs associated with the potential game are either local or global maximizers of the utility function [92].
- Myopic one-sided learning based on either the best response or the better response learning methods can be applied to the game so as to guide the game to reach the utility function maximizers, i.e., the NEs [83, 92].

Lemma 1. G$(\boldsymbol{N}, \boldsymbol{A}, \boldsymbol{U})$ *is a potential game.*

Proof. According to [83, 92], a game is a potential game if a potential function Pot, exists, defined as follows:

$$Pot(a'_i, a'_{-i}) - Pot(a''_i, a''_{-i}) = U_i(a'_i, a'_{-i}) - U_i(a''_i, a''_{-i}), \tag{4.15}$$

where i, a', and a'' are any player and any two strategies in the game, respectively. From Eqs. (4.8) and (4.15), $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ can satisfy the definition of a potential game, where

$$Pot = U_{Network}(\Psi); \forall i. \tag{4.16}$$

□

From lemma 1, we can see that $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ is a potential game. Based on the properties of potential games and NEs, we can guarantee that the formulated game, $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, will converge to a conscious between players, i.e., a stable state, which is a utility function maximizer. Better response and best response are two notable learning techniques that guarantee convergence to a utility maximizing NE of potential games [83, 92]. Denote the negotiation step to be t, then players acting as per the better response learning choose their actions as follows:

$$a_i^{t+1} = \begin{cases} a_i^{rand} & \text{if } (U_i(a_i^{rand}, a_{-i}^{rand}) > U_i(a_i^t, a_{-i}^t)) \\ a_i^t & \text{otherwise.} \end{cases} \tag{4.17}$$

According to the better response learning technique each player selects a random strategy in its turn. The player keeps the random strategy if it results in a better utility than that of the previous strategy it had in its previous turn, and vice versa if the utility resulting from the random action results in less utility than that of the former action. Players acting on the best response learning technique choose their actions as follows:

$$a_i^{t+1} = \arg_{\forall a} \max U_i(a). \tag{4.18}$$

Here, the player chooses the action that makes its utility maximum. Best response learning, based on Eq. (4.18), is fast to converge to the utility function maximizer. However, it exhibits a higher computation cost compared to that of the better response learning technique, based on Eq. (4.17). Yet, better response has slower convergence speed when compared with best response. That is to say that best and better

Algorithm 1 Game-theoretic data collection method: CH-side game. © 2014 IEEE.

begin
Receive message from the UASs that initializes of negotiation process
repeat
  $a_i^{rand} \leftarrow$ random strategy
  if $(\omega(a_i^{rand}, a_i^t) >$ random number$[0,1])$ **then**
    $a^{t+1} \leftarrow a_i^{rand}$
  else
    $a^{t+1} \leftarrow a_i^t$
Transmit a^{t+1} to the M UASs
Wait for time slot assignment of the M UASs
until the $\mathcal{T}$ time units are finished
end

response have contrasting features in terms of convergence time to the utility maximizer and computational complexity.

It is worth noting that in some cases $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ might converge to a stable solution that is a local optimum of the utility function, even though the global optimum exists. In such a situation the network can achieve a better outcome, i.e., that of the global optimum. Furthermore, since this suboptimal stable solution is one instance of NE and according to the definition of NE in *Definition* 1, the players have no motive to change their actions, since they cannot increase their utility functions and hence will remain at the local optimum NE action profile, $\hat{a}_{LO-NE}$. To avoid players being insnared in a suboptimal NE, many researchers have employed the smoothed better response learning technique [79, 91] that introduces the factor of randomness to the learning process. Smoothed better response has been proved to converge with a high probability to the global optimal equilibrium [93]. Thus, we use the smoothed better response learning technique in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$.

A player acting according to the smoothed better response learning technique probabilistically chooses its actions according to the following function:

$$a_i^{t+1} = \begin{cases} a_i^{rand} & \text{with probability } (\omega) \\ a_i^{t} & \text{with probability } (1-\omega). \end{cases} \tag{4.19}$$

Here, ω is defined as a function of a_i^t and a_i^{rand} as follows:

$$\omega(a_i^{rand}, a_i^t) = \frac{e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta}}{e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta} + e^{U_i(a_i^{t}, a_{-i}^{t})/\zeta}}. \tag{4.20}$$

As can be seen from Eq. (4.19), smoothed better response integrates randomness to the learning process. The player chooses to act upon the new action a_i^{rand} with a probability proportional to the difference between $e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta}$ and $e^{U_i(a_i^{t}, a_{-i}^{t})/\zeta}$. In case the difference is adequate to a certain level, the player will choose the new random action a_i^{rand} with a high probability. Inversely, if the difference is low, the player will keep its former action with a high probability. However, if the difference is small, then $\omega \cong 0.5$, and the player will choose either a_i^{rand} or a_i^t in a random manner. By employing such randomness in the learning behavior, the players are able to evade a current local optimal stable solution to eventually reach a different stable solution.

The smoothing factor ζ is a parameter responsible for controlling the balance between an algorithm's performance outcome and the convergence speed. A significantly large value of the smoothing factor ζ

Algorithm 2 Game-theoretic data collection method: UAS-side game.

begin
Transmit message to CHs that initializes of negotiation process
repeat
  Wait for CHs strategies
  Initialize $S_{decided}$
  repeat
    $S_{rand} \leftarrow$ random slot assignment
    if S_{rand} *satisfies* β **then**
      if $U_{Network}(S_{rand}) > U_{Network}(S_{decided})$ **then**
      $S_{decided} \leftarrow S_{rand}$
  until $\mathcal{L}$ learning steps are finished
  Transmit $S_{decided}$ to CHs
until the CHs do not change their strategies
end

results in an extensive action search and slower convergence. However, a small value of ζ is associated with a narrower strategy exploration and a shorter convergence time of the algorithm. It is worth noting that when the value of the smoothing factor ζ is zero, i.e., ($\zeta = 0$), renders the smoothed better response learning to behave precisely in the same manner as better response, in which the players jump from one action to another. Similar to research works in [79, 91, 94], we use the principle of temperature on simulated annealing to set the value of the smoothing factor dynamically to be equal to $\zeta = \frac{10}{t^2}$.

4.4.3 Proposed Game-Theoretic Data Collection Method based on $\boldsymbol{G}(\mathbf{N}, \mathbf{A}, \mathbf{U})$

We propose our game-theoretic algorithm based on the formulations in the Sections 4.4.1 and 4.4.2 as a negotiation-based algorithm for slot assignment that converges to a global optimum NE with high probability. We refer to it as data collection method for brevity. The data collection method is played between the M UAS and N CHs, and aims at increasing network energy efficiency. The interactions of the data collection method are modeled as a two-stage game, and are detailed in Algorithms 1 and 2. Algorithm 1 is played by the N CHs in order to improve their own utilities by acing as per the smoothed best response learning technique. The UAS-side algorithm, Algorithm 2, needs to be only played at one designated UAS to assign time slots of the M UASs to the N CHs. Algorithm 2 entails the designated UAS to act as auctioneer acting upon the better response learning technique to create a slot assignment S that improves $U_{Network}$ such that β is satisfied. Furthermore, we introduce the finalization criteria, $\mathcal{T}$, which gives the negotiation a method to terminate. The finalization criteria ($\mathcal{T}$) can reflect any parameter of interest to the network designer. Its values can reflect the maximum number of negotiations, time limit, computation load, or utility function thresholds. Similar to the research work conducted in [91], we employ the maximum number of negotiations as the finalization criteria, $\mathcal{T}$. Also, we define $\mathcal{L}$ as the number of learning steps for Algorithm 2.

Researchers have defined numerous metrics to quantitatively measure an algorithm's limitations due to resource constraints, which include the lack of information for on-line algorithms or the lack of unbounded computational resources for approximation algorithms. PoA [95] is one of these metrics that is important in game theory that measures how the efficiency of a system degrades due to the greedy behavior of players in game-theoretic algorithms compared to that of a non-realtime centralized algorithm.

4.5 Price of Anarchy Analysis

As previously mentioned that potential games are prone to being trapped in local optimal NEs regardless of the existence of global optimal NEs under some kinds of of learning techniques. Under such a scenario, it is interesting to measure the system's performance. PoA, Price of Anarchy, was first proposed by Koutsoupias and Papadimitriou [95]. In the area of utility function maximization, it quantifies the efficiency of a game-theoretic algorithm compared to that of a non-realtime centralized algorithm. Thus, it can be used to indicate the ratio between the utility of the worst possible NE to that of the non-realtime brute force method. It is important to note that such a brute force solution cannot be computed in real time due to its computational burden. PoA is defined as follows.

Definition 3. Price of Anarchy
let *NE* be the set of all possible NEs.

$$\text{PoA} = \frac{\max_{\Psi' \epsilon \Psi} U_{Network}}{\min_{e \epsilon NE} U_{Network}}. \tag{4.21}$$

The nominator of PoA is highest value of $U_{Network}$, the associated slot assignment is referred to as $S_{\max U_{Network}}$. The denominator of the

PoA is the $U_{Network}$ of the worst possible NE, which will be derived from the following lemmas.

Lemma 2. *The slot assignment that is created if all players restrict their* α *values to allow only for the highest SNR transmissions* (S_{greedy}) *is a NE.*

Proof. We prove this lemma by contradiction. Assume that S_{greedy} is not a NE(contradictory to this lemma). Then, a player can increase its utility by an arbitrary value (ε) through changing its action. Yet, such a move will allow for transmissions with less SNR, which will result in a decrease in the player's utility, according to Eqs. (4.4) and (4.7), or at best case leave it constant. Hence, this player acting on the BR correspondence has no motive to adjust its action and will stay in the current state. Similarly, such an argument applies to all players in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$. Thus, we have reached a contradiction of our preliminary assumption. □

Lemma 3. S_{greedy} *renders* $\min_{\Psi' \in \Psi} U_{Network}$ *in* $\mathrm{G}(\boldsymbol{N}, \boldsymbol{A}, \boldsymbol{U})$.

Proof. For the best value of $\max_{\Psi' \in \Psi} U_{Network}$, if a player restricts its α to allow the transmissions with the highest SNRs only, $U_{Network}$ will have a value less than or equal to $\max_{\Psi' \in \Psi} U_{Network}$. Furthermore, if all players apply the same α restriction, $U_{Network}$ will have the lowest possible value, $U_{Network-min}$. $U_{Network-min}$ occurs from the NE (S_{greedy}). □

Lemma 4. $\min_{e \in NE} U_{Network}$ *occurs at* S_{greedy}.

Proof. Consider that $NE \subset \Psi$, and apply lemmas 2 and 3.

□

4.6 Performance Evaluation

Table 4.2: Parameter settings. © 2014 IEEE.

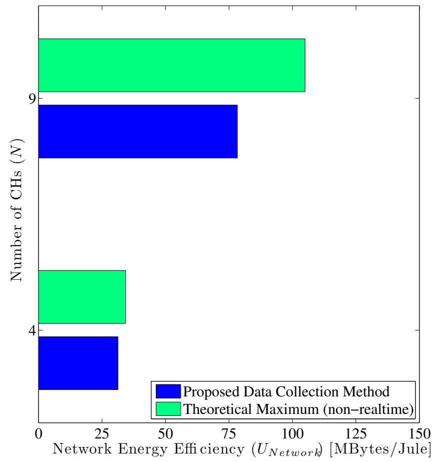
Parameter	**Value**
Number of CHs (N)	50-175
Number of UASs (M)	2-10
Sensor field dimensions	30000×15000 m^2
Altitude (h)	150 m
Trajectory radius (r)	5300 m
Velocity (v)	90 km/h
Symbol duration	4 μ s
Time slot duration	50 ms
Target BER requirement (BER_0)	10^{-3}
Frequency	2 GHz
Bandwidth (B)	30 KHz
Transmit power (P)	125-250 mWatts

In this section, we perform an evaluation of our proposed game-theoretic algorithm that enhances the fair energy efficiency in multiple UAS-aided networks. We configure our simulation to exemplify the UAS-aided network reaching the NE through the negotiations among CHs. The CHs use adaptive modulation as described in Sec. 4.3. The simulation scenario was configured using a custom-built simulator with the parameters listed in Table 4.2. The trajectory parameters, i.e., altitude (h), radius (r), and velocity (v), are set to values reported in [57], and are elaborated in Table 4.2. The symbol duration is set to a value of a common wireless interface [96]. Herein, a description of these parameters is going to be presented. The sensor field is constructed as a rectangular field with dimensions of 30000 × 15000 m^2. Unless specified otherwise, the fairness criterion (β) is set to 0.5 in our proposal. We simulated our proposed data collecting method with $\mathcal{T}$ set to 1000 for the CHs and $\mathcal{L}$ set to 30 for the UAS. The simulation is repeated 25 times with different seeds to calculate the average. The target BER requirement, BER_0, is set to ($BER_0 = 10^{-3}$), similar to the values adopted in [68, 76]. The frequency is chosen to be in the range of most standardized wireless technologies [78], the same also applies to system bandwidth (B). The transmission power of CHs (P) is chosen to be in a low range, as such settings are practical for low power devices that need to be deployed for prolonged periods of time without battery replenishment. The path loss exponent, φ, is set to ($\varphi = 2.5$), which is in the range of values reported in numerous research works [88, 89, 97].

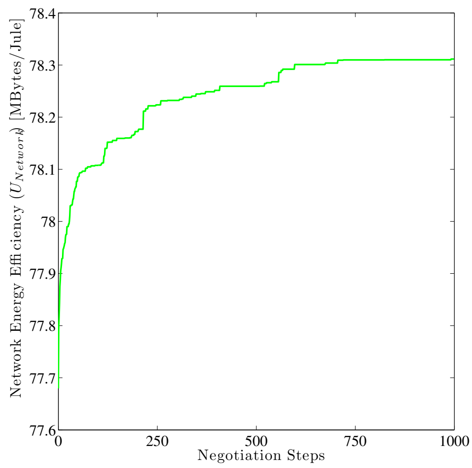
Table 4.3: PoA values for different N. © 2014 IEEE.

N	4	9
PoA	1.1	1.34

Moreover, sensors generate data according to a random variable to simulate the effect of heterogeneous data sources. The performance evaluation is decided into two parts. The first part presents a comparison of our proposed data collection method with a theoretical non-real time optimal, the negotiation process of our proposal, and PoA anal-



(a) The performance of the proposed game-theoretic data collection method compared with that of the theoretical non-realtime maximum.



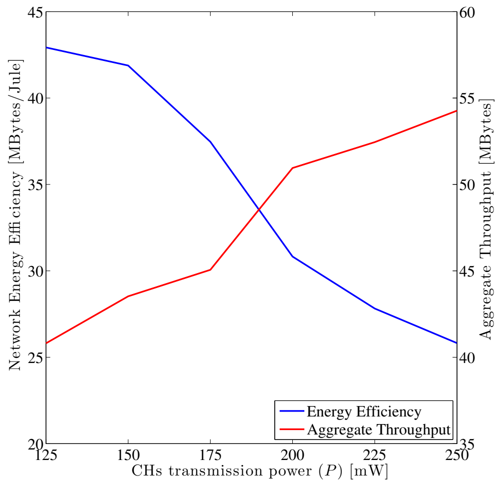
(b) The time slot assignment negotiation process between N CHs for the time slots of M UASs.

Figure 4.2: Performance and negotiation of proposed method. © 2014 IEEE.

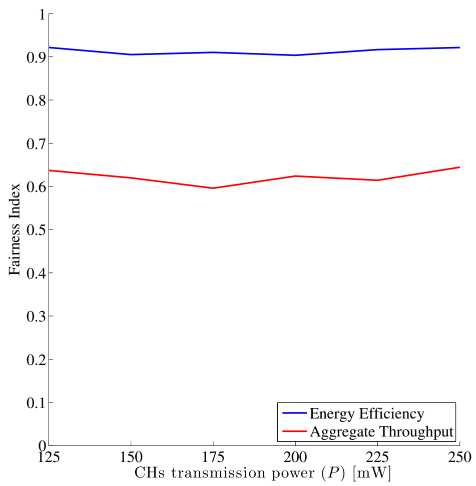
ysis. In the second part, we study the effect of transmission power, number of CHs, and the number of UASs on the performance our proposal.

4.6.1 Comparison with a theoretical non-real time optimal, learning, and PoA analysis.

In the first part of our performance evaluation, which is reproduced from [98], we examine the performance of our proposed game-theoretic method with that of the non-realtime theoretical maximum. Towards this end, we configure two grid topologies consisting of 4 and 9 CHs, with a grid step of 800 m and 400 m, respectively. In contrast with the remaining of the simulation settings, one UAS is considered for this comparison. Such small topologies allow for computation of the approximate non-realtime theoretical maximum. The UAS travels with a velocity of 30 km/h in a trajectory that is centered at the grids center and has a radius of 150 m. Fig. 4.2(a) shows the results of this comparison in terms of network energy efficiency with the fairness criteria ($\beta = 0.2$). This result shows that our proposal's performance is considerably close to that of the non-realtime theoretical maximum. Fig. 4.2(b) shows the negotiation process of our proposal to reach the NE. As the graph shows, the network is converging towards the utility function maximizer. This behavior confirms the analysis derived in Section. 4.4.2. Moreover, Table 4.3 shows the PoA values for different grid topologies. The results show that the PoA of our proposed method is small, which indicates that the worst case performance of our proposed method is not far from the non-realtime theoretical maximum.



(a) The effect of transmission power on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.



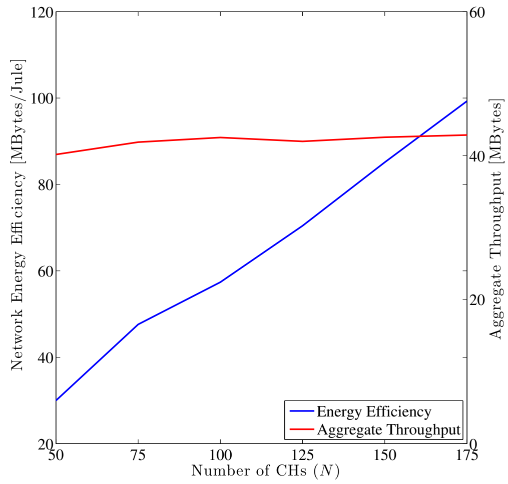
(b) The effect of transmission power on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Figure 4.3: The effect of transmission power (P) on the Performance of the proposed method. © 2014 IEEE.

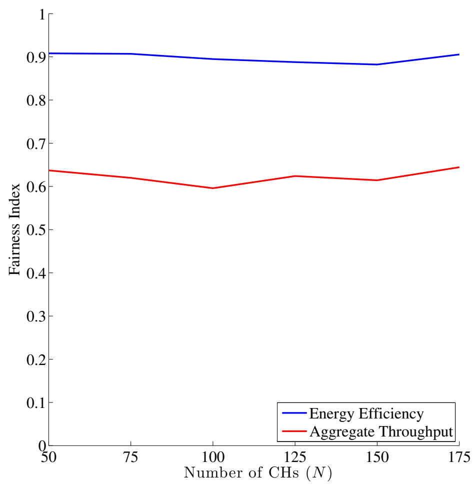
4.6.2 The effect of transmission power, number of CHs, and the number of UASs.

In this portion of the performance evaluation, we examine the effect of transmission power, number of CHs, and the number of UASs on the performance our proposal. Two UASs wheel with trajectories centered at (7500,7500) and (22500,7500), respectively. We constructed a random node topology comprising 75 CHs set according to the parameters listed in Table 4.2 and conducted the simulation for 25 different seeds.

Fig. 4.3(a) shows performance of the proposal with respect to network energy efficiency and aggregate throughput for different values of CH transmission power. The plot aggregate throughput is the aggregate throughput for a UAS revolution. The plot shows that for the given parameters, the network energy efficiency is decreased with the increase of CH transmission power. This behavior is accounted for by the fact that a twofold increase of the transmission power equivalently increases by the denominator of the CH's utilities, Eq. (4.7). In comparison the increase of aggregate throughput is relatively small due to path loss, Eq. (4.1). Consequently, the nominator of the CH's utilities has a small increment. Also, we can see that the aggregate throughput is proportional to the CH transmission power. Intuitively, this trend can be understood from the fact that increasing transmission power allows the CHs to transmit at higher modulation levels. This undoubtedly increases the network throughput. Fig. 4.3(b) shows the results of the proposed method in terms of fairness of both throughput and energy efficiency with different values of CH transmission power, respectively. The plots indicate that the value of fairness in terms of energy efficiency is sustained for the simulated values of CH transmission power. It is important to point out that the value plotted



(a) The effect of the number of CHs (N) on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.



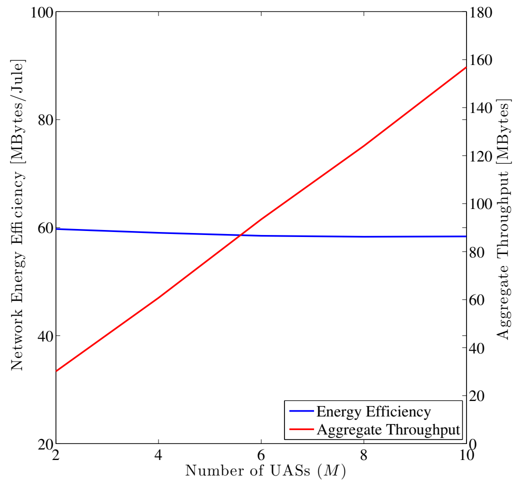
(b) The effect of the number of CHs (N) on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Figure 4.4: The effect of the number of CHs (N) on the Performance of the proposed method. © 2014 IEEE.

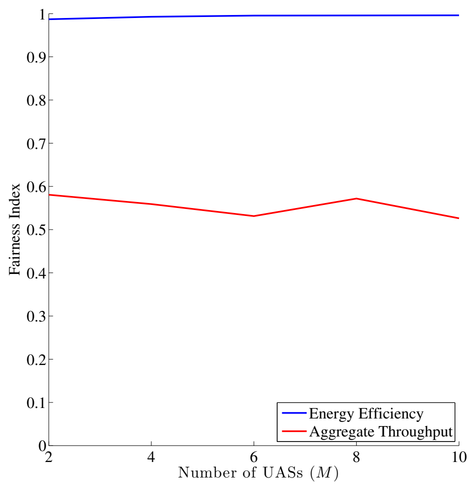
is significantly larger than the threshold value specified by ($\beta = 0.5$) control parameter. Furthermore, the plot shows a similar pattern of aggregate throughput in terms of the performance being significantly larger than the control parameter.

Herein, we investigate how our proposal performs under topologies with a different number of CHs. Fig. 4.4(a) shows the network energy efficiency and aggregate throughput for topologies of different sizes. The graph shows the increase of network energy efficiency with the growth of number of CHs. This behavior is to be expected from the definition of network energy efficiency in Eq. (4.8), as the increase of number of CHs increases the number of terms in the summation of Eq. (4.8). Also, the figure shows that the aggregate throughput is predominantly non-changing. Fig. 4.4(b) gives the fairness index of both energy efficiency and aggregate throughput. It can be seen that the proposal can maintain fairness for large topology sizes.

Finally, we investigate the influence of the number of UASs (M) on the performance of our proposal. For this portion of the experiment, $N = 100$, $P = 125\ mWatts$, and $r = 2500\ m$. The other parameters are set according to the values in Table 4.2. r is chosen so that no overlap occurs between the UAS' trajectories for the UAS positions indicated by the information shown in Table 4.4. These positions are chosen so that a grid topology is formed by the UASs. Inter-UAS x-displacement and inter-UAS y-displacement is the distance between any two consecutive UASs with on the x and y axes, respectively. Furthermore, inter-UAS x-displacement and inter-UAS y-displacement also indicate the space between the border of the simulated sensor field and the closest UAS on the x and y axes, respectively. Fig. 4.5(a) shows the



(a) The effect of the number of UASs (M) on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.



(b) The effect of the number of UASs (M) on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Figure 4.5: The effect of the number of UASs (M) on the Performance of the proposed method. © 2014 IEEE.

network energy efficiency and aggregate throughput for networks with a different number of UASs. The graph shows that proposed method can sustain network energy efficiency for different numbers of UASs. Also, it can be seen that the throughput increases with the increase of the number of UASs. This behavior is explained by understanding that the number of slots in the network increase by increasing the number of UASs. Consequently, the aggregate throughput is increased. Fig. 4.5(b) gives the fairness index of both energy efficiency and aggregate throughput. It can be seen that the proposal can maintain fairness well above the fairness criterion for large topology sizes.

Table 4.4: UAS' Positions. © 2014 IEEE.

M	**Inter-UAS x-displacment**	**Inter-UAS y-displacment**
2	10000 m	7500 m
4	10000 m	5000 m
6	7500 m	5000 m
8	6000 m	5000 m
10	5000 m	5000 m

In conclusion, the simulation results show that our proposed game-theoretic data collection method is capable of improving the fair network energy efficiency for UAS-aided networks, comprising M UASs and N adaptive modulation capable CHs.

4.7 Summary

In this chapter, we proposed a method to improve energy efficiency while ensuring fairness in multiple UAS-aided networks with adaptive modulation. The considered UAS-aided network comprises M UASs and N CHs. Furthermore, for the mobility pattern of UASs, we showed how adaptive modulation behaves. We formulated the problem by using the framework of potential games. Additionally, we substantiated the properties of the game that guarantee the efficiency of the obtained solution such as stability, optimality, and convergence. A game-theoretic data collection method was proposed to improve the energy efficiency while taking into consideration of the fairness in UAS-aided networks using the formulated game. Moreover, we analyzed the PoA of our proposed data collection method. Finally, extensive simulations were conducted to evaluate the performance of our proposed method. Our results could validate that the proposed game-theoretic method could provide near optimal performance in terms of network energy efficiency. In conclusion, we should that our proposed game-theoretic method can improve the network energy efficiency while taking account of fairness.

Chapter 5

Energy Efficient Data Gathering within Clusters

5.1 Introduction

Many operations such as disaster relief or surveillance operations are carried out in situations with no infrastructure support. Wireless ad hoc networks, shown in Fig. 5.1, are a robust solution that allow nodes to organize themselves into a network without the need for infrastructure support. Furthermore, in the absence of infrastructure it is difficult to have centralized Medium Access Control (MAC), therefore decentralized Carrier Sense Multiple Access (CSMA) is more practical to realize. Energy efficiency is very important for battery-powered wireless ad hoc networks. Also, since the share of energy consumption attributed to communications is larger than the computation costs [99], many researchers have investigated power-aware routing for wireless ad hoc networks.

According to [9,10,100], the following equation can quantify the energy consumption of a single successful transmission.

$$e(d_{Transmit}) = \epsilon_1 d_{Transmit}^{\vartheta} + \epsilon_2. \tag{5.1}$$

Here, $e(d_{Transmit})$ is proportional to the displacement between the transmitting node and the receiving node, $d_{Transmit}$. The parameter ϑ is the path loss exponent that is dependent on the wireless fading environment, its value is usually from 2 to 4. The term ϵ_1 is a constant specific to the wireless system. ϵ_2 is the electronics energy, characterized by factors such as digital coding, modulation, filtering, and spreading of the signal.

Based on only the energy consumed for a successful transmission, most contemporary work on power-aware routing has advocated the use of short distance transmissions[1] [101, 102]. Fig. 5.1 shows an example of the aforementioned transmission strategy. The transmitting node S wants to transmit a packet to node D. Since the path that goes through the relay node R_1 requires longer transmission distances than the other path, a contemporary power-aware routing scheme opts for the latter path because it uses short transmission distances. However, using short transmission distances increases the number of hops, and

[1] The minimum (shortest) transmission distance is determined by the closest relay node to the transmitting node. This changes depending on each node's position.

also the number of required transmissions. These two factors increase the probability of packet collision, which results in increased energy consumption for retransmissions. Therefore, there is a relationship between the transmission distance and the power consumed to deliver a packet from source to destination, which still remains largely unknown.

The previous works that have investigated the transmission distance that minimizes the energy consumption failed to grasp the above mentioned relationship due to assuming an ad hoc network that is saturated, i.e., where all nodes have an infinite number of packets to transmit, and the probability of transmission depends solely on the Contention Window (CW) parameter of IEEE 802.11. However, it is noticeable that even within the same path from source to destination, the number of nodes that buffer and forward varies significantly with the transmission distance, and that the transmission probability of a node will also accordingly change.

In our chapter, we consider a general CSMA/CA, where each node has a limited number of packets to transmit and the probability of transmission is closely related to the transmission distance to accurately capture the relationship between the transmission distance the energy consumed in the network. The reminder of the chapter is organized as follows. Sec. 5.2 presents research works related to research in this chapter, followed by Sec. 5.3, which presents our energy consumption model. Sec. 5.4 presents numerical results of our model. We finalize this chapter with a conclusion in Sec. 5.5.

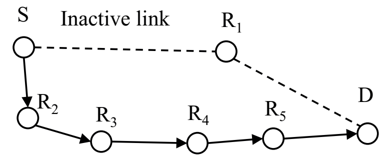


Figure 5.1: An example of a power-aware routing algorithm. Node S wants to send a packet to node D. Nodes R_1–R_5 are possible relay nodes. The power-aware routing algorithm chooses the path with short transmission distances. © 2013 IEEE.

5.2 Research Direction

Banerjee and Misra [99] pointed out that formulating the link cost based on only the energy consumption of a single transmission is misleading, and a proper metric should include the cost for necessary retransmissions due to link errors. They propose a power-aware routing cost in which links have a specific error rate. The error rate they use does not have any relationship with the condition of the network, i.e., it does not take into account the relationship between the transmission distance and probability of collision.

Deng *et al.* [100] analyzed the transmission distance that increases energy efficiency. They define energy efficiency as the ratio between the progress of a transmission to the energy consumption of the transmission. Then use this definition of energy efficiency to find the optimal transmission distance. Progress of a transmission is how close the packet that is being transmitted gets to its destination. In their work, the energy consumption of a transmission is that of a single successful transmission, which does not take account of transmission failures.

Gobriel *et al.* [103] investigated the issue of choosing the optimal trans-

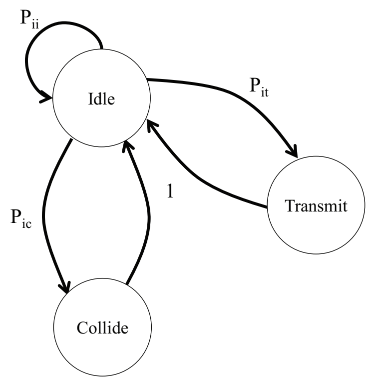


Figure 5.2: The considered Markov chain model with three states, idle, transmit, and collide, and state transition probabilities, P_{ii}, P_{it}, and P_{ic}. © 2013 IEEE.

mission distance such that the energy consumption is minimal in an IEEE 802.11 network. They use a collision model composed of two Markov chains to evaluate the effect of collisions on the energy consumption. In their network all nodes have an infinite number of packets to transmit, and the probability of transmission depends solely on the CW parameter of IEEE 802.11. The work of Alawieh and Assi [104] has studied the effect of transmission distance on energy consumption in an IEEE 802.11 network with directional antennas. They use a similar collision model to that of Gobriel *et al.* [103], and make the same assumptions of infinite amount of packets to send and probability of packet transmission of Gobriel *et al.* [103]. Both [103, 104] assume that the probability of transmission is independent of the transmission distance. In contrast, our work takes into account the transmission distance when calculating the probability of collision so that the relationship between the transmission distance and the energy consumption can be accurately captured.

Table 5.1: Model variables. © 2013 IEEE.

Parameter	**Definition**
P_{ii}	Transition probability from the idle state to itself
P_{it}	Transition probability from the idle to the transmit state
P_{ic}	Transition probability from the idle to the collide state
p	Probability that a packet arrives to a node
φ	Node density
Φ	State transition matrix
S	Steady-state vector
ω_i	Steady-state probability of idle state
ω_t	Steady-state probability of transmit state
ω_c	Steady-state probability of collide state
$E[h]$	Average hop count
σ	Packet generation rate
N	Number of nodes in the network
T	Number of time slots per round

5.3 Energy consumption model

In this section we derive an analytical model to study the effect of transmission distance, $d_{Transmit}$, on the total energy consumed to transmit a packet from source to destination, which includes the energy consumed for retransmissions due to collisions. This model will show $d_{Transmit}$ that renders the minimum energy consumption of the wireless ad hoc network. To include the energy consumption of retransmissions due to collisions we use the collision model in Sec. 5.3.1. The mean value for traffic per node is given in Sec. 5.3.2, which allows the calculation of the probability of packet arrival in Sec. 5.3.3, which will be used in the collision model. Finally, Sec. 5.3.4 gives an expression for energy consumption as a function of $d_{Transmit}$ and other parameters.

Before going forward with the derivation, we describe our model assumptions, which are unique to this work. For tractability, we assume a uniformly distributed network like many other works [99, 103]. A single channel is spatially shared among nodes in the same area (spatial reuse) , in other words, if a pair of nodes are communicating, a collision occurs when one or more node(s) transmit within the transmission distance of either the transmitting or receiving node. Nodes use a 1-persistent access strategy, wherein a node that has a packet to transmit senses the channel. If the channel is sensed free, the packet is transmitted. If the channel is busy, the node monitors the channel and transmits the packet when the channel is sensed idle. The transmission distance is equal for all nodes in the network, which is a very commonly used assumption [100, 104]. All nodes have equal priority to transmit, each node can have at most a single packet to transmit per time slot, and all packets are of the same size. Each node has a finite number of packets to transmit in a round. A round is a specific period of time in which a node transmits all its packets.

5.3.1 Collision model

We model the wireless node's states by using a three-state Markov chain similar to that of [105,106], the model is shown in Fig. 5.2, and it has three states, namely, idle, transmit, and collide. The variables used in our analytical model are listed in Table. 5.1. Furthermore, as shown in Fig. 5.2, P_{ii}, P_{it}, and P_{ic} are the state transition probabilities, which correspond to the probabilities of transmission from idle state to idle, transmit, and collide, states respectively. Their derivation method is similar to that in [105]. The probability that no transmission occurs, P_{ii}, can be quantified as follows:

$$P_{ii} = (1 - P_{Transmit})^{A}. \tag{5.2}$$

Here, $P_{Transmit}$ denotes the probability that a packet arrives at a node to be transmitted, and A is the number of nodes in the area covered by the transmission distance of a single node, shown in Fig. 5.3, which can be written as,

$$A = \varphi \pi d^2_{Transmit}. \tag{5.3}$$

The probability that a node successfully transmits, P_{it}, is when only one node within the areas A and B shown in Fig. 5.3 transmits. It takes the following form:

$$P_{it} = p(1 - p)^{A+B}. \tag{5.4}$$

Here, the number of node in area B, shown in Fig. 5.3, can be evaluated according to the following equation [107]:

$$B = \varphi\{\pi d_{Transmit}^2 - 2d_{Transmit}^2(\arccos\frac{1}{2} - \frac{1}{2}\sqrt{1 - \frac{1}{4}})\}. \tag{5.5}$$

Since the summation of P_{ii}, P_{it}, and P_{ic} is equal to one, the probability of collision, P_{ic}, takes the following form:

$$P_{ic} = 1 - P_{ii} - P_{it}. \tag{5.6}$$

The state transmission matrix, Φ, of the Markov chain is

$$\Phi = \begin{pmatrix} P_{ii} & 1 & 1 \\ P_{it} & 0 & 0 \\ P_{ic} & 0 & 0 \end{pmatrix}. \tag{5.7}$$

Since all the entries of the above matrix are positive, this matrix is regular and has a steady state. Let S be the steady state vector of Φ whose elements are the steady state probabilities of the Markov chain shown in Fig. 5.2. S takes the following form:

$$S = \begin{pmatrix} \omega_i & \omega_t & \omega_c \end{pmatrix}^T, \tag{5.8}$$

where ω_i, ω_t, and ω_c are the steady-state probabilities of the Markov chin shown in Fig. 5.2 in the idle, transmit, and collision states, respectively. S is an eigenvector of Φ with an eigenvalue $\lambda = 1$ [106], therefore,

$$\Phi S = S$$

$$(\Phi - I_3)S = 0. \tag{5.9}$$

Here, I_3 is the identity matrix of rank 3. The above equation describes a homogeneous system of linear equations with $\Theta = (\Phi - I_3)$, where

$$\Theta = (\Phi - I_3) = \begin{pmatrix} P_{ii} - 1 & 0 & 0 \\ P_{it} & -1 & 0 \\ P_{ic} & 0 & -1 \end{pmatrix}. \tag{5.10}$$

Also, the system described in Eq. (5.9) has many possible solutions, and to get a unique solution an extra condition is required. Since S is a probability vector, its elements should add up to one, i.e.,

$$\omega_i + \omega_t + \omega_c = 1. \tag{5.11}$$

We exchange any row from Eq. (5.9) with Eq. (5.11) to get a unique solution (we choose the first row). Thus, the result is,

$$\begin{pmatrix} 1 & 1 & 1 \\ P_{it} & -1 & 0 \\ P_{ic} & 0 & -1 \end{pmatrix} \begin{pmatrix} \omega_i \\ \omega_t \\ \omega_c \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}. \tag{5.12}$$

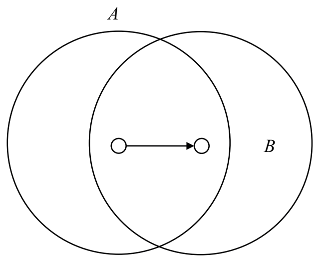


Figure 5.3: A pair of communicating nodes. A is the area covered by the transmission distance of the transmitter. B is the area covered by the transmission distance of the receiver that is not intersecting with A. © 2013 IEEE.

The above system's solution can be easily found with algebraic manipulations.

$$\omega_i = \frac{1}{2 - P_{ii}} \tag{5.13}$$

$$\omega_t = P_{it}\omega_i \tag{5.14}$$

$$\omega_c = P_{ic}\omega_i. \tag{5.15}$$

5.3.2 Average traffic per node

Here, we give an expression for the average amount of traffic flowing through a node. Similar to the analysis of [103, 104, 108], our model assumes that the traffic patterns are uniform, i.e., the source and the destination nodes are randomly chosen. Let each node generate packets at a rate of σ. Consider two nodes, i and j. Let $E[h]$ denote the average hop count, which can be formulated as

$$E[h] = \frac{d_{s->d}}{d_{Transmit}}, \tag{5.16}$$

where $d_{s->d}$ is the average displacement between sources and destinations. On average there are $(E[h]-1)$ relay nodes between any source and any destination. Node i may become a relay node for node j with probability

$$\frac{(E[h]-1)}{N-1}. \tag{5.17}$$

Here, N is the number of nodes in the network. The expected value of relay traffic arriving at node i from node j is

$$\frac{\sigma(E[h]-1)}{N-1}. \tag{5.18}$$

Since there are $(N-1)$ other nodes in the network, node i may be a relay node for the other $(N-1)$ nodes with a probability of

$$(N-1) \times \frac{(E[h]-1)}{N-1} = (E[h]-1). \tag{5.19}$$

Also, the expected value for relay traffic for node i is

$$\sigma(E[h]-1). \tag{5.20}$$

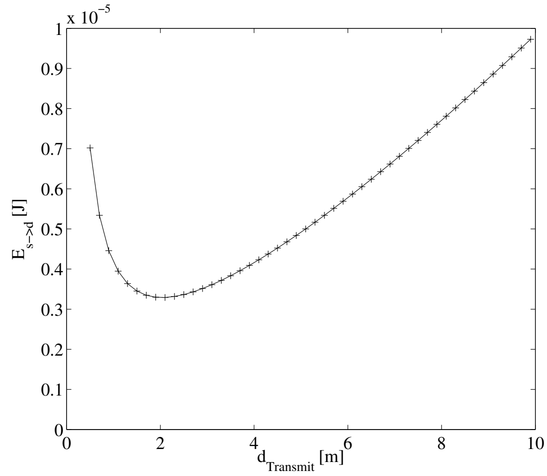


Figure 5.4: Energy consumption, $E_{s->d}$, with respect to transmission distance, $d_{Transmit}$. © 2013 IEEE.

The average traffic per node is equal to the traffic generated by the node itself and the traffic it has to relay, i.e.,

$$\begin{aligned}\text{Average traffic} &= \text{own traffic} + \text{relay traffic}\\ &= \sigma + \sigma(E[h] - 1) = \sigma E[h] \qquad (5.21)\end{aligned}$$

5.3.3 Packet arrival

We derive an expression for the probability of packet arrival. Let there be T time slots per round. If on average there are on average $\sigma E[h]$ packets flowing through each node, then the average traffic rate per time slot is.

$$\sigma_T = \frac{\sigma E[h]}{T}. \qquad (5.22)$$

Assuming that the traffic is Bernoulli such as that in [109–111], then the probability that a packet arrives, p, can be given as:

$$p = \sigma_T. \tag{5.23}$$

5.3.4 End-to-end energy consumption

Herein, we derive a formula for the energy consumption attributed to transmitting a packet from a source to destination, $E_{s->d}$. In general, $E_{s->d}$ is given as:

$$\begin{aligned} E_{s->d} &= \text{Average hop count} \times \text{energy consumption per hop} \\ &= E[h] \times \{E_{Transmit} + E_{Collision}\}. \end{aligned} \tag{5.24}$$

Here, $E_{Transmit}$ and $E_{Collision}$ are the energy consumed for a successful transmission and energy consumed for retransmissions due to collisions, respectively. $E_{Transmit}$ can be calculated from Eq. (5.1). $E_{Collision}$ can be expressed as:

$$\begin{aligned} E_{Collision} = {} & \text{number of collisions} \times \\ & \text{probability of } i\text{th collision} \times \\ & \text{energy consumption of a collision}. \end{aligned} \tag{5.25}$$

The energy consumption of a collision is equal to that of single successful transmission. Similar to [112], we assume that the probability of

Table 5.2: Network parameters. © 2013 IEEE.

Parameter	**Value**
ϵ_1	42 $[nJ/\mathrm{m}^2]$
ϵ_2	0.21 $[mJ/\mathrm{m}^2]$
ϑ	2 (free space)
φ	1 [node/m^2]
Node distribution	Uniform
$d_{s->d}$	16 [m]
σ	1 [packet/round]
T	1000

collision is independent of the number of previously occurred collisions. Thus, we can rewrite Eq. (5.25) as:

$$\begin{aligned} E_{Collision} &= \sum_{i=1}^{\infty} e(d_{Transmit})\omega_c^i \\ &= e(d_{Transmit}) \sum_{i=1}^{\infty} \omega_c^i. \end{aligned} \tag{5.26}$$

Here, since ($\omega_c < 1$), Eq. (5.26) converges to:

$$E_{Collision} = \frac{\omega_c}{1-\omega_c} e(d_{Transmit}). \tag{5.27}$$

5.4 Numerical results

By using the model derived in Sec. 5.3 we show the energy consumption of a uniformly distributed wireless ad hoc network. Table. 5.2 lists the parameter settings used in this chapter. The constants of Eq. (5.1), ϵ_1

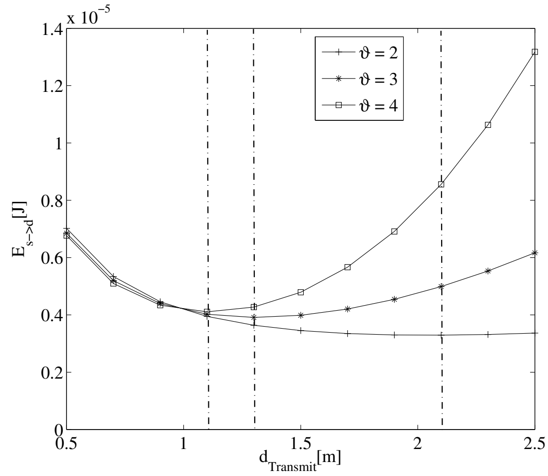


Figure 5.5: The effect of the path loss exponent, ϑ, on the optimal transmission distance, $d_{Transmit}$, that yields the lowest energy consumption, $E_{s->d}$. The vertical lines indicate the optimal values of $d_{Transmit}$ with respect to $E_{s->d}$. ©2013 IEEE

and ϵ_2, are set according to the values reported in [113]. The path loss exponent, ϑ, is set to 2 according to the value adopted in [100, 103]. The average displacement between sources and destinations, $d_{s->d}$, is set according to the value reported in [103]. Number of time slots per round, T, is set to a relatively high value of 1000 to accommodate all operations in the network. The node density, φ, and packet generation rate, σ, are both set to unity for simplicity.

Fig. 5.4 shows the plot of Eq. (5.24). The transmission distance is varied from 0.5 to 10 m. As can be clearly seen from the graph, the energy consumption for transmitting from source to destination is minimum when the transmission distance is approximately 2.1 m. This point achieves the optimal balance between short and long distance transmissions, such that both the energy consumption per transmission and for retransmissions due to collisions are minimized.

Table 5.3: The values of path loss exponent and resulting optimal values of transmission distance. © 2013 IEEE.

ϑ	2	2.5	3	3.5	4
Optimal $d_{Transmit}$ [m]	2.1	1.51	1.31	1.11	1.11

Although the value of the path loss exponent, ϑ, is assumed to be 2 in most works, Eq. (5.1) indicates that its effect on the energy consumption is nontrivial. Therefore, we explore its effect on the optimal value of transmission distance, $d_{Transmit}$, that yields the minimum $E_{s->d}$. Fig. 5.5 shows the plot of Eq. (5.24) for several values of path loss exponent, ϑ. The optimal values of $d_{Transmit}$ are indicated with vertical lines. The results show that when an environment has a large value of ϑ, the value of $d_{Transmit}$ that decreases the energy consumption of the wireless ad hoc network is also decreased. The reason behind this, is that the growth of Eq. (5.1) significantly increases with higher values of ϑ. The optimal values of $d_{Transmit}$ for different ϑ are listed in Table. 5.3.

sFrom the results of our analysis, we conclude that minimum transmission distance does not result in the minimum energy consumption, and find the transmission distance that does result in the minimum energy consumption.

5.5 Summary

In this chapter, we have investigated the issue of choosing the optimal transmission distance to minimize the energy consumption of wireless ad hoc networks. While most contemporary research attempts to minimize the energy consumption via short distance transmissions, choosing the minimum transmission distance does not lead to minimum energy consumption. In practice, decreasing the transmission distance increases the number of concurrent transmissions in the network, which increases the probability of collision and thus requires more energy for retransmissions. We show via analytical modeling that the minimum transmission distance does not lead to the minimum energy consumption, and find the optimal transmission distance that results in the minimum energy consumption.

Chapter 6

Conclusion

In this dissertation we have addressed a fundamental research challenge stunting the development of WSNs, namely, energy efficient data gathering. Towards this end, we proposed a data gathering method from sensor nodes in a manner that is energy efficient and leads to a longer lifetime of battery powered sensor nodes. Towards this end, focus on two aspects, namely, data gathering from clusters and data gathering within clusters. Our contribution is detailed as follows.

(a) In chapter 2, we conducted a literature review on data gathering methods for WSNs. We classify immobile sink node energy-aware data gathering methods into five categories according to their network architecture: flat data gathering that finds paths to minimize energy consumption or increase sensor network lifetime, hierarchical data gathering that creates a hierarchy and applies *data-aggregation* to reduce energy consumption, hybrid data gathering that is a combination of the former two and mitigates the energy hole problem, *data-centric* data gathering that performs in-network *data-aggregation* to eliminate wasteful transmissions, and location-based data gathering that uses location information to reduce the energy consumption of the wireless sensor network. Furthermore, we present a cross-cutting discussion which addresses *data-aggregation*, network lifetime definition, routing overhead, the energy hole phenomenon, and collisions/interferences. Moreover, we examine methods for data gathering with mobile sinks.

(b) In chapter 3, we gave an overview of the architecture of the mobile-sink-based WSN examined in this thesis, along with justification for the design decision. Furthermore, we gave a detailed description of the composite parts, namely, that of data gathering from clusters to the mobile sink, in addition to that of data gathering within clusters to the cluster head.

(c) Chapter 4 addressed a fundamental research challenge stunting data gathering for mobile-sink-based WSNs, which is how to fairly maximize the energy efficiency (throughput per energy) in networks comprising adaptive modulation-capable cluster heads. For the mobility pattern of mobile sinks, we demonstrated how adaptive modulation is affected. Furthermore, we formulate the problem of maximizing fair energy efficiency as a potential game that is played between the multiple cluster heads, and substantiated its stability, optimality, and convergence. Based on the formulated potential game, a data collection method is proposed to maximize the energy efficiency with a fairness constraint. Additionally, we analyze the Price of Anarchy (PoA) of our proposed game-theoretic data collection method. Extensive simulations exhibit the effectiveness of our proposal under varying environments.

(d) In chapter 5, we addressed the problem of how to collect data within a cluster. This problem is crucial to insure the longevity of such networks. Most contemporary research that attempts to minimize the energy consumption does so via short distance transmissions. However, this transmission strategy leads to an increase in the number of network operations, and thus increases the probability of collision, which results in extra energy consumption for retransmissions. We showed that the minimum transmission distance does not result in the minimum energy consumption, and find the optimal transmission distance such that the energy consumption of the ad hoc network is minimal.

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Appendix A

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