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Comparison of Cell-Based and Topology-Control-Based Energy Conservation in Wireless Sensor Networks

Douglas M. Blough, Mauro Leoncini, Giovanni Resta, and Paolo Santi

In this chapter we compare the effectiveness of two popular energy conservation strategies, namely topology control protocols and cooperative cell-based approaches, to reduce the energy consumption, and thus extend the lifetime, of wireless sensor networks. To this end, we define a realistic (although necessarily idealized in some respects) and unified framework of investigation. Using this framework, we prove lower bounds on network lifetime for cell-based cooperative strategies with node densities that are known to be sufficient to ensure a connected network. We also perform a number of simulation experiments, under a traffic model specifically designed for sensor networks, to evaluate and compare cell-based approaches with topology control. This is the first attempt at a comprehensive understanding of the conditions under which one of these approaches outperforms the other. Indeed, our study reveals a number of properties of the techniques investigated, some of which are not at all obvious. As expected, cell-based cooperative approaches, which completely power down network interfaces of certain nodes for extended time periods, produce longer network lifetimes when node density is very high. However, even with moderately high density of nodes, cell-based approaches do not significantly extend lifetime when it is defined in terms of connectivity. While it is not surprising that cell-based approaches do not extend lifetime under low density conditions, we find that topology control techniques *can* significantly increase network lifetime under those conditions and, in fact, they substantially outperform cooperative approaches in this respect. More details on the precise findings can be found in Section 31.7.

31.1 Introduction

Recent advances in MEMS, mixed-mode signaling, RF, and low-power circuit design have enabled a new type of computing device, namely a battery-powered intelligent sensor with wireless communication capability.[22] Applications for networks of these new sensor devices are many and potential applications are virtually unlimited. Examples of applications include monitoring of environmental change in areas such as forests, oceans, and deserts; detection of chemical, biological, and nuclear contamination; monitoring of traffic conditions; and surveillance. The issue of energy conservation is paramount in sensor networks due to the reliance on power-intensive RF circuitry, the use of battery power, and a limited ability to replace or recharge batteries in many sensor environments.

Cooperative strategies and topology control protocols have been recently proposed in the literature as major approaches to reducing energy consumption in wireless networks. Cooperative strategies are motivated by the fact that, for many wireless transceivers, there is little difference between the energy consumed by the interface during transmission, reception, and listening, while significant energy savings can be achieved if the radio is shut down completely. These strategies therefore operate by having neighboring nodes coordinate times during which they can turn off their interfaces, potentially resulting in large energy savings if the coordination overhead is limited. The goal of a good cooperative strategy is to achieve energy savings while not significantly reducing the network capacity. Topology control protocols, on the other hand, try to take advantage of the at least quadratic reduction in transmit power that results from reducing the transmission range, while still attempting to guarantee that each node can reach a sufficient number of neighbors for the network to remain connected. In addition to reducing energy consumption, topology control protocols have the additional advantage of increasing network capacity, due to the reduced interference experienced by the nodes.[10]

Cooperative techniques and topology control protocols can be considered orthogonal techniques. Cooperative strategies take advantage of a "dense" communication graph, in which some nodes can turn off their radios without impairing network connectivity; the goal of topology control, on the other hand, is to produce a relatively sparse communication graph, where only energy-efficient links are used to communicate.

Despite the common goal of extending network lifetime through energy conservation, cooperative strategies and topology control protocols have not, to date, been directly compared in a unified framework. Thus, it is not clear under what conditions each technique is more effective than the other. In this chapter, we make a first step toward answering this question. We consider a cell-based cooperative strategy and a number of topology control algorithms, and we define an idealized framework for comparison. Using this framework, we compare the performances of the various protocols (in terms of network lifetime extension) considering various definitions of network lifetime and varying traffic loads, under a traffic model specifically designed to represent sensor networks.

It is our opinion that the results presented here represent novel contributions toward a better understanding of:

- The relative performance of the two techniques under different conditions (e.g., load, node density, and node number)
- The effect of the lifetime definition on the results
- The relative performance of the two approaches under a realistic sensor network traffic model.

31.2 Related Work and Motivation

Measurements on the Medusa II sensor node's wireless transceiver have shown sleep:idle:receiving: transmitting ratios of 0.235:1:1.008:1.156.[23] Cooperative strategies exploit this by shutting down the interface most of the time. Clearly, the node's sleeping periods must be carefully scheduled, because otherwise the network functionality may be compromised. Typically, the awake nodes form a connected backbone, which is used by the other nodes as a communication infrastructure. To establish the backbone, some classes of "routing equivalent" nodes are identified, and only one node in every class (called the *representative*, or *leader*, node) is left active. Periodically, the set of active nodes is changed to achieve a more uniform energy consumption or to deal with mobility.

Cooperative strategies are based on the following idea. Assume that a given set S of nodes provides a functionality F to the rest of the system; instead of keeping all the nodes in S operative, a representative node u can be selected, and the remaining nodes can be turned off in order to save energy. The representative node selection is obtained as the result of a negotiation protocol executed by nodes in S, which is repeated when u dies, or after a certain wake-up time. This way, considerable energy savings can be potentially achieved. Observe that the exact definition of the cooperative strategy depends on the kind of functionality in which we are interested. For example, F could be defined as the capability of nodes in S to relay messages on behalf of the remaining nodes, without compromising network connectivity (i.e., nodes are equivalent from the point of view of a routing protocol). In the case of sensor networks, F can also be defined as the capability of sensing a given sub-region of the deployment region R.

Several routing cooperative strategies have been recently proposed in the literature. Xu et al.[34] introduce the GAF strategy, which is based on a subdivision of the network deployment region into an appropriate number of nonoverlapping square cells. The cells are used to identify equivalent nodes: all the nodes lying in the same cell are proved to be routing equivalent. An election algorithm is periodically executed to elect the leader in every cell. The cell-based approach is also used.[30] In this work, the focus is on sensor networks, and it is assumed that a loose time synchronization mechanism is available to the nodes (which is quite likely to occur in sensor networks). Given this loose synchronization, the authors present and analyze deterministic and randomized leader election algorithms. In the SPAN algorithm proposed by Chen et al.,[7] nodes decide whether to be active or not based on two-hop neighborhood information: a node is eligible as leader if two of its neighbors cannot reach each other either directly or via one or two leaders. Eligible nodes decide whether to become leaders based on a randomized algorithm, where the probability of being elected depends on the *utility* of the node (which can be informally understood as the number of additional pairs of nodes that would be connected if the node were to be elected leader) and on the amount of energy remaining in the node's battery. The CPC strategy[32] is based on the construction of a connected dominating set: nodes in the dominating sets are the representatives, and coordinate the sleeping periods of the other units. Routing equivalence is ensured by the fact that, by the definition of dominating set, every node in the network has at least one leader node as an immediate neighbor, and by the fact that the nodes in the dominating set are connected.

Cooperative strategies rely on a homogeneity assumption on the node transmitting ranges, namely that all the nodes have the same range r, which can be intended as the maximum range. This assumption is vital in the GAF strategy and in the protocols presented by Santi and Simon[30] because the value of r is used to determine the size of the cells used to partition the deployment region. SPAN and CPC are based on neighborhood relationships between nodes and, in principle, could work also if the homogeneity assumption does not hold. However, it should be observed that routing cooperative strategies are effective only when the communication graph is very dense, and many disjoint paths exist between source–destination pairs. If this is not the case, several nodes will remain active for a long time,* thus reducing considerably the energy savings achieved by the strategy. Hence, the assumption that all nodes transmit at the maximum range r is also essential for SPAN and CPC in practice.

Contrary to cooperative strategies, topology control techniques leverage the capability of nodes to vary their transmitting ranges dynamically, in order to reduce energy consumption. In fact, the power needed to transmit data depends on the sender–receiver distance. More precisely, the power p_i required by node i to correctly transmit data to node j must satisfy inequality

$$\frac{p_i}{\delta_{i,j}^{\alpha}} \geq \beta, \tag{31.1}$$

where $\alpha \geq 2$ is the *distance-power gradient*, $\beta \geq 1$ is the *transmission quality* parameter, and $\delta_{i,j}$ is the Euclidean distance between the nodes. While β is usually set to 1, α is in the interval $[2, 6]$, depending on environmental conditions.[26] A simple (but widely adopted) energy model can then be devised by simply turning Equation (31.1) into an equality. According to this, if a node transmits at distance, say, $\frac{r}{2}$ and $\alpha = 4$, it consumes $\frac{1}{16}$ of the energy required to transmit at full power.

Observe that Equation (31.1) refers to the transmit power only, and does not account for the power consumption of other components of the wireless transceiver. Thus, the energy savings achieved in a realistic setting might be considerably different than predicted by Equation (31.1). This point is discussed in detail in the remainder of the chapter.

Several topology control protocols have been recently proposed in the literature[2,3,12,15,16,25,27,33]. They differ in the type of topology generated and in the way it is constructed. Typically, the goal of a topology control algorithm is to build a connected and relatively sparse communication graph that can be easily maintained in the presence of node mobility. Having a sparse communication graph has the further

*We recall that the goal of cooperative strategies is to reduce energy consumption *while preserving capacity (hence, connectivity) as much as possible.*

advantage of making the task of finding routes between nodes easier because there are relatively few paths between source–destination pairs. For a survey on topology control, the reader is referred Ref. 24.

Energy-efficient routing protocols[4–6,11,31] can be used in conjuntion with either cooperative approaches or topology control to produce further energy savings. Most of these works are targeted toward ad hoc networks, while Heinzelman et al.[11] consider sensor networks. In our traffic model used to compare the two approaches, we assume the most energy-efficient paths are used without specifically considering the underlying routing algorithm. This follows our philosophy of attempting to evaluate the network lifetime extensions possible with these approaches under the best possible conditions.

31.3 Overview of System Model

We consider a set of n nodes distributed uniformly at random over a fixed-size region. In Section 31.4, where we derive an analytical lower bound on network lifetime for cell-based approaches, we consider one-, two-, and three-dimensional regions, but we make the simplifying assumption that network traffic is uniformly distributed over the cells in the region. Beginning with Section 31.5, we focus on two-dimensional regions, which are the most common scenario, and we consider a more realistic traffic model. For this situation, we assume that sensor nodes supply data to external entities through a set of k gateway nodes, also referred to as data collection sites, which are distributed uniformly at random across the boundary of the region. The traffic model consists of all sensor nodes communicating an equal amount of traffic to their closest (in an energy cost sense) data collection site.

We assume that the nodes have uniform transceivers, each of which has a maximum communication range r. We assume that the energy-intensive RF communication is the dominant energy cost incurred by the nodes. When analyzing cooperative approaches, we assume that nodes have the capability to shut down their transceivers; and for topology control protocols, we assume the ability to vary the transmit power used by the transceivers. Because the energy used when no energy conservation measures are employed is highly dependent on r, we compare both approaches against the situation where r is chosen *a priori* as small as possible while still guaranteeing that the resulting network is connected with high probability. Such a choice can be considered a simple static form of topology control, which is already a crude mechanism for energy conservation. Thus, the lifetime extensions we report for the two approaches are improvements over and above those achieved by this simple energy conservation mechanism.

This system model corresponds to a class of sensor networks where the network is active at all times or at least is periodically active. That is, there is a continuous or regular quantity to be measured by the network, and this requires regular communication across the network. Another class of sensor networks are event driven; that is, they monitor for specific events and might only need to communicate information when those events occur. In event-driven sensor networks, other energy conservation approaches are likely to be more effective than those studied herein (e.g., using ultra-low-power wake-up channels to wake up nodes and turn on their higher-power radios only when absolutely necessary).

More details on our precise assumptions are provided in the next section.

31.4 A Lower Bound to Network Lifetime for an Idealized Cell-Based Energy Conservation Approach

Measurements of the energy consumption of the Medusa II sensor node have shown that the energy required to sense the channel is only about 15 percent less than the energy required to transmit.[23] In nodes such as these, approaches to energy conservation that completely shut down the network interface during idle periods therefore seem to have the most promise in terms of network lifetime extension. In this section, we analyze an idealized version of a popular class of these approaches, which we refer to as cooperative cell-based energy conservation.

31.4.1 A Model for Idealized Cell-Based Energy Conservation

The effectiveness of a cooperative strategy depends heavily on the node density. Intuitively, if node density is low, almost all the nodes must stay up all the time, and no energy saving can be achieved. Considering the overhead required for coordination of nodes, the actual network lifetime could actually be reduced with respect to the case where no cooperative strategy is used. Conversely, if node density is high, consistent energy savings (and, consequently, extension of network lifetime) can be achieved. This behavior is displayed by the GAF protocol,[34] while the energy savings achieved by SPAN does not increase with node density. This is due to the fact that the overhead required for coordination with SPAN tends to "explode" with node density, and thus counterbalances the potential savings achieved by the increased density. For this reason, in the following we focus attention primarily on a class of approaches based on the GAF protocol, that is, cell-based cooperative energy conservation techniques. Several existing protocols fall into this category.[30,34]

Observe that the positive effect of an increased node density on network lifetime could be counterbalanced by its detrimental effect on the network capacity. In fact, it is known that, for stationary networks, the network capacity does not scale with node density, and the end-to-end throughput achievable at each node goes to 0 as the density increases.[10] Furthermore, increasing node density entails a higher network cost. On the other hand, node density cannot be too low because, otherwise, network connectivity would be impaired. Hence, the trade-off between node density, network lifetime, and capacity/cost must be carefully evaluated. As a first step in this direction, in the following we investigate the relation between the expected benefit of cooperative strategies and the node density, under the following simplifying hypotheses:

- *a1*. n nodes are distributed uniformly and independently at random in $R = [0, l]^d$, with $d = 1, 2, 3$.
- *a2*. Nodes are stationary.
- *a3*. Nodes can communicate directly when they are at distance at most r; that is, there exists the bidirectional link (i, j) in the communication graph if and only if $\delta_{i,j} \leq r$.
- *a4*. r is set to the minimum value of the transmitting range that ensures that the communication graph is connected with high probability.
- *a5*. F is defined as the capability of nodes in S to relay messages on behalf of the remaining nodes, without compromising network connectivity. To this end, R is divided into nonoverlapping d-dimensional cells of equal side $\frac{r}{2\sqrt{d}}$*1. The total number of cells is then $N = \frac{k_d l^d}{r^d}$, where $k_d = 2^d d^{d/2}$.
- *a6*. We consider an ideal cooperative strategy, in which the overhead needed to coordinate nodes amongst themselves is zero. Hence, the energy savings derived in the following can be seen as the best possible a cooperative strategy can achieve.
- *a7*. Network lifetime is defined in terms of connectedness.
- *a8*. The traffic is balanced over all cells.
- *a9*. The energy consumed by other components of a node is negligible compared to the energy consumption of its transceiver.

Observe that, by Assumption *a8*, all cells are subject to the same load. If this load must be handled by a single node, it will die at the *baseline time* T; however, if a cell contains h nodes, the load can be evenly divided among them, and it follows from Assumptions *a6* and *a9* that the last node in the cell will die at time hT. Hence, a lower bound to the network lifetime can be obtained by evaluating the probability distribution of the minimum number of nodes in a cell, and occupancy theory[13] can be brought to bear on the problem.

*This ensures that a node in one cell can communicate with all nodes in the complete neighborhood of cells surrounding it. Note that the side of the cell as defined here is slightly different from that used in the GAF protocol,[34] which ensures that nodes residing in a cell can communicate with all the nodes in the upper, lower, left, and right cell. However, this slight difference does not impair the validity of our analysis for the GAF protocol.

31.4.2 Analysis of the Lower Bound

In this section we will use the standard notation regarding the asymptotic behavior of functions, which we recall. Let f and g be functions of the same parameter x. We have:

$f(x) = O(g(x))$ if there exist constants C and x_0 such that $f(x) \leq C \cdot g(x)$ for any $x \geq x_0$
$f(x) = \Omega(g(x))$ if $g(x) = O(f(x))$
$f(x) = \Theta(g(x))$ if $f(x) = O(g(x))$ and $f(x) = \Omega(g(x))$. In this case, we also use the notation $f(x) \approx g(x)$
$f(x) = o(g(x))$ if $\frac{f(x)}{g(x)} \to 0$ as $x \to \infty$
$f(x) \ll g(x)$ or $g(x) \gg f(x)$ if $f(x) = o(g(x))$

The probability distribution of the minimum number of nodes in a cell can be evaluated using some results of occupancy theory,[13] which studies properties of the random independent allocations of n balls into N urns* when $n, N \to \infty$. Let $\eta(n, N)$ be the random variable denoting the minimum number of nodes in a cell. The form of the limit distribution (i.e., of the probability distribution of $\eta(n, N)$ when $n, N \to \infty$) depends on the asymptotic behavior of the ratio $\frac{\alpha}{\ln N}$, where $\alpha = \frac{n}{N}$. The following theorem holds:[13]

Theorem 31.1 *If $\frac{\alpha}{\ln N} \to 1$ as $n, N \to \infty$ and $h = h(\alpha, N)$ is chosen so that $h < \alpha$ and $Np_h(\alpha) \to \lambda$, where $p_h(\alpha) = \frac{\alpha^h}{h!}e^{-\alpha}$ and λ is a positive constant, then:*

$P(\eta(n, N) = h) \to 1 - e^{-\lambda}$
$P(\eta(n, N) = h + 1) \to e^{-\lambda}$

Theorem 31.1 states that if $\frac{\alpha}{\ln N} \to 1$ as $n, N \to \infty$, then $\eta(n, N)$ is either h or $h+1$ asymptotically almost surely** (a.a.s. for short), where h is such that $Np_h(\alpha) \to \lambda$, for some positive constant λ. Similar results[13] determine the limit distribution of $\eta(n, N)$ when $\frac{\alpha}{\ln N} \to x$, for some $x > 1$, or when $\frac{\alpha}{\ln N} \to \infty$. However, for our purposes, it is sufficient to note that denoting by $\eta_1(n, N)$, $\eta_x(n, N)$ and $\eta_\infty(n, N)$ the value of $\eta(n, N)$ for the three asymptotic cases, it is $\eta_1(n, N) \leq \eta_x(n, N) \leq \eta_\infty(n, N)$ a.a.s. This follows immediately by the fact that in the three asymptotic cases, either a strictly increasing number of nodes are distributed into the same number of cells, or the same number of nodes is distributed in a smaller number of cells.

Observe that Theorem 31.1 gives very precise information on the asymptotic value of $\eta(n, N)$, but gives no explicit value of h. To determine the value of h, we have to do some hypotheses on the relative magnitude of r, n, and l.

Assume $n = dk_d \frac{l^d}{r^d} \ln l$, where $d = 1, 2, 3$ and $k_d = 2^d d^{d/2}$. Further assume that $r \ll l$. With these hypotheses, we have $\lim_{l \to \infty} n = \infty$. Let $N = k_d \frac{l^d}{r^d}$ be the number of cells into which the deployment region $R = [0, l]^d$ is divided. Under the assumption $r \ll l$, we have $\lim_{l \to \infty} N = \infty$. That is, by setting n and N as above, we can use the results on the asymptotic distribution of the minimally occupied urn derived in the occupancy theory. In particular, we want to apply Theorem 31.1. To this end, we have to check that $\lim_{n,N \to \infty} \frac{\alpha}{\ln N} = 1$.

In the hypotheses above we have:

$$\lim_{n,N \to \infty} \frac{\alpha}{\ln N} = \lim_{l \to \infty} \frac{\ln l^d}{\ln \frac{k_d l^d}{r^d}}. \tag{31.2}$$

It is immediate to see that the limit above equals 1 under the further assumption that $r^d = \Theta(1)$ (we remark that this assumption does not contradict assumption $r \ll l$).

*For consistency, in the following we will use the words *node* and *cell* instead of *ball* and *urn*, respectively.

**We say that an event E_m, describing a property of a random structure depending on a parameter m, holds *asymptotically almost surely* if $P(E_m) \to 1$ as $m \to \infty$.

We are now in the hypotheses of Theorem 31.1. What it is left to do is to determine h such that $h < \alpha$ and $Np_h(\alpha) \to \lambda$, where λ is a positive constant.

Define $h = \alpha - \epsilon$, where ϵ is an arbitrarily small, positive constant. It is immediate to see that $h < \alpha$. Let us now consider $\lim_{n,N\to\infty} Np_h(\alpha)$. Under the hypotheses above, the limit can be rewritten as:

$$\lim_{l\to\infty} \frac{k_d(\ln l^d)^h}{r^d h!} \tag{31.3}$$

Because $r^d = \Theta(1)$ by assumption, (31.3) $\approx \frac{(\ln l^d)^h}{h!}$. Taking the logarithm, we have:

$$\ln \frac{(\ln l^d)^h}{h!} = h \ln(\ln l^d) - \ln h! \approx h \ln(\ln l^d) - h \ln h = h \ln \frac{\ln l^d}{h}$$

Plugging $h = \alpha - \epsilon$ into the equation above, we obtain:

$$(\ln l^d - \epsilon) \ln \frac{\ln l^d}{\ln l^d - \epsilon} = (\ln l^d - \epsilon) \ln \left(1 + \frac{\epsilon}{\ln l^d - \epsilon}\right)$$

Because $\epsilon/(\ln l^d - \epsilon) \to 0$ for $l \to \infty$, we can use the first term of the Taylor expansion and write:

$$(\ln l^d - \epsilon) \ln \left(1 + \frac{\epsilon}{\ln l^d - \epsilon}\right) \approx (\ln l^d - \epsilon) \frac{\epsilon}{\ln l^d - \epsilon} = \epsilon > 0.$$

Thus, we have proved that, defining h as above, we have $Np_h(\alpha) \to \lambda$ for some positive constant λ. We can then conclude that when $n = dk_d \frac{l^d}{r^d} \ln l$, $r \ll l$, and $r^d \in \Theta(1)$, the minimum number of nodes in a cell is at least $h = \ln l^d - \epsilon$ a.a.s. Note that this condition implies that every cell contains at least one node a.a.s, which in turn implies that the network is connected a.a.s. So, in the conditions above, we also have a.a.s. connectivity.

What happens if n is set as above but $r^d \gg 1$? In this case, we can prove by a scaling argument (i.e., by dividing r, n, and l by r) that a similar result holds under the assumption $r \in O(l^\beta)$, for some $0 < \beta < 1$. However, in this case we are able to prove a less precise result, that is, that $h \in \Omega(\ln l)$. Finally, what happens if $n > dk_d \frac{l^d}{r^d} \ln l$? For any possible setting of r (intended as a function of l) with $r \in O(l^\beta)$, we have just proved that the minimum cell occupancy is at least $h \in \Omega(\ln l)$ when $n = dk_d \frac{l^d}{r^d} \ln l$. So, if we increase n with respect to this value, we can only increase the cell occupancy (recall that N does not depend on n) and the statement still holds. We can then conclude with the following theorem.

Theorem 31.2 *Assume that n nodes with transmitting range r are distributed uniformly and independently at random in $R = [0, l]^d$, for $d = 1, 2, 3$, and assume that $n \geq d \cdot k_d \frac{l^d}{r^d} \ln l$, where $k_d = 2^d d^{d/2}$. Further assume that $r \in O(l^\beta)$, for some $0 < \beta < 1$. If a cooperative strategy is used to alternately shut down "routing equivalent" nodes, then $P(NL_l \geq hT) \to 1$ as $l \to \infty$, where NL_l is the random variable denoting network lifetime and $h \in \Omega(\ln l)$.*

It turns out that the condition on n stated in Theorem 31.2 is also a sufficient condition for obtaining a.a.s. connectivity (see Theorem 8 in Ref. 29). Thus, Theorem 31.2 gives a lower bound to an ad hoc network's lifetime under a sufficient condition for the network to be connected with high probability.

It should be observed that in the optimal case, that is, when the n nodes are evenly distributed into the N cells, the network lifetime is exactly $d \cdot k_d \ln l$. The result stated in Theorem 31.2 therefore implies that, in the case of nodes distributed uniformly at random, the network lifetime differs from the optimal at most by a constant factor.

31.4.3 Limitations of the Analysis

The lower bound of Theorem 31.2 on network lifetime is mainly of theoretical interest for $d = 2, 3$. This is because reported simulations[30] have shown that, while the sufficient condition for a.a.s. connectedness is tight for $d = 1$, it becomes looser for two- and three-dimensional networks. Thus, the transmitting range r specified in the theorem might actually be substantially larger (or equivalently, the node density might be substantially greater) than what is necessary for connectedness for higher-dimensional regions. Hence, a careful evaluation of network lifetime under true minimum density conditions is still necessary. Identifying the true minimum density condition would also allow us to study the scalability of network lifetime with node density. These would provide a more accurate picture of the lifetime extension possible for cell-based approaches for $d = 2, 3$. Simulations investigating this issue were reported.[1] The remainder of this chapter focuses on $d = 2$ and compares cell-based approaches against topology control.

To make the preceding analysis tractable, we made use of Assumption *a8*, which states that traffic is balanced over all cells. In a realistic environment, this balanced traffic assumption will not hold. This assumption was also used in the simulation results.[1] In the next section, we present a more realistic traffic model that is designed for sensor networks.

The next section complements the analysis of this section by identifying (through simulation) the true minimum density conditions for $d = 2$ and formulating a more realistic traffic model. These are then used in simulations to perform a comprehensive evaluation and comparison of cell-based approaches and topology control.

31.5 A Framework for Comparison of Topology Control and Cell-Based Approaches

In this section, we define a framework for the comparison of cell-based and topology control techniques. The framework is *unified* because we make the same assumptions (to the extent to which this is possible*), especially on what concerns the traffic and the energy model. This framework builds on the idealized model presented in Section 31.4 for cell-based strategies.

31.5.1 The Cooperative Cell-Based Approach

As in Section 31.4, we focus on cell-based techniques because they appear to be the most promising of the cooperative approaches. In the remainder of the chapter, we adopt Assumptions *a1* through *a9* with the following changes. We restrict ourselves to the two-dimensional unit square region, as is common in ad hoc and sensor networks research, and we adopt a realistic traffic model, which is discussed in Section 31.5.3.

In view of Assumption *a6*, the energy savings derived in the following can be seen as the best possible any cell-based cooperative strategy can achieve. However, we want to remark that at least in the case a loose synchronization mechanism is available to the nodes, energy savings very close to this ideal value can be achieved in practice.[30] That is, at least under certain conditions, the message overhead required for node coordination can actually be considered negligible.

Assumption *a4* is motivated by the fact that, in principle, the nodes' transmitting range should be set to the minimum value that makes the communication graph connected, known as the *critical transmitting range*. When the transmitting range is set to the critical value, the network capacity is maximal and the node energy consumption is minimal.[8,10,14,17] Setting the transmitting range to the critical value can be seen as a limited form of topology control, in which all the nodes are forced to use the same transmit power. That is, the results presented in this chapter, both referring to cooperative strategies and topology control protocols, must be interpreted as relative lifetime extensions *with respect to a simple energy saving approach*. Thus, we believe that even relatively small lifetime extensions (say, in the order of 30 percent) can be regarded as significant in this setting.

Although computing the critical transmitting range in a distributed manner is feasible,[17] it is quite common to characterize it using a probabilistic approach, that is, determining the value r of the transmitting

*Some assumptions will be simply not relevant for the topology control setting.

range that ensures connectivity with high probability (w.h.p.).[9,28,29] In this chapter, we will follow this probabilistic approach (see Section 31.6 for details).

31.5.2 Topology Control Protocols

Ideally, a topology control protocol should build a connected and relatively sparse communication graph. Furthermore, the protocol should preserve energy-efficient links between nodes, while avoiding energy inefficient multihop paths. Another desirable feature of the communication graph is a small node degree, which in principle implies reduced interference between nodes. Finally, a topology control protocol should be able to build the communication graph using local information only, and exchanging as few messages as possible. Clearly, designing a protocol with all these features is not an easy task. Among the many protocols proposed in the literature, in this chapter we consider the CBTC protocol presented by Li et al.[15] and Wattenhofer et al.[33] and the KNeigh protocol. CBTC is one of the most popular topology control protocols, and is based on the idea of connecting each node to the closest node "in every direction," that is, in all nonoverlapping cones of a certain angle centered at the node. In KNeigh, every node is connected to the k closest neighbors, where k is a properly tuned network parameter. For details on these protocols, see Refs. 2, 15, and 33. The choice of considering these two protocols is motivated by the fact that they show good performance in terms of energy savings, and that they can be implemented exchanging relatively few messages. In particular, KNeigh requires that any node sends only two messages. Thus, our simplifying assumption of negligible message overhead (i.e., the counterpart of Assumption *a6*) can be regarded as quite realistic (at least in the case of stationary networks).

31.5.3 Multihop Traffic Generation

A typical strategy for generating multihop data traffic in WSN is the following: there are one or more fixed data collection sites (also called base stations) that are usually situated on the boundary of the deployment region; the (sensor) nodes generate CBR traffic directed to the collection sites. In this case, multihop traffic is generated when a node cannot reach a collection site directly.

In our experiments we have considered a variation of the above strategy. The basic idea is to compute the average load generated on every node when a (possibly) multihop message circulates in the network. We first compute, for every sensor node s, the most energy-efficient path $P_{sd} = \{s, u_1, \ldots, u_k, d\}$ that connects s to some data collection site d. If there are multiple energy optimal paths between a certain s, d pair, we randomly select one of them. Under the assumption that transmissions are perfectly scheduled (i.e., that no collision to access the wireless channel occurs), exactly $k + 1$ transmissions are needed to communicate a message from s to d. Using this information, the total number S_i of send operations and the total number R_i of receive operations performed by node i can be determined. The average load of node i when C multihop messages are transmitted in the network is then set equal to $C\frac{S_i}{n}$ send and $C\frac{R_i}{n}$ receive operations.

We stress that the above scheme (that uses energy-efficient routes) is only used to generate average node loads and does not prevent our approach from being used with any routing protocol.

31.5.4 The Energy Model

Our energy model for WSN is based on the measurements reported by Raghunathan et al.,[23] which refers to a Medusa II sensor node. That article reported the *sleep*:*idle*:*rx*:tx_{min}:tx_{max} ratios to be 0.235:1:1.008: 0.825:1.156, where tx_{min} corresponds to a transmit power of 0.0979 mW, and tx_{max} to a power of 0.7368 mW. The measurements refer to a data rate of 2.4 Kb/sec. Note that in this model, the energy consumed to transmit at minimum power is lower than that consumed to receive, or to listen the wireless channel (idle state). This means that nodes that reduce their transmitting range significantly will actually consume substantially less energy when transmitting than when receiving or listening. Thus, nodes that transmit a lot might actually live longer than nodes that do not transmit often. This point, which is quite counter-intuitive, will be carefully investigated in our simulations.

TABLE 31.1 Values of the Critical Transmitting Range r for Different Values of n

n	r	n	r
10	0.65662	250	0.15333
25	0.44150	500	0.10823
50	0.32582	750	0.08943
75	0.27205	1000	0.07656
100	0.23530		

31.6 Simulation Setup

In this section we discuss some details of our simulation setup, including (1) node placement, (2) routing, (3) traffic generation, (4) energy consumption, (5) simulation time period, and (6) network lifetime definition.

31.6.1 Node Placement and Communication Graph

The simulator distributes n nodes in the deployment area $R = [0, 1]^2$ uniformly at random. Then it distributes $k = 4k'$ data collection sites in the region's boundary according to the following rule: for each side of R, k' base stations are located uniformly at random on that side. The transmitting range of a node depends on the particular scenario. In case of no energy saving (NES) or cell-based (CB) approach, this is set to the critical value r for connectivity (see Assumption *a4*). The values of the critical transmitting range are taken from Santi and Blough.[29] and are reported in Table 31.1. These values of r are also used to define the desired cell size in the CB scenario.

Under topology control, the transmitting range depends on the node placement itself and the particular protocol considered (CBTC or KNeigh). At the end of the execution of a given protocol,* a node u in the network is assigned a certain transmitting range r_u, with $r_u \leq r$.

For a given placement of the nodes, we then build the communication graph as follows:

- In the NES and CB scenario, we insert a bidirectional edge (i, j) whenever nodes i and j are at distance at most r (see Assumption *a3*).
- In case of topology control, we put a bidirectional edge between nodes u and v if and only if $\delta(u, v) \leq \min\{r_u, r_v\}$, where $\delta(u, v)$ denotes the Euclidean (two-dimensional) distance between u and v.

Note that, in all cases, we only consider bidirectional communication links.

The communication graphs generated by the various topology control protocols for a particular random instance are shown in Figure 31.1(b) and (c). Figure 31.1(a) shows the communication graph on the same set of nodes in the NES/CB scenario.

31.6.2 Routing

We assume that messages are routed along the most energy-efficient path from a sensor node to any data collection site. Note that in the NES/CB scenario in general, there exist several paths with minimal energy consumption for a given sensor node. In fact, the nodes use the same transmitting power, and any path connecting s to a collection site with minimum hop count is optimal from the energy efficiency

*In case of CBTC, the cone width is set to $2/3\pi$ (see Ref. 33 for details); the value of k in KNeigh is chosen according to the data reported by Blough et al.[2]

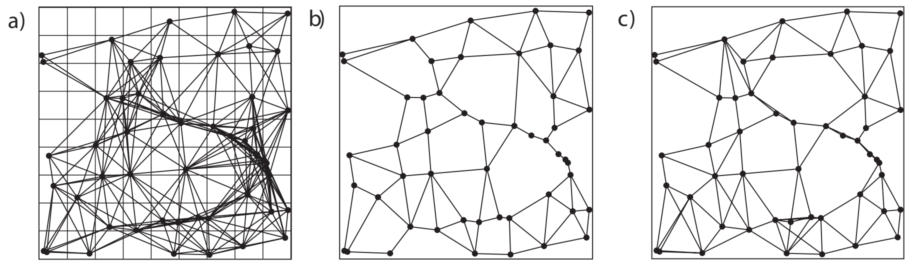

FIGURE 31.1 Communication graphs in the NES/CB scenario (a), and with CBTC (b) and KNeigh (c) topology control.

point of view. Thus, we must define a strategy to route the messages from the sensor node to the closest collection site in this scenario. In our simulation, we have implemented a cell-based routing algorithm, which can be seen as an instance of the widely studied class of geographical routing algorithms.

The cell-based routing algorithm is defined as follows. Given the communication graph G, we build a *cell graph* CG by inserting one node for every non-empty cell. Then we insert the bidirectional edge (i, j) in CG if and only if there exist nodes u, v in G such that $u \in C_i$, $v \in C_j$, and $(u, v) \in G$, where C_i (resp., C_j) denotes the cell to which node i (resp., j) corresponds. For any node x, let i_x denote the node in CG that corresponds to the cell to which x belongs. Now, for any source s, we compute one possible single source shortest path tree rooted at i_s, by selecting at random the node to be expanded next, among those eligible, in the classical Dijkstra's algorithm. We then use such tree for all the messages originating at s.

Note that the cell-based routing algorithm defined above does not specify completely the path from the source to the collection site: nodes in the same cell are perfectly equivalent from the routing algorithm's point of view, thus capturing the intuition upon which the cell-based strategy is founded. Indeed, the routing algorithm, as defined here, does not account for possible intra-cell communications needed to transmit/receive the message to/from the current leader node. That is, we make the following assumption, which is coherent with our idealized setting: node states and transmissions are perfectly scheduled; that is, when a node is scheduled to transmit/receive, it is also active.

31.6.3 Traffic Load

For the cell-based approach, we first compute the cell load by assigning counters S and R (see Section 31.5.3) to every cell in CG. For every sensor node, we select the path in CG that connects the corresponding cell to a collection site using the routing algorithm specified above and update the counters accordingly. The load of each cell C_i is then equally subdivided among the $n_i \geq 1$ nodes in it. That is, we assume that the routing algorithm is "smart," and that it perfectly balances the load between the nodes in the same cell. The assumption of perfect balance is again coherent with our idealized setting.

In the case of topology control, the evaluation of the per-node load is simpler because the minimum energy path that connects any sensor node to a data collection site is unique.

In both cases, the load is then normalized with respect to the total number of sensor nodes, and multiplied by n (i.e., we assume that n multihop messages, one for each node, are generated in the network). An example of the load generated in the NES/CB and with KNeigh topology control when $n = 25$ is shown in Figure 31.2. The numbers refer to the values of the sum of the send and receive counters. In case of CB, the counters are referred to the cell, while in case of topology control they are referred to the nodes. As expected, when an equal number of multihop messages circulate in the network, the traffic generated with topology control is higher than in the NES/CB scenario. This is due to the fact that the average hop distance between nodes and the closest base station is larger in case of topology control. For example, in Figure 31.2, a total of 33 send/receive operations are performed in the NES/CB scenario, while 65 operations are performed in the case of topology control.

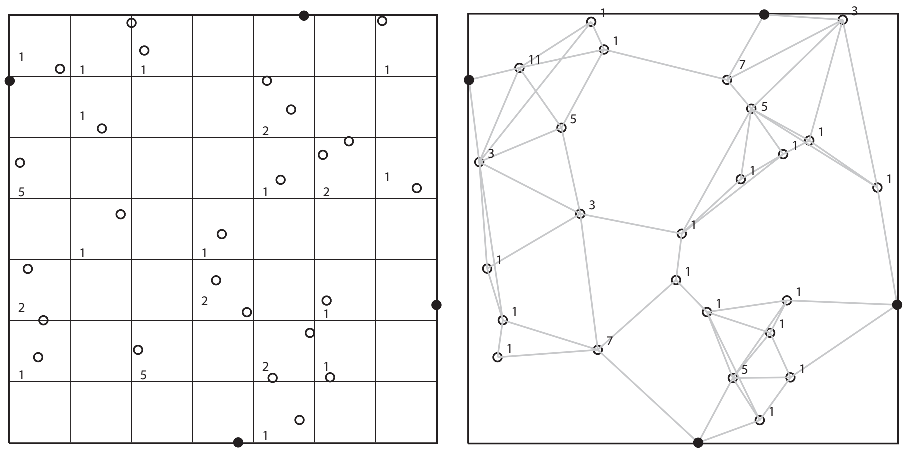

FIGURE 31.2 Load generated when $n = 25$ multihop messages are circulating in a network composed by n nodes in the NES/CB scenario (left) and with KNeigh topology control (right). Nodes (cells in the NES/CB scenario) are labeled with the sum of their S and R counters.

31.6.4 Energy Consumption

Let us first consider the NES scenario. Let $L_i = S_i + R_i$ be the overall load of cell C_i, and let n_i be the number of nodes in C_i. Assuming no contention, cell C_i will take L_i time units to handle the traffic. Let us consider a period of time T, with $T > L_i$ (we discuss how to set T later). If the traffic load in each cell is evenly distributed, every node in C_i spends $\frac{L_i}{n_i}$ units of time sending or receiving messages. The amount of energy consumed by a node $u \in C_i$ in this period is $\frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$, where rx is the energy needed to receive a message and tx_{max} is the energy needed to send a message at distance r.* In the remaining time $T - \frac{L_i}{n_i}$ of the period, the node remains idle, consuming one unit of energy per time unit. Thus, the energy consumption of node u during the period T is $E_u^{NES} = T - \frac{L_i}{n_i} + \frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$. Dividing this value by T, we obtain the average energy consumption per time unit of node u during the period T. Assuming that the traffic load is time invariant, the average energy consumption per time unit can then be used to compute the lifetime of node u.

Let us now consider the CB scenario. Every node in cell C_i sleeps for a fraction $(1 - \frac{1}{n_i})$ of the time period T. During this time, any node $u \in C_i$ has an energy consumption of $sleep \cdot (1 - \frac{1}{n_i})T$. In the fraction $\frac{T}{n_i}$ of the period, node u is active and spends $\frac{L_i}{n_i}$ units of time sending/receiving, consuming $\frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$ units of energy. In the remaining $\frac{T - L_i}{n_i}$ units of time, the node is idle, consuming $\frac{T - L_i}{n_i}$ units of energy. Thus, the energy consumption of node u during the period T is $E_u^{CB} = sleep \cdot (1 - \frac{1}{n_i})T + \frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i} + \frac{T - L_i}{n_i}$. As in the previous case, we divide this value by T, obtaining the average energy consumption per time unit which will be used to evaluate the lifetime of node u.

Finally, let us consider the case of topology control. Let again S_u (respectively, R_u) denote the number of send (respectively, receive) operations performed by node u (its load), and let us consider a period of time T as above. The node requires $L_u = S_u + R_u$ time units to handle the traffic, consuming $rx \cdot R_u + f(r_u) \cdot S_u$ units of energy. Here, r_u is the transmitting range of node u as set by the topology control protocol, and $f(r_u)$ is defined as follows: $f(r_u) = tx_{min} + (tx_{max} - tx_{min}) \cdot (r_u/r)^2$. With this definition, we have $f(0) = tx_{min}$ (energy consumed to send a message at minimum transmit power), and $f(r) = tx_{max}$ (when the transmitting range is set to the critical value r, the unit consumes energy tx_{max} to send a

*Without loss of generality, we assume that the power needed to transmit a message at distance r is the maximum transmit power.

message). In the remaining time $T - L_u$, node u remains idle, consuming $T - L_u$ units of energy. Thus, the energy consumption of node u during the period T is $E_u^{TC} = rx \cdot R_u + f(r_u) \cdot S_u + T - L_u$.

Note that in order to reduce the complexity of our experiments, we made some simplifying assumptions: no contention, traffic load evenly distributed in the cell, and time invariant traffic load. Admittedly, these assumptions may affect the significance of the *absolute* figures obtained. While this is clearly a point that deserves more investigations (see also Section 31.8), we observe that here we are primarily interested in the *relative* values of network lifetime extensions.

31.6.5 Simulation Time Period

The value of T is set as follows. Let $\bar{L}_i$ be the average per-cell load in the NES/CB scenario; T is set to $k \cdot \bar{L}_i$, where k is a parameter that accounts for the network load. For example, setting k to 10 corresponds to considering a network in which (on the average) a cell spends 10 percent of the time in communications.

31.6.6 Network Lifetime

We have used three different definitions of network lifetime, which are representative of notions of lifetime commonly used in the literature and which account for connectivity and the number of alive nodes.

Definition 31.1 Network lifetime is defined as:

1D: the time for the first node to die
DISC: the time to network disconnection
90LC: let N_C be the set of nodes which are connected to at least one data collection site; 90LC is defined as the time for $|N_C|$ to drop below $0.9n$

Before concluding this section, we give a numerical example of the node energy consumption computed according to the traffic and energy models described above. Recall that the power ratios we assume are *sleep:idle:rx:tx*$_{min}$*:tx*$_{max}$ equal to 0.235:1:1.008:0.825:1.156. Suppose node u belongs to cell C_i, with $n_i = 3$, and assume $S_i = R_i = 5$. Let us set k to 20, which corresponds to a 5 percent average load scenario. We have $T = 100$, and the energy consumption per time unit is 1.002 in the NES scenario and 0.492 in the CB scenario. Suppose that the load of node u in the KNeigh scenario is $S_u = R_u = 12$ and that $r_u = \frac{r}{2}$. With these settings and the same value for T, we obtain an energy consumption per time unit of 0.989. Setting $k = 5$ (20 percent average load) yields an energy consumption per time unit of 1.011, 0.501, and 0.959 in the NES, CB, and KNeigh scenarios, respectively. Note that the energy consumption in the KNeigh is comparable to that in the NES scenario, and that considerable savings are achieved only with the cell-based approach. It is interesting to note that, in the KNeigh scenario, an increased traffic load results in decreased energy consumption.

31.7 Simulation Results

The goal of our simulation experiments is to answer the following questions:

- Given the same "minimal" node density for connectivity, which one between cell-based and topology control is more effective in extending network lifetime?
- How does the lifetime extension achieved by the two approaches scale with the node density?

We have performed experiments considering three values of the average load (5, 10, and 20 percent), three definitions of lifetime (1D, DISC, and 90LC), and different numbers of base stations (4, 8, and 12). Due to space limitations, we report only the most representative results. In particular, we have observed very similar performance in case of 1D and DISC lifetime definition. In case of CB, this is due to the fact that nodes tend to die in groups: first those that are alone in their cell, then those that are in a cell with two nodes, and so on. Because in the minimum density scenario cells on the average contain relatively few nodes,[1] the death of the nodes in the first group is very likely to disconnect the network. In the case of topology control, the graphs generated are quite sparse (see Figure 31.1), so the death of the first node is quite likely to disconnect the network also. Given this observation, in the following we report only the results obtained with the 1D and 90LC lifetime definition.

The results obtained with CBTC and KNeigh are practically indistinguishable in all the experiments. For this reason, in the graphics we report only the plots relative to the KNeigh protocol.

All the results reported are averaged over 1000 experiments.

31.7.1 Lifetime with Minimum Density

In the first set of experiments, we evaluated network lifetime in the NES, CB, and topology control scenarios under the hypothesis that the node density is the minimal for connectivity: given a value of n, we have set the maximum transmitting range to the critical value, as reported in Table 31.1.

The results of our simulations in the case of four data collection sites and 5 percent average load when network lifetime is defined as 1D are reported in Figure 31.3. The results of the same experiments with 20 percent average load are reported in Figure 31.4. Figures 31.5 and 31.6 report the results of similar experiments obtained with the 90LC lifetime definition.

A few remarks are in order:

- Topology control outperforms the CB strategy in all the experiments performed. However, the relative advantage of topology control with respect to CB depends heavily on the definition of lifetime: it is very evident with the 1D definition, while it is only marginal in case of 90LC definition. This indicates that topology control significantly postpones the times of first node death and loss of connectivity, but does not postpone the time at which large numbers of nodes begin to die, relative to the static and homogeneous range assignment policy embodied by NES.
- In absolute terms, topology control achieves considerable savings with respect to the NES scenario, as high as 370 percent for large networks with high load and 1D lifetime definition.

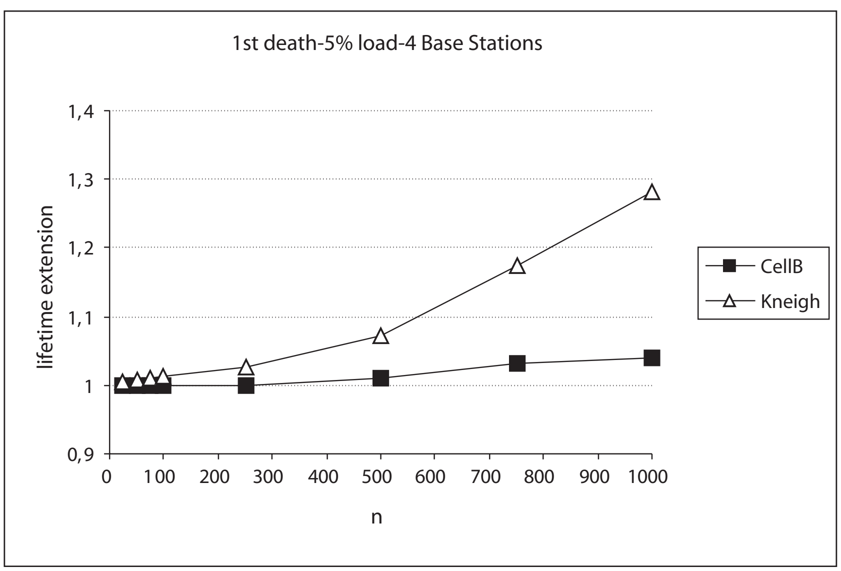

FIGURE 31.3 Lifetime extension for the CB strategy and KNeigh topology control for increasing values of n. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. Four base stations are used to collect data, and the average load is 5 percent.

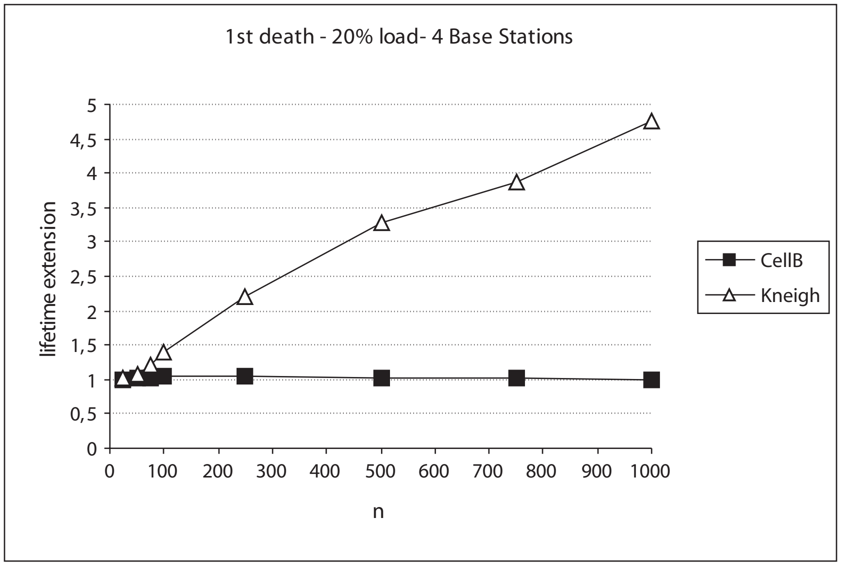

FIGURE 31.4 Lifetime extension for the CB strategy and KNeigh topology control for increasing values of *n*. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. Four base stations are used to collect data, and the average load is 20 percent.

The fact that topology control provides relatively better performance with high network load deserves some discussion as well. This better performance is due to the fact that nodes in NES transmit at maximum power. Thus, the large number of send operations generated in the 20 percent load scenario induces a better relative performance of topology control.

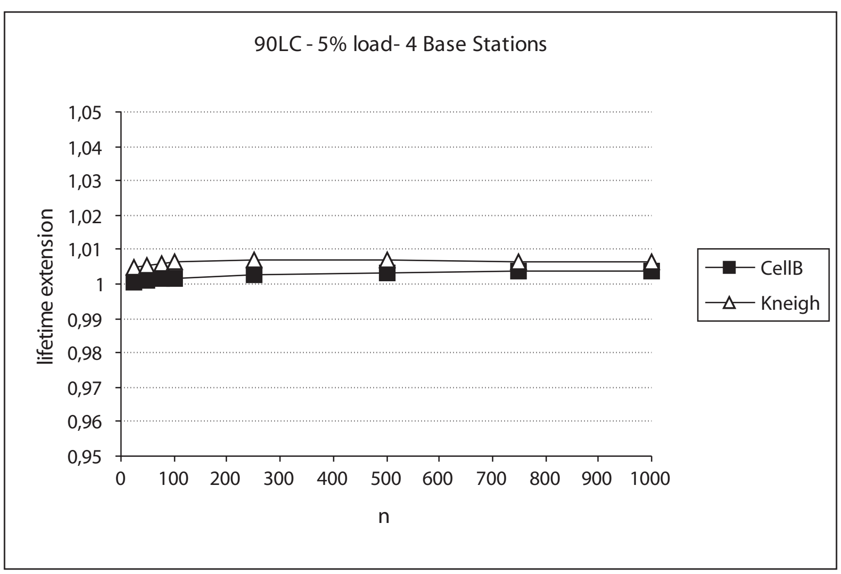

FIGURE 31.5 Lifetime extension for the CB strategy and KNeigh topology control for increasing values of *n*. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. Four base stations are used to collect data, and the average load is 5 percent.

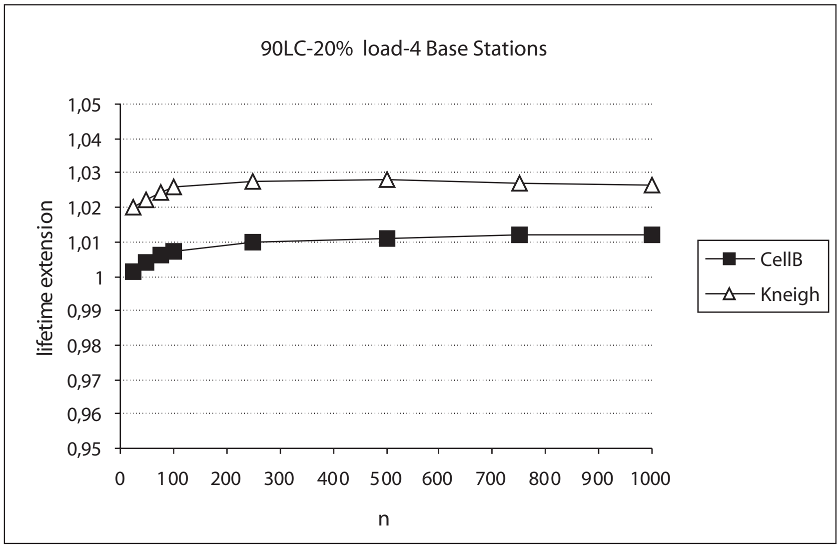

FIGURE 31.6 Lifetime extension for the CB strategy and KNeigh topology control for increasing values of *n*. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. Four base stations are used to collect data, and the average load is 20 percent.

We have repeated a similar set of experiments varying the number of data collection sites (4, 8, and 12 sites). The only difference with respect to the previous results is a somewhat decreased performance of topology control with respect to NES. For example, Figure 31.7 reports the results of the simulations with 12 base stations, the 1D definition of lifetime, and 20 percent load.

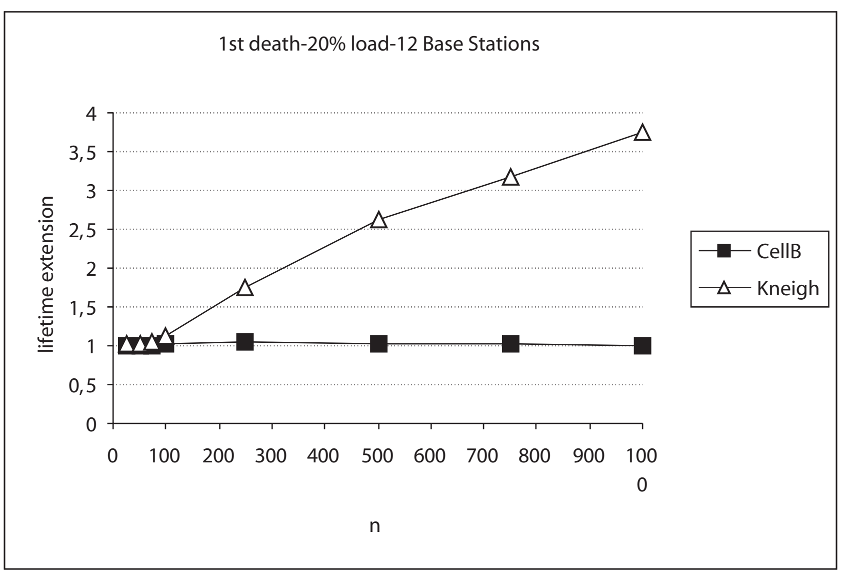

FIGURE 31.7 Lifetime extension for the CB strategy and KNeigh topology control for increasing values of *n*. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. Twelve base stations are used to collect data, and the average load is 20 percent.

31.7.2 Lifetime for Increasing Density

In the second set of experiments, we investigated how the lifetime extension achieved by CB and topology control scales with node density, relative to the minimum density scenario with $n = 50$ (hence with $r = 0.32582$, see Table 31.1). We increased node density by distributing ρn nodes and leaving the value of the transmitting range, and consequently also the cell size, unchanged. As the expected number of nodes in a cell is ρ times that of the minimum density scenario, the CB strategy is likely to achieve better energy savings as ρ increases. In case of the topology control, we simply computed the various topologies on the set of nodes as in the previous experiments. In this situation, the advantage of having a higher node density is that the transmitting range r_u of a generic node u is likely to be smaller than in the minimum density scenario. Thus, because $r = 0.32582$ independently of the node density, the node lifetime should, in principle, be longer than in the case of minimum density. However, whether or not the relative savings of topology control with respect to the NES scenario increase with density is not clear, due to the effect of multihop data traffic. This effect can be explained as follows. In the NES scenario, when the density is very high, the average hop-length between node pairs tends to be quite small, because the transmitting range is fixed. On the other hand, in the case of topology control the nodes' transmitting ranges are adjusted in order to build a sparse graph even when the node density is very high. Because the absolute number of nodes in the network increases, the average hop-length between node pairs increases as well. Because there is a considerable fixed energy cost associated with any one-hop communication, it could be the case that the high average hop-count in case of topology control counterbalances the potential benefits of the reduced transmitting ranges.

The results of our experiments for values of ρ ranging from 1 to 10 (i.e., n ranging from 50 to 500) are reported in Figures 31.8 and 31.9, which refer to a 20 percent load with 1D and 90LC lifetime definitions, respectively. The number of base stations is set to 4. Contrary to the previous set of experiments, we have obtained very similar results for low load (5 percent), and for different number of data collection sites. For this reason, the results of these experiments are not reported.

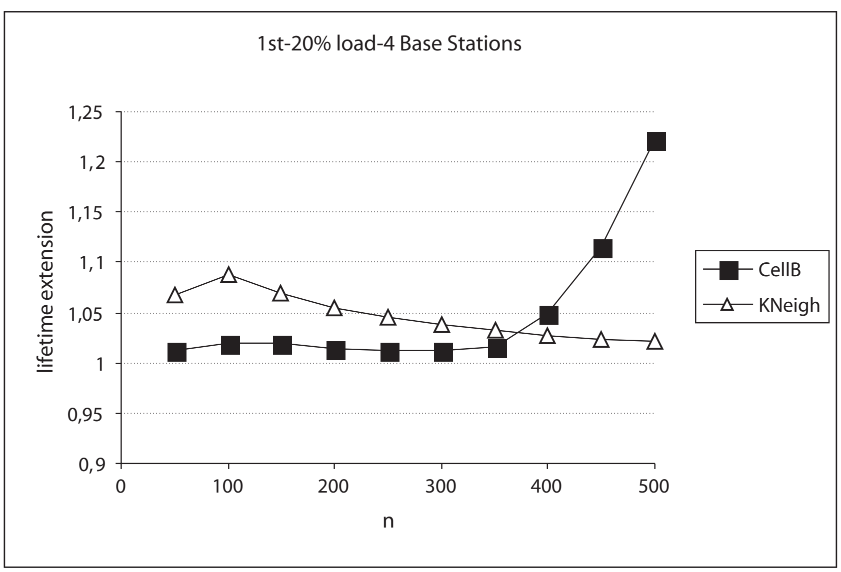

FIGURE 31.8 Lifetime extension for increasing values of the node density ρ. Network lifetime is defined as the time for the first node to die, and is expressed as a multiple of the lifetime in the NES scenario. The number of base stations is set to 4, and the load is 20 percent.

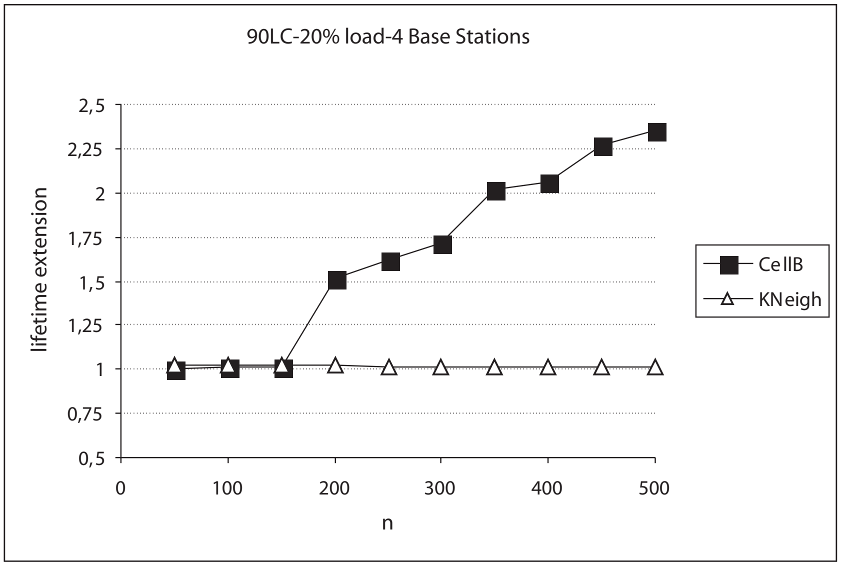

FIGURE 31.9 Lifetime extension for increasing values of the node density ρ. Network lifetime is defined as 90LC, and is expressed as a multiple of the lifetime in the NES scenario. The number of base stations is set to 4, and the load is 20 percent.

We remark that:

- The situation is reversed with respect to the case of minimum node density: with high node density, CB performs considerably better than topology control, especially when lifetime is defined as 90LC. In this case, CB can extend network lifetime by as much as 130 percent as compared to NES. Note, however, that when 1D lifetime is considered, node density must be *very* high before the benefits of CB become clear. For example, even when 3.5 times the minimum number of nodes are present, the lifetime extension is only about 1 percent. The benefits of CB become clear much earlier when considering the 90LC lifetime definition.
- The potential benefits of topology control due to the reduced transmit power consumption and the negative effect of the increased average hop-length balance almost perfectly, Almost independently of the node density, topology control protocols achieve basically the same savings as in the NES scenario. We believe this result is quite interesting and should not be underestimated. In fact, topology control has the potential to increase considerably the network capacity in very dense networks. So, increasing capacity while saving as much energy as a very simple energy saving technique is a very good feature in this scenario.
- As in the previous case, the definition of lifetime has a strong influence on the investigated energy saving techniques. For example, if we consider the 1D definition, CB extends lifetime by as much as 23 percent with respect to NES; with the 90LC definition, the relative extension can be as high as 130 percent. Note, however, that differently from the minimum density scenario, the better savings are achieved with the 90LC lifetime definition.

31.8 Discussion and Future Work

Our study has yielded a number of interesting insights into the issue of network lifetime and the studied approaches to energy conservation. First, we have seen that the lifetime definition has a significant effect on the results, both at minimum node density and at higher densities. We found that, in minimum density conditions, topology control was effective at postponing the times until first node death and loss of connectivity, but it was not effective at delaying the time at which large numbers of nodes die. Conversely, at moderately high densities, we found that the cell-based cooperative approach was able to significantly increase the lifetime when it is defined in terms of a large number of node deaths, but it did not significantly delay the times to first node death and connectivity loss. At very high densities, the cell-based approach significantly extends network lifetime according to all of the definitions we considered.

In comparing the cell-based approach with topology control, we can summarize the results as follows. When node density is near the minimum necessary for connectivity and the number of nodes is large, topology control performs better. However, the cell-based cooperative approach has a clear performance advantage over topology control at higher node densities. It is worth repeating that for lifetime definitions of first death and loss of connectivity, we have found that node density must be very high (at least four times more nodes than necessary for connecticity) to achieve significant benefits.

There are several points worthy of additional research.

- *Consideration of the relative performances of the two approaches in ad hoc networks*. Both the energy consumption parameters as well as the traffic model must be altered to consider an ad hoc network environment. It is not at all clear that the results we report herein will translate to this different setting.
- *Accounting for channel contention*. In general, topology control increases network capacity because of reduced contention. This fact has not been considered herein, where contention is nonexistent due to the perfect scheduling assumption. Indeed, achieving perfect scheduling in CB, especially with moderate load, could be very difficult. Refining our analyses to take collisions into account is the subject of future work.
- *Investigating the combined benefits of topology control in terms of energy reduction and capacity improvement*. In this chapter, we focused solely on evaluation of energy conservation. However, as noted earlier, topology control has the added benefit of reducing channel contention and therefore increasing overall network capacity. Quantifying the capacity improvement attained by topology control, and combining this with its energy reduction benefits to present a complete picture of its capabilities, is a worthy endeavor.

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