A Fair and Energy-Efficient Topology Control Protocol for Wireless Sensor Networks

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ABSTRACT

In energy constrained wireless sensor networks, energy conservation techniques are to be applied in order to maximize the system lifetime. We tackle the problem of increasing network lifetime through the topology control assignment. In a two-dimensional random sensor deployment, the nodes can estimate the distances to their neighbors and can vary their transmission ranges accordingly. Supporting self-organization of the sensor nodes, each node locally selects its appropriate neighbors according to a neighbor eligibility metric. Here, we introduce the notion of weighted relaying regions defined over the plane of a searching node. This is aimed at dropping out inefficient links in the network in order to reduce the overall energy consumption. Contrary to most topology control protocols that rely on nearest neighbor approaches, we use a distance measure that is radio characteristic and channel condition dependent. This in turn, proves more adequate for energy conservation in dense network deployments. Considering network dynamics that might arise due to node mobility or node failures, our topology control protocol is to be run periodically. Fairness between the nodes can be increased in updating the topology considering the changing energy reserves of the nodes. We verify the performance of the protocol through simulation results on network graph properties and energy consumption.

1. INTRODUCTION

A wireless sensor network consists of a number of small sensing nodes that communicate with one another in a wireless fashion. The role of the nodes in the network is to sense their surroundings for special events and send their data to a single final destination, the base station. This is the traditional scenario of a sensor network as represented in [12]. The base station is then linked to an external infrastructure, where the delivered data from the sensors are exploited. Thus, sensor networks are often referred to as data gathering systems [1] in which collected data are not interpreted at the sensors, but only handled further to the base station where data evaluation takes place. In Figure 1 a typical sensor network architecture is illustrated.

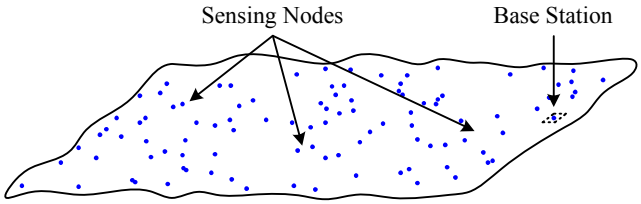

Figure 1: Random sensor deployment with the base station positioned at one end.

Such data gathering systems usually have an arbitrary and random deployment. The positioning of the nodes is usually carried out without taking into account any defined structure or pattern. For instance, sensor node positions could be dependant on the architectural plan of a construction in indoor scenarios, or on the geographical nature of a region in an environmental monitoring scene. Hence, ease of deployment at the installation phase is necessary. In addition, the construction of the communication network as well as its configuration should be done without much prior apprehension of the system. Therefore, a sensor network should self-configure itself according to the deployment task. The positions of the nodes is in general assumed to be stationary. However, their frequent breakdowns and the always changing nature of the wireless channel results in a variable network topology. Therefore, robustness of the network and its adaptation to these changes should be accounted for. Wireless sensors should be designed to operate in harsh conditions where unavoidable failures of single nodes should not greatly affect the overall system. Therefore, the nodes should be autonomous and self-organizing in order to adapt to the changing environments which come along to the various deployment scenarios of such monitoring systems.

Self-organization in sensor networks, is supported through the communication protocols and algorithms that work on the consisting sensor nodes [17]. That is, the nodes exchange messages between themselves in order to maintain the network requiring no global control. Each node keeps track of its neighbors, with whom it cooperates, in order to develop and conserve a connected network in which it functions.

A lot of interest has been gained in wireless sensor networks

in the field of environmental monitoring. An application of wireless sensor networks is in observing the species that live in a given region as described in [10]. The sensors have an advantage of being small which allows researchers to monitor sensitive wildlife in a non-intrusive way. Moreover, in disaster relief applications such as wild fire detection [20] wireless sensor networks can also play an essential role. By the use of thermometers and humidity sensors, the temperature map of a monitored area can be revealed. On critical temperature increases, immediate action can be taken to hinder fire breakouts. In such applications, often are the sensors deployed by the use of airplanes. The sensors then determine their own location relative to each other or in absolute coordinates which aids in the localization of the delivered data.

In such applications, the sensors have to be durable under a range of environmental stresses. Moreover, they must be so energy efficient that they can remain in operation with little human interaction and maintenance for years at a time. Therefore, energy conservation techniques for wireless sensor networks are to be addressed at all layers of the network protocol stack. Topology control protocols have the duty of trimming out inefficient links in the network. This reduces the number of neighbors of each node with whom it can directly communicate with. Thus, reducing the overhead impacted on routing protocols as well as MAC protocols in functioning over the topology. Less amount of communication links in the network reduces the burden in finding optimal routes to the base station, which in turn conserves the energies spent in message exchange for building the routes. Due to the nonlinear attenuation of the received signal power with distance, transmission over shorter hops is beneficial in requiring less total transmit powers. However, many short hops can cause an increase in total receive power consumption which increases the overall energy consumption in the network. Carefully selecting link distances and trimming inefficient links can build an overall energy efficient network topology.

We propose a localized algorithm that enables the self-organization of the sensor nodes to build the topology of the network. Taking into account the overall power consumption in the network, we produce an energy-efficient topology that should prolong the system lifetime in wireless sensor networks. This is achieved through defining a neighbor eligibility measure that cares for reducing the energy consumption in the overall network and increasing at the same time the fairness between the nodes.

This paper is organized as follows. First, we discuss related work in Section 2. Afterwards, we state our problem definition. Section 4 gives the system model which is used to characterize our method to build the network topology. In Section 5, we reveal our topology control protocol. Evaluation of the protocol is made in Section 6. This paper ends with a discussion of the achieved work.

2. RELATED WORK

There has been considerable research in the field of topology control for wireless networks, and a considerable number of protocols has been introduced. However, most of these protocols address the general ad hoc networks case and not the all-to-one design of wireless sensor networks. Generally, the proposed protocols support computational geometry techniques to build sparse graphs, or compare to proximity graphs that have the property of ensuring strong network connectivity. Moreover, the techniques to build the topology differ along with the type of local information available at the nodes.

In the family of Neighborhood Graphs, a topology control protocol is presented in [8] and denoted as the r-Neighborhood graph. The authors introduce an adjustable neighborhood region of a node which determines its neighbors. This, in turn, is used to tune the topology of the network for an optimization on the node degree which is a trade off to the power stretch factor of the underlying graph. Further work with optimization on the node degree is the XTC protocol [19]. Their constructed graph is shown to be a subgraph of the Relative Neighborhood Graph (RNG) [7] and is proven to have a maximum node degree of six, unlike the RNG which has its node degree unbounded. The protocol is attractive in that local information consist only of neighbors' signal strength information.

The protocol in [15] denoted as R&M, is one of the earliest protocols to present minimum power topologies. The work presents the concept of relay regions to determine the enclosure of each node. This protocol is similar to ours in that all the nodes potentially send their information to a single master site or base station. However, the overall link efficiency is not studied. The LINT protocol in [13] is noted to be the first to use different transmit powers for global topological property through physical linking. The number of physical neighbors is varied according to different transmission powers. It is shown that keeping the number of neighbors of a node within a low and high threshold centered around an optimal value ensures network connectivity. Simulations are made on random mobile nodes, however no update policy is presented. They evaluate their protocol on the aspects of maximum and average transmit power. In our protocol, the total power consumption is valuable, since it reflects the overall communication efficiency.

A similar protocol to LINT is the K-Neigh protocol presented in [2]. In this work, a distributed topology control protocol is proposed that uses distance estimation to nearest neighbors in order to assign the transmission ranges of every node. As in the LINT protocol, physical links are maintained. The transmission power is determined according to the distance to the nearest kth neighbor. The value of k is evaluated according to simulation results to guarantee a connected resulting network graph. The protocol is localized and uses an asynchronous update policy. Furthermore, biconnectivity in the resulting communication graph is accomplished through trimming unidirectional links. Finally, an optional pruning phase is applied in order to further delete inefficient links in the constructed graph and reduce transmission ranges. Our protocol has a similar structure to the K-Neigh protocol in its different phases. First, the nodes are ordered. Then, the first k nodes are chosen as neighbors. In our protocol, due to a logical ordering assignment, the built links are logical links. However, assigning the corresponding transmission power to every neighbor has proven to produce more energy savings than the static trans-

mit power assignment[9].

In [1], a theoretical study on the upper bounds on the lifetime of data gathering sensor networks is made. The authors provide an optimal number of hops to relay data which should determine the most energy efficient path to the base station. The number of hops depends on a characteristic distance and the total distance to the base station. Moreover, the derived characteristic distance is dependant on the propagation environment and radio parameters. This work has inspired and is the basis for the overall link efficiency model presented in this paper. An appealing work supporting our work is given in [5], where the author gives twelve reasons not to route over many short hops. Convincing reasons have been given and shown that longer transmissions are desirable in ad hoc and sensor networks. Our protocol is not based on nearest neighbor criteria, and thus supports routing over longer hops.

3. PROBLEM DEFINITION

Given a random deployment of wireless sensor nodes in the two-dimensional plane, our main goal is to build and maintain the topology of the network in a way to maximize the lifetime of the network.

Definition 1. Network lifetime is the duration of time until the first battery drain-out among all the nodes in the network occurs. This is the same as the minimum lifetime over all nodes [3].

Since the network lifetime is related directly with the lifetime of each node in the network, the aim would be the same as to establish fairness between the nodes and maximize the lower bound of the average node lifetime. Furthermore, the overall network energy consumption should be minimized. Since building the topology is made in a distributed manner, the problem should be seen from the view point of the node. Each node in the network determines its optimal neighbors and builds logical links[1] with them. Our problem can be formulated as follows:

Problem 1. How does a node select its neighbors according to local information in order to maximize network lifetime through fairness and granting overall link efficiency?

Definition 2. Fairness is achieved when all the batteries of the nodes are exhausted similarly. The variance between the energy reserves in the nodes at anytime is minimized.

Definition 3. Overall link efficiency characterizes the efficiency of the overall energy dissipation in the multi-hop communication link to the base station. The sum of the energy consumed in all transmissions and receptions within the link is minimized.

Our problem is to be tackled utilizing only local information available at each node. We assume the nodes have relative position information of their neighboring nodes. This can be provided using relative location estimation techniques [11], such as received signal strength (RSS) measures or time of arrival (TOA) of the received signal. The second assumption we adopt is the presence of, to an instinct, updated amount of energy reserves of the neighboring nodes. This information can be made available at each node either through direct message exchange, or utilizing the routing protocol route discovery overhead in order to update such information. Generally, energy-aware routing protocols assume the availability of battery information along the established routes.

A third assumption which is an optional requirement to our protocol, is the availability of exact position information of the nodes as well as the location of the base station. This assumption is a very costly one since to obtain such information, either complex algorithms are to be applied on the network such as triangulation techniques [16], or low power global positioning systems (GPS) are to be used. Moreover, the position information can also be programmed explicitly to each node. This aspect of absolute position information is often important in different scenarios especially in environmental sensing applications such as water quality monitoring or precision agriculture, where sensing data and knowing the corresponding sensor location is essential.

4. SYSTEM MODEL

Given a flat network topology[2] of n nodes placed randomly in the euclidian plane, let $\mathcal{V}$ be the set of vertices representing the nodes and $\mathcal{E}$ be the set of undirected edges representing the communication links between them. The graph of the network is denoted as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. In addition, let $\mathcal{G}_{digraph}$ represent the digraph[3] of the network with $\mathcal{E}_{digraph}$ the set of undirected edges.

Each node i, $i \in \mathcal{V}$, has an identity, id_i, and is represented in the euclidian plane with its coordinates. A directed edge between two nodes i and j is denoted as $[i \rightarrow j]$, $[i \rightarrow j] \in \mathcal{E}_{digraph}$, and has a distance of $d(i,j)$. An undirected edge between i and j is denoted as $[i \leftrightarrow j]$, $[i \leftrightarrow j] \in \mathcal{E}$. This paper assumes a completely random distribution of the nodes in a rectangular field, which pertains to a wide sensor networks application area. A completely random distribution is represented in stochastic geometry [18] with the poisson point process. The points are equally likely to occur anywhere within a bounded region $\mathcal{A}$, and the probability of finding n nodes in $\mathcal{A}$ is given as:

$$\Pr[n \text{ nodes in } \mathcal{A}] = e^{-\lambda} \cdot \frac{(\lambda \cdot \mathcal{A})^n}{n!} \quad (1)$$

The set of neighbors of i, with which i is directly connected to, are given in the set $\mathcal{N}(i)$ and defined as $\mathcal{N}(i) = \{j | [i \rightarrow j] \in \mathcal{E}_{digraph}\}$. Let $\mathcal{N}_L(i)$ be the neighbor table list, where the properties belonging to each neighbor of i in $\mathcal{N}(i)$ are stored. $\mathcal{N}_L(i)$ contains the identity, energy reserve, eligibility as neighbor measure, and required transmission power to reach each neighbor. Each node has a maximum transmit power of P_{t-max} and can assign varying transmit powers corresponding to each neighboring node. The transmission

[1]Logical links are links made from a node to its neighbors according to a logical criterion.

[2]A flat topology has all its nodes with similar qualifications to do sensing and organization tasks.

[3]A digraph is a graph with directed edges.

power from node i to j is denoted as P_{t-ij}. The residual energy of a node i at time t is denoted as e_i^t. Furthermore, all nodes start with equal initial battery capacity E.

Communication in the network is done over the wireless medium in which the transmitted signals are attenuated over distance. It is essential to formulate the loss in signal strength of the transmitted signal in terms of the traveled distance. This aids in the design of the network topology and the representation of the dissipated energy during communication. During transmission, the electromagnetic wave experiences three basic propagation mechanisms which decrease its strength over the traveled distance. These physical effects are reflection, diffraction, and scattering. The received signal power, in general, decays as a power law function of the distance separating the transmitter and the receiver [14]. Thus, the received signal power can be written as:

$$P_{rx} \propto \frac{P_{tx}}{d^{\gamma}}, \tag{2}$$

where γ is the path-loss exponent which indicates the rate at which the path loss increases with distance. Depending on the type of environment different values of γ are defined.

The power consumption model of the radio transceiver used in this paper is influenced by the model presented in [6, 1], which consider varying transmission powers to meet minimum receiver sensitivity requirements. This assumption is certified, since most existing transceivers have the functionality of varying their transmit power levels in several steps. An example of such a transceiver is the Texas Instruments Chipcon CC2420 [4]. Moreover, the model includes the energy consumed in signal reception which is in today transceivers a not negligible amount of energy. The transmitter and receiver consume energy in mainly three sections; In digital signal processor (DSP), in the front end circuit, and in the signal amplifier. The power consumption of transmitting a message at r bits/s over a distance of d meters can be formulated as [6]:

$$P_T(d) = (\alpha_{11} + \alpha_2 \cdot d^{\gamma})r \tag{3}$$

and the power consumed to receive this message is [6]:

$$P_R = \alpha_{12} \cdot r. \tag{4}$$

The metrics α_{11} and α_{12} are constants and depend on several factors such as the digital coding and decoding, modulation and demodulation, and filtering of the signal. Whereas α_2 depends on varying factors such as antenna characteristics, channel conditions, amplifier efficiency, and receiver sensitivity.

5. FETC: FAIR AND EFFICIENT TOPOLOGY CONTROL

5.1 Weighted Relaying Regions

The aim in this section, is to formulate a model that represents weighted relaying regions in the plane for a generic node in the network. The weighted regions claim the eligibility of a neighboring node, positioned in the defined regions of a transmitting node, for it to act as a relaying node. This is done in an anticipation to increase the overall energy efficiency in the multi-hop link to the base station. Knowing that the nodes should only acquire local information on their neighboring nodes, the efficiency model is hence only an estimation. This is the case since the overall link property is indefinite for the single node. However, it is sufficient to contribute a criteria for each node to determine its neighbors in a biased manner.

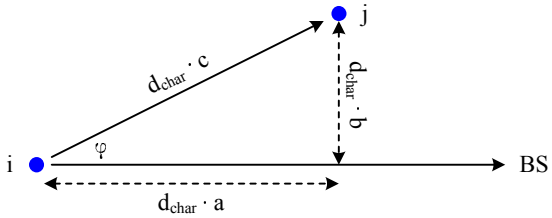

Figure 2: Illustration of the hop model.

5.1.1 Background

In [1], M. Bhardwaj, A. Chandrakasan, and T. Garnett investigate the upper bounds of the lifetime of a wireless sensor network. This drives to the calculation of the minimum amount of energy that can be dissipated in a multi-hop link. Hence, if there is the option of deciding the placement of the intervening nodes between the first and the final node, then how many nodes are to be placed and at what distances away from one another. In other words, given two nodes separated by D meters, what is the optimal number of hops or the optimal distances separating the intervening nodes located between them, such that the overall power consumption is minimized. The authors prove that the optimal number of hops K_{opt} is always one of [1],

$$K_{opt} = \left\lfloor \frac{D}{d_{char}} \right\rfloor \ or \ \left\lceil \frac{D}{d_{char}} \right\rceil \tag{5}$$

where d_{char} is introduced as the characteristic distance, independent of D and calculated as [1]:

$$d_{char} = \sqrt[\gamma]{\frac{\alpha_1}{\alpha_2(\gamma - 1)}}. \tag{6}$$

where $\alpha_1 = \alpha_{11} + \alpha_{12}$.

From any node, placing the next hop node at a distance of d_{char} on the straight line directing to the base station leads to an energy efficient hop. However, for a random deployment of the nodes in the plane, the next hop node is in general deviated from that optimal position. Interesting is to model the inefficiency in the energy consumption for the overall link when relaying through that node. In the next section, the hop model with reference to the characteristic distance is designed.

5.1.2 Hop Model

In order to formulate the weighted region in the plane of a searching node, we define a hop model which represents the position of a neighboring node with respect to an optimal position. Hence, in a multi-hop link between an arbitrary node in the network and the base station, a single hop can be modeled as illustrated in Figure 2. Assuming node i is the searching node, the position of the relaying node j is represented in terms of its deviation from an optimal relaying position from node i.

Lemma 1. The number of hops, K'_{opt}, is greater in one hop or equal to K_{opt} in Equation 5, if equal distances of d_{char} are taken from each node to its relaying node on the direction axis to the base station.

PROOF. Starting from a node i, placing relaying nodes in successive distances of d_{char} from one another till the base station leaves a residual distance in the last hop which is smaller than d_{char} and greater or equal to zero. Hence, $K'_{opt} = \left\lceil \frac{d(i,BS)}{d_{char}} \right\rceil$. Therefore, from Equation 5, K'_{opt} has a difference in one or is equal to K_{opt}. □

Theorem 1. The optimal position of a node j for relaying a message originating from a node i, lies on the direction axis to the base station and has a distance of d_{char} from i. The characteristic distance, d_{char}, is given in Equation 6.

PROOF. According to Lemma 1, relaying over a node at a distance of d_{char} on the direction axis to the base station has a multi-hop link with K'_{opt} hops. Hence, a relaying distance of d_{char} from each node leads to an efficient multi-hop link. □

From any node i there exists an axis directing to the base station and will be represented as the x-axis where node i is the origin of the coordinate system. The x- and y-coordinates of a node j in the plane of a node i, are expressed as $d_{char} \cdot a$ and $d_{char} \cdot b$ respectively, where $a, b \in \mathbb{R}$. The distance from i to j is $d(i,j) = d_{char} \cdot c$, where $c = \sqrt{a^2 + b^2}$. In this model, the x-coordinate of j represents the progress[4] of the hop, since it measures the distance traversed in the direction of the destination. The measure a represents the normalized progress over d_{char}. The angle of deviation of the node j with respect to the direction axis is given as φ.

Now, in a multi-hop link with the nodes deviating from the optimal relaying position, of value is to formulate the number of hops K with respect to the optimal number of hops K'_{opt} and the progress achieved per hop.

Theorem 2. The number of hops K is equal to the ratio of the continuous value of K'_{opt}, $K'_{opt-continuous}$, and the normalized average progress per hop, $\bar{a}$, such that

$$K = \frac{K'_{opt-continuous}}{\bar{a}}, \tag{7}$$

Defining D as the absolute distance from a node i to the base station, $K'_{opt-continuous} = \frac{D}{d_{char}}$ and $\bar{a} = \frac{1}{K} \cdot \sum_{n=1}^{K} a_n$.

PROOF. Starting from an arbitrary node, the absolute distance to the base station can be written as follows:

$$\begin{aligned} d_{char} \cdot (a_1 + a_2 + ... + a_K) &= D \\ \sum_{n=1}^{K} a_n &= \frac{D}{d_{char}} \\ \bar{a} \cdot K &= K'_{opt-continuous} \\ K &= \frac{K'_{opt-continuous}}{\bar{a}} \end{aligned}$$

[4]Progress is the "effective" distance traversed in one hop.

Hence we get Equation 7 which concludes the proof. □

The optimal value of the number of hops is a natural number as given in Lemma 1. For a multi-hop link with K hops and whose optimal number of hops K'_{opt} we define the measure $\tilde{a}$:

Definition 4. The estimated overall-link hop progress normalized over the characteristic distance and denoted as $\tilde{a}$, is the ratio of the optimal number of hops, K'_{opt}, and the number of hops, K:

$$\tilde{a} = \frac{K'_{opt}}{K} \tag{8}$$

For the single hop case, a neighboring node having $\tilde{a}$ could possibly result in $\frac{K}{K'_{opt}}$ increase in the number of hops to the base station. Given this hop model, we can determine an estimation of the single hop energy efficiency with respect to the overall link. In the following section, we derive the efficiency model.

5.1.3 Hop Efficiency

In order to develop an efficiency measure for the single hop, we compare the energy consumption of a theoretically optimal multi-hop link to the base station with a link resulting from our hop model given in the previous section.

The rate of energy consumption of a node acting as a relay, is the sum of the power consumption for data reception and transmission over a distance d. The power consumption in one relay can be formulated as:

$$P_{relay}(d) = (\alpha_1 + \alpha_2 d^{\gamma}) r. \tag{9}$$

Knowing that the most efficient route a message can take from a node to the BS is the one along the direction axis with equidistant hops of distances d_{char}, the minimum energy rate $P_{link-min}$ that can be achieved is given as:

$$P_{link-min}(D) = K'_{opt} \cdot P_{relay}(d_{char}), \tag{10}$$

where D is the total distance to the BS. However, in a randomly deployed sensor network, the power consumed in a link of distance $D' \geq D$ with intervening nodes deviating from the direction axis can be formulated as:

$$P_{link}(D') = \sum_{i=1}^{K} P_{relay}(c_i \cdot d_{char}). \tag{11}$$

Taking $P_{link-min}(D)$ as a relative measure, building the ratio of $P_{link-min}(D)$ over $P_{link}(D')$ gives a measure of the efficiency of a chosen link. In maximizing this ratio, the most energy efficient link can be determined.

$$\frac{P_{link-min}(D)}{P_{link}(D')} = \frac{K'_{opt} \cdot P_{relay}(d_{char})}{\sum_{i=1}^{K} P_{relay}(c_i \cdot d_{char})} \tag{12}$$

Theorem 3. The overall link efficiency measure, Λ, of a multi-hop link can be formulated as:

$$\Lambda \leq \frac{\tilde{a} \cdot \gamma}{\bar{c}^{\gamma} + \gamma - 1} \tag{13}$$

where $\bar{c}$ is the normalized average link distances over d_{char}.

PROOF. Defining $\Lambda = \frac{P_{link-min}(D)}{P_{link}(D')}$, we can write:

$$\begin{aligned}\Lambda &= \frac{K'_{opt} \cdot P_{relay}(d_{char})}{\sum_{i=1}^{K} P_{relay}(c_i \cdot d_{char})} \\ &= \frac{K'_{opt}(\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma})r}{\sum_{i=1}^{K}(\alpha_1 + \alpha_2(c_i \cdot d_{char})^{\gamma})r} \\ &= \frac{K'_{opt}(\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma})}{K \cdot \alpha_1 + \alpha_2 \cdot d_{char}^{\gamma} \sum_{i=1}^{K} c_i^{\gamma}} \\ &= \frac{K'_{opt}(\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma})}{K\left(\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma} \cdot \frac{1}{K} \cdot \sum_{i=1}^{K} c_i^{\gamma}\right)}\end{aligned}$$

Having c^{γ} a strictly convex function ($c \in \mathbb{R}^{+},\ 2 \leq \gamma \leq 6$), we can use Jensen's inequality for convex functions to get

$$\bar{c}^{\gamma} \leq \frac{\sum_{i=1}^{K}(c_i)^{\gamma}}{K}, \tag{14}$$

Using this and Definition 4, we can further write

$$\Lambda \leq \frac{\tilde{a}(\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma})}{\alpha_1 + \alpha_2 \cdot d_{char}^{\gamma} \cdot \bar{c}^{\gamma}}.$$

Substituting d_{char} given in Equation 6 in the inequation, we get

$$\begin{aligned}\Lambda &\leq \frac{\tilde{a}\left(\alpha_1 + \alpha_2\left(\frac{\alpha_1}{\alpha_2(\gamma-1)}\right)\right)}{\alpha_1 + \alpha_2\left(\frac{\alpha_1}{\alpha_2(\gamma-1)}\right)\bar{c}^{\gamma}} \\ &\leq \frac{\tilde{a}(\alpha_1 + \frac{\alpha_1}{\gamma-1})}{\alpha_1 + (\frac{\alpha_1}{\gamma-1})\bar{c}^{\gamma}} \\ &\leq \frac{\tilde{a}(1 + \frac{1}{\gamma-1})}{1 + (\frac{1}{\gamma-1})\bar{c}^{\gamma}} \\ &\leq \frac{\tilde{a} \cdot \gamma}{\bar{c}^{\gamma} + \gamma - 1}\end{aligned}$$

□

The searching node has only information on the neighboring nodes. Therefore, we need to apply our efficiency model to the single hop case. A searching node, hence, can only estimate which nodes in its neighborhood can achieve an efficient relaying with respect to the overall link. We adapt Theorem 3 for the single hop case, in substituting the average values with the single hop values. A neighboring node j in the plane of a searching node is Λ_j efficient for the overall link. Hence, its eligibility of being a neighbor of node i is determined accordingly.

$$\Lambda_j = \frac{a \cdot \gamma}{c^{\gamma} + \gamma - 1} = \frac{\cos\varphi \cdot c \cdot \gamma}{c^{\gamma} + \gamma - 1} \tag{15}$$

If a searching node does not have the direction information to the base station, then it can not estimate the deviation to the direction axis. Hence, φ is set to zero and Λ can be written as:

$$\Lambda_j = \frac{c \cdot \gamma}{c^{\gamma} + \gamma - 1} \tag{16}$$

5.2 Node Eligibility Metric

The eligibility metric Λ_j derived in the previous section, defines an efficiency measure for a position in the region of transmission range of a node. Thus, a neighboring node j within the transmission range of node i acquires this measure Λ_j as its eligibility for being a neighbor, from which the link to the base station is assumed to have high efficiency over other nodes. This is one aspect to consider when building the network, which is essential to reduce the amount of energy dissipated in the overall network. Another aspect, that of higher concern to routing protocols is fairness between the nodes. We adapt to this issue in that nodes that have relatively high energy reserves are also prioritized to be selected as neighboring nodes. This achieves further fairness in the network regarding their energy reserves. Routing protocols usually consider this aspect in establishing paths with high battery capacities. However, in order to give higher option to such protocols and unconceal nodes with high energies, we define the metric $\Upsilon_j = \frac{e_j}{E}$. Like the overall efficiency metric Λ, Υ_j is applied on a neighboring node to reveal the relative amount of energy it has with respect to the other nodes. Combining both metrics, we can achieve overall link efficiency and fairness through a common eligibility measure of a neighboring node. Thus, we define:

$$\Psi_j = \Lambda_j \cdot \Upsilon_j \tag{17}$$

A node i having node j in its transmission range calculates Ψ_j, $0 \leq \Psi_j \leq 1$. This determines a measure for node j, for which node i can estimate how eligible it is to be a neighbor.

In the presence of node failures and node mobility, the topology control protocol is to be run periodically to adapt to such changes. Therefore, message exchange between the nodes is to be done regularly. Hence, information on energy reserves can be as well interchanged, and the topology is updated correspondingly. This update shows that the topology of the network might change over time and is dynamic. Depending whether the nodes have information on the direction of the base station, the topology of the network differs. We denote the graph where the nodes have direction information to the base station with FETCD, else, the developed graph is denoted as FETC.

5.3 Protocol Description

In this section, we describe our topology control protocol, which is divided in two phases. The first phase is the neighbor discovery phase where each node selects k nodes in its neighborhood. The neighbor selection is carried out according to the node eligibility criterion. The network graph that is created after this phase is not symmetric. The second phase of our protocol is concerned in building a symmetric graph of the already built graph in phase 1. The symmetry is obtained by adding the reverse edge to every asymmetric link. The phases of the graph are represented as follows:

Phase 1: Choosing k Neighboring Nodes (For a generic node i)

1. Node i wakes up at time t_1, and announces its identity (id_i) and energy reserve ($e_i^{t_1}$) at maximum power (P_{t-max}).
2. Node i receives the messages from the neighboring nodes and stores their identities in its neighbor list $\mathcal{N}(i)$.
3. Node i estimates the distance to each node in $\mathcal{N}(i)$. Node i has the energy reserves of the neighboring nodes

(e_j) as well as the distances to them ($d(i,j)$), where $j \in \mathcal{N}(i)$.

4. Node i calculates Ψ_j, for each neighbor in its list.
5. Node i chooses the k neighbors in its list $\mathcal{N}(i)$ that have the highest value of Ψ. If originally node i has less than k neighbors, then all nodes are chosen.
6. Node i updates its neighbor list according to the chosen nodes in step 5.

The developed graph according to phase 1 of the protocol, has directed links and the graph is a directed graph, $\mathcal{G}_{digraph}$. Hence, a symmetry phase is necessary to enforce symmetry in the graph. In this phase we build the symmetric super-graph of $\mathcal{G}_{digraph}$.

Definition 5. The symmetric super-graph of $\mathcal{G}_{digraph}$ is defined as the undirected graph $\mathcal{G}$ obtained from $\mathcal{G}_{digraph}$ by adding the undirected edge $[i \leftrightarrow j]$ whenever edge $[i \rightarrow j]$ or $[i \leftarrow j]$ is in $\mathcal{G}_{digraph}$. That is, $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{E} = \{[i \leftrightarrow j] | [i \rightarrow j] \in \mathcal{E}_{digraph}$ or $[i \leftarrow j] \in \mathcal{E}_{digraph}\}$.

Phase 2: Enforcing Graph Symmetry (For a generic node i)

1. At time t_2, node i announces its identity (id_i) and list of Neighbors ($\mathcal{N}(i)$) at maximum power (P_{t-max}).
2. Node i receives the neighbor lists, and calculates the set of symmetric neighbors. Node i checks all neighbor lists and finds if it exists there. When that is the case, it checks if the neighbor list originates from a neighbor in its neighbor list. If not, the corresponding neighbor is added to its list $\mathcal{N}(i)$.

After the symmetric graph is constructed, node i determines for each neighbor in $\mathcal{N}(i)$ the minimum required transmission power to reach it and stores it in it neighbor table list $\mathcal{N}_L(i)$. On communication with a node in its neighbor list, the messages are transmitted at the corresponding power level. The selected neighbors of a node i are surely its logical neighbors. That is, there exist nodes in its maximum assigned transmission range that are not selected in its neighbor list. These nodes in $\mathcal{N}(i)$ are used for the purpose of routing. That is, in order to determine the routes in the communication graph, only the nodes in the neighbor list are considered.

6. EVALUATION

6.1 Experimental Set Up

In order to perform comparisons between the network topologies developed through different protocols and our protocol, we run simulations using MATLAB®. First we generate the node deployment which mainly determines the positions of the nodes. Then, by using these positions and the channel characteristics, we build the topologies which define for each node a set of neighbors with whom it can communicate directly with.

We denote the Disk Graph, with disk radius equals to the maximum transmission range, d_{max}, as the original topology (Original). Each node in the network has in its neighbor list the nodes within its maximum transmission range. The name "Original" is given for two reasons. First, in a topology control protocol, the main criteria of choosing a neighbor of a node is that this node lies within transmission range. Hence, taking the original topology and trimming it in relation to the used topology control protocol satisfies this aspect. Second, the original topology has the property that it contains all possible communication links.

Of the proximity graph topologies, we choose the Gabriel Graph [7] and the Relative Neighborhood Graph, represented as GG and RNG respectively, as network topologies to compare with. Starting from the original topology, the GG and RNG topologies do not necessarily contain all the links as in the theoretically built graphs on the deployment. Links that are longer than the highest transmission range do not exist. Hence, the graph may lose some of its properties if the density of the nodes is low. The KNeigh protocol, as described in [2], builds the topology based on the k nearest neighbors. The preferred value of k is as well derived in that work and set to 9. We include for the simulations the introduced optional pruning phase.

The simulations can be divided in two categories. First, is the study made in graph theoretical aspects such as the graph connectivity and node degree. Second, is the aspect of energy conservation made when events take place in the network and a flow between the nodes and the final destination is generated. Starting with the deployment phase, we define our region of deployment having 500 $m \times 500$ m dimensions. The number of nodes deployed in this region is taken as 100, 200, 300, 400, and 500. In turn, different deployment densities are examined. The base station is chosen to be the furthest node with the highest x-coordinate in the deployment. This leaves the base station at the edge of the deployment which is the case in many deployment scenarios. Furthermore, in a real scenario, the base station has usually infinite energy supply. This is interesting since our protocol considers the energy capacities remaining in the nodes in order to determine the eligibility of building the links. Therefore, the base station gets a definite high eligibility if it is within transmission range, which in turn increases the number of nodes that are directly connected to it.

The path between each node and the base station is determined and stored in each node. We use Dijkstra's algorithm to find the shortest path from each node to the base station. On this level, experimentation on the network can be done. We denote a period of time as a time step where 100 nodes are randomly chosen from the deployment and one bit of information is sent from them to the base station. In this case, for each event starting from node i, the nodes that are along the path decrease their energies respective to our energy model. A relaying node consumes reception power as well as transmission power according to the distance to its next hop neighbor. The path-loss exponent γ is chosen as either 2 or 4 according to the required transmission distance. Here we introduce the crossover distance, $d_{crossover}$, as in [6]. If the transmission distance is less than $d_{crossover}$, γ is taken as 2. Else, γ is taken as 4. In Table 1, the parameter

Table 1: Parameter values.

Parameter	Value
E	2 J
γ	2 or 4
r	1 bits/s
d_{max}	137 m
$d_{crossover}$	86.2 m
α_{11}	50 nJ/bit
α_{12}	50 nJ/bit
α_2	10 pJ/bit/m^2 ($\gamma = 2$) 0.0013 pJ/bit/m^4 ($\gamma = 4$)
d_{char}	100 m ($\gamma = 2$) 71 m ($\gamma = 4$)

values used for simulations are represented.

6.2 Simulation Results

We choose two values of n to test the connectivity of our graph. We generate 100 random graphs for each k and the specified node density and we calculate the rate of connectivity of the graphs. In Figure 3, the connectivity rate for deployments of 100 and 250 nodes is plotted. We observe that the connectivity rate is high for high density deployments, such that choosing $k = 1$ can lead to a high rate of connectivity. However, for $k = 5$ the connectivity of the graph is secured even for low densities, and this measure is taken as sufficient to assure connectivity of our graph. We use this value of k for further simulations in this section.

For the five deployment densities, we test the node degree of the different network graphs. The node degree is the maximum number of neighbors a node has in the topology. Minimizing the node degree in the network lessens the overhead in finding routes in the topology. In addition, each node has to maintain a small number of neighbors in cases of node mobility. In Figure 4 we compare the node degrees of the different topologies to increasing values of the deployed nodes. According to our simulations, the RNG graph has the lowest node degree with respect to the other topologies as is expected. Whereas, the KNeigh and GG graphs have a slightly higher node degree. Interesting in these three graphs is the constant node degree with respect to node density. The FETC and FETCD topologies have higher node degrees than the KNeigh, GG, and RNG graphs which makes our graph not a sparse one. However, according to the original topology, the increase in the node degree is small with node density. the FETCD graph has higher node degree than the FETC graph, for the following reason. Since the FETCD protocol has directional information to the base station, each node selects in the first phase of the protocol k nodes that are in the direction of the base station almost exclusively. In the second phase of the protocol where graph symmetry is made, the links that are behind the nodes with respect to the base station are added. With the directional information property, more links are added in the symmetry phase of FETCD graph than the FETC graph which explains these results.

There are two aspects that should be studied when comparing the energy consumption of the different network topologies. These are the overall network energy consumption and

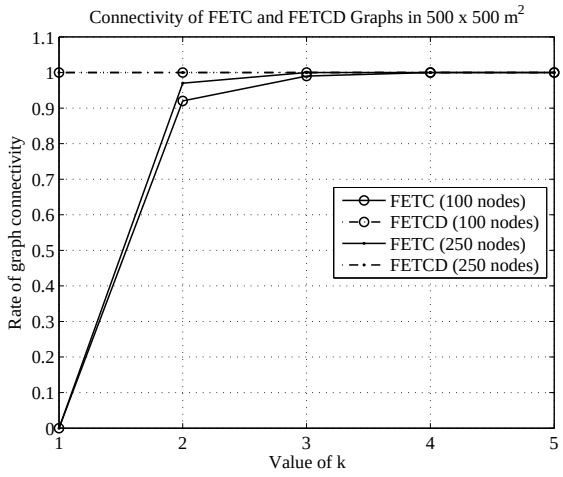

Figure 3: Rate of graph connectivity of FETC and FETCD network graphs.

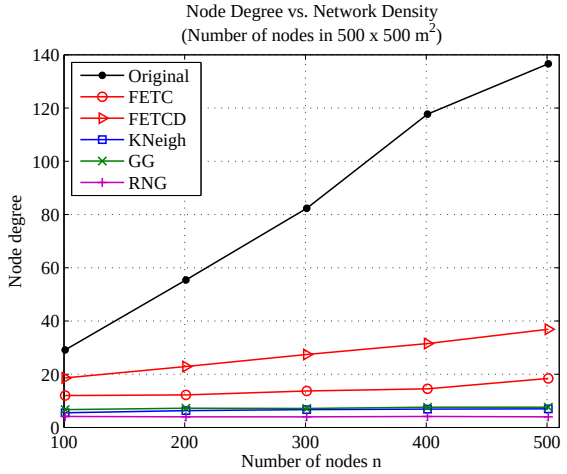

Figure 4: Network graph node degree for different deployment densities.

the achieved fairness between the nodes. Fairness is revealed when the variances between the energy reserves of the nodes is minimized such that the nodes have almost similar energies after a duration of network operational time. As defined earlier, a time step constitutes of 100 events (nodes) randomly chosen in the network. In analyzing the energy consumption of the network, we run 100 time steps for the five network densities in the deployment region. For each network density 10 random deployments are generated on which the events take place. The mean of the results on the 10 deployments is made to construct the results for the corresponding network density.

First we study the rate of energy consumption in the network. The rate of energy consumption is the amount of energy dissipated in the overall network per time step. In Figure 5, the results are illustrated. Both our graphs, the FETC and FETCD, acquire the least energy consumption in the network. With increasing network densities there is a variation in the energy consumption which is strongly seen

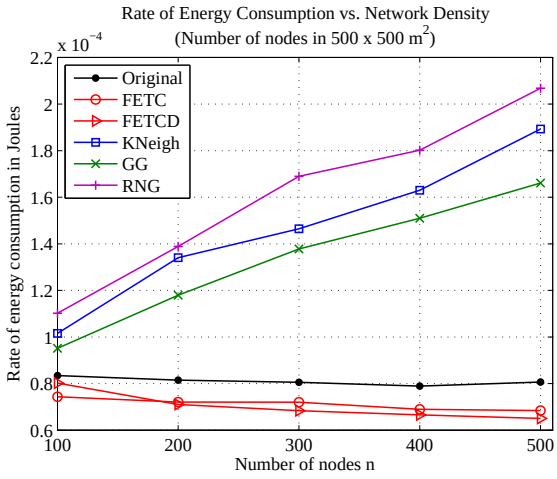

Figure 5: Rate of energy consumption in the overall network.

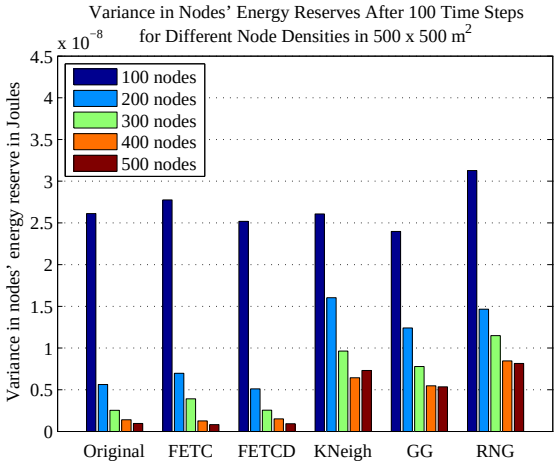

Figure 6: Variance in the energy reserves of the nodes after 100 time steps.

in the KNeigh, GG, and RNG topologies. These graphs suffer from the increased number of hops on the paths since they build the topologies according to nearest neighbors. This increases the amount of total receive energy consumption which comes from the excessive relaying in the overall network.

The second aspect of comparison between the different topologies is the variance in the energy reserves between the nodes with increasing time steps. The variance in the energy reserve of a nodes at a specific time is calculated as such: Variance in energy reserve of a node = (Mean of the energy reserves of all nodes - energy reserve of node)^2. We plot the average of all variances of all nodes at the corresponding time step. In Figure 6, the variance of the nodes energy reserves after 100 time steps is plotted. We have chosen the same number of events in a time step for all network densities. In doing so, no analysis can be made between the variance in energy reserves corresponding to different node densities of the same graph. Hence, we compare only the results of the network graphs for the corresponding node density. The KNeigh, GG, RNG achieve lower fairness between the nodes as the original, FETC and FETCD topologies for different network densities except for the 100 nodes topologies. In sparse topologies such as the 100 nodes topologies, nearest neighbor routing has an efficient transmission distance which leads to comparably good results. For different densities, the FETCD accomplishes the lowest variances between the nodes. In comparison to the other topologies, the FETC and FETCD topologies have a good distribution of the energy dissipation. Hence, the distances between the nodes in the FETC and FETCD graphs are energy efficient and fair. The FETCD has its nodes with the least difference in energy capacities. This shows, that the longer hops in the original topology can be unfair for the corresponding nodes in reducing their energy capacities considerably. In that case, fewer nodes relaying the messages leads to unfairness in the network.

Decreasing both the overall energy consumption in the network as well as maintaining similar energy levels between the nodes in a network is a prerequisite for system lifetime maximization. According to the simulation results, this issue has been achieved and fulfilled.

7. CONCLUSION

Especially in applications as environmental monitoring, the prolongation of the network lifetime is a benefit for better research results. Dense deployment is often is desired to increase the sensing coverage and the preciseness of the gathered data. Considering such applications of wireless sensor networks, we have introduced a topology control protocol that is designed to meet their requirements. Our assumptions vary between whether directional information of the base station at the nodes exist. This, in turn brings us in analyzing two topologies corresponding to the measure of local information at the nodes. In order to support self-organization, we restrict our construction of the network topology for a localized algorithm. That is, each node uses the information present from its immediate neighbors to make the neighbor selection decision. Each node, selects a definite number of neighbors that acquire a high eligibility measure for the defined energy efficiency problem. Moreover, to catch the dynamics of the network and discover node mobility or node failures, the topology control protocol is to be updated regularity. Our protocol enables an asynchronous update policy, where each node can initiate the protocol. The message complexity of our protocol is $2n$ since each node has to send two messages to determine its final neighbors.

The energy efficiency of the network and hence the lifetime maximization problem is tackled through considering two aspects: The overall network energy consumption efficiency and the achieved fairness between the nodes. Based on theoretical work on upper bounds of the network lifetime, we exploit a defined distance measure, d_{char}, that is dependent of the radio characteristics and the channel conditions. From a node's view point, an estimation is made over the neighboring nodes on their overall link efficiency in relaying a message. This is done according to their positions relative to an optimal relaying position and the position of the base station (if existing at the nodes). In turn, the efficiency

of a single hop is estimated. The second aspect of lifetime maximization through fairness is attained in the following manner. Through introducing the energy reserves of the nodes in the neighbor selection criteria, distinction between the nodes in the aspect of their energy capacities is made. Nodes with high capacities are more appropriate to relay messages than other nodes. Hence, on protocol update such an optimization can be made.

Our results show that our topology is not sparse as the RNG, GG, and KNeigh topologies. However, with respect to the original topology, the node degree is slightly increasing with network density. In energy conservation, interesting results concerning the energy dissipation rate in the overall network have been shown. The rates are not affected by increasing network densities such as the other topologies. Moreover, on the aspect of the differences in energy reserves between the nodes, contrary to the RNG, GG, and KNeigh topologies, we have minimized this measure. The results show that nearest neighbor topologies are energy inefficient for increasing network densities. The original topology, on the other hand, contains inefficient long links which as well decrease the energy efficiency of the network. These results show that our network topology suits to prolong the lifetime of the network.

8. REFERENCES

[1] M. Bhardwaj, T. Garnett, and A. Chandrakasan. Upper bounds on the lifetime of sensor networks. *Communications, 2001. ICC 2001. IEEE International Conference on*, 3:785–790 vol.3, 2001.

[2] D. M. Blough, M. Leoncini, G. Resta, and P. Santi. The k-neigh protocol for symmetric topology control in ad hoc networks. In *MobiHoc '03: Proceedings of the 4th ACM international symposium on Mobile ad hoc networking & computing*, pages 141–152, New York, NY, USA, 2003. ACM.

[3] J.-H. Chang and L. Tassiulas. Energy conserving routing in wireless ad-hoc networks. *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 1:22–31 vol.1, 2000.

[4] Chipcon, SmartRF CC2420, 2.4 GHz IEEE 802.15.4 / ZigBee-ready RF Transceiver. Chipcon Product data sheet. `http://www.chipcon.com/files/CC2420_Data_Sheet_1_0.pdf`.

[5] M. Haenggi. Twelve reasons not to route over many short hops. *Vehicular Technology Conference, 2004. VTC2004-Fall. 2004 IEEE 60th*, 5:3130–3134 Vol. 5, 26-29 Sept. 2004.

[6] W. Heinzelman. *Application-specific protocol architectures for wireless networks*. PhD thesis, Cambridge: Mass. Inst. Technol., 2000.

[7] J. Jaromczyk and G. Toussaint. Relative neighborhood graphs and their relatives. *P-IEEE*, 80:1502–1517, 1992.

[8] A. A.-K. Jeng and R.-H. Jan. The r-neighborhood graph: An adjustable structure for topology control in wireless ad hoc networks. *IEEE Trans. Parallel Distrib. Syst.*, 18(4):536–549, 2007.

[9] B. H. Liu, Y. Gao, C. T. Chou, and S. Jha. An energy efficient select optimal neighbor protocol for wireless ad hoc networks. In *LCN*, pages 626–633. IEEE Computer Society, 2004.

[10] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson. Wireless sensor networks for habitat monitoring. In *WSNA '02: Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, pages 88–97, New York, NY, USA, 2002. ACM.

[11] N. Patwari, I. Hero, A.O., M. Perkins, N. Correal, and R. O'Dea. Relative location estimation in wireless sensor networks. *Signal Processing, IEEE Transactions on [see also Acoustics, Speech, and Signal Processing, IEEE Transactions on]*, 51(8):2137–2148, Aug. 2003.

[12] D. Puccinelli and M. Haenggi. Wireless sensor networks: applications and challenges of ubiquitous sensing. *Circuits and Systems Magazine, IEEE*, 5(3):19–31, 2005.

[13] R. Ramanathan and R. Rosales-Hain. Topology control of multihop wireless networks using transmit power adjustment. *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 2:404–413 vol.2, 2000.

[14] T. S. Rappaport. *Wireless Communications: Principles and Practice*. IEEE Press, Piscataway, NJ, USA, 1996.

[15] V. Rodoplu and T. Meng. Minimum energy mobile wireless networks. *Selected Areas in Communications, IEEE Journal on*, 17(8):1333–1344, Aug 1999.

[16] C. Savarese, J. Rabaey, and J. Beutel. Location in distributed ad-hoc wireless sensor networks. *Acoustics, Speech, and Signal Processing, 2001. Proceedings. (ICASSP '01). 2001 IEEE International Conference on*, 4:2037–2040 vol.4, 2001.

[17] K. Sohrabi, J. Gao, V. Ailawadhi, and G. J. Pottie. Protocols for self-organization of a wireless sensor network. *Personal Communications, IEEE [see also IEEE Wireless Communications]*, 7(5):16–27, 2000.

[18] D. Stoyan, W. S. Kendall, and J. Mecke. *Stochastic Geometry and its Applications*. John Wiley and Sons, Chichester, 1987.

[19] R. Wattenhofer and A. Zollinger. Xtc: a practical topology control algorithm for ad-hoc networks. *Parallel and Distributed Processing Symposium, 2004. Proceedings. 18th International*, pages 216–, 26-30 April 2004.

[20] L. Yu, N. Wang, and X. Meng. Real-time forest fire detection with wireless sensor networks. *Wireless Communications, Networking and Mobile Computing, 2005. Proceedings. 2005 International Conference on*, 2:1214–1217, 23-26 Sept. 2005.