A Cooperative Approach for Topology Control in Wireless Sensor Networks

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Abstract

The choice of the transmission power levels adopted in Wireless Sensor Networks (WSNs) is critical to determine the performance of the network itself in terms of energy efficiency, connectivity and spatial reuse, since it has direct impact on the physical network topology.

In this paper, a cooperative, lightweight and fully distributed approach is introduced to adaptively tune the transmission power of sensors in order to match local connectivity constraints. To accurately evaluate the topology control solution, a small-scale testbed based on MicaZ sensor nodes is deployed in indoor and outdoor scenarios. Practical measures on local and multi-hop connectivity, convergence time and emitted power are used to compare the proposed approach against previous solutions. Moreover, mathematical programming formulations of the topology (power) control problem are introduced to assess the optimality of the distributed algorithm. Finally, simulation analysis complements the experimental evaluation in large-scale static and mobile WSN scenarios, where a testbed implementation becomes unfeasible.

1 Introduction

Wireless Sensor Networks (WSNs) are increasingly emerging as a viable solution to support several types of applications ranging from environmental and building monitoring to object tracking and exploration of remote areas through mobile robots [1]. The wireless connectivity and the compact sensors' size make WSNs suitable even in harsh environments, where human support and control are limited.

However, to fully unleash the potential of the WSN technology, large effort must be put forth by researchers and practitioners to devise energy-aware solutions preserving battery power. In particular, network topology has a huge impact on efficiency: at the MAC layer, the more connected is the network the higher is the collision probability, whereas the routing layer requires high connectivity degrees to set up effective routes. Hence, the availability of a practical and effective control on the network topology is fundamental to determine the success of ad hoc and sensor network technologies themselves. Referring to the definition of topology control given in [2], the goal of a topology control algorithm is to dynamically tune the nodes' transmission power to enforce specific properties of the communication graph, while accounting for energy efficiency also.

In the field of WSNs, the design of topology control protocols/solutions have to account for specific network requirements/characteristics:

(i) a central coordination is often hard to have;

(ii) the network topology may be highly variable due to node mobility, wireless link fluctuations and activity cycling;

(iii) sensor nodes have often limited processing and energy capabilities.

To this extent, any topology control solution designed for WSNs must be fully or partially distributed **(i)**, highly flexible and adaptive **(ii)**, and extremely lightweight in terms of both code compactness and limited protocol overhead **(iii)**.

In this paper we are interested in topology control as a way to determining the sensors' degree K, i.e. the number of neighbors directly connected to a given sensor through a bidirectional wireless link. Existing work [3, 4] proves that an optimal value of K does exist and should be maintained during the entire life of the system to ensure global network connectivity properties [5] under network topologies of different characteristics. We start off from these results to design a novel protocol for topology control in WSNs which leverages the concepts of cooperation among sensors through the periodical exchange of neighborhood list. Unlike most of the published papers on the topic of topology control which rely on either simulation or analytical tools, in order to demonstrate the suitability of our approach to real scenarios, we develop a comprehensive small-scale experimental testbed of indoor and outdoor WSNs based on the popular MicaZ motes [6]. We exploit the testbed to compare the performance of our topology control solution against those of other approaches.

To validate and confirm the experimental results from the testbed, we introduce and solve to optimality two analytical formulations of the topology control problem based on Mixed Integer Programming (MIP), showing that the proposed distributed topology control protocol is able to design nearly optimal network topologies in the considered testbed scenarios. Finally, simulation analysis is carried out to assess the performance of the proposed topology control protocol in large-scale static and mobile WSNs.

To summarize, the main contributions of the present paper[1] are:

- We propose a lightweight, cooperative and distributed topology control protocol for WSNs;
- We implement and evaluate the aforementioned protocol in small scale testbed;
- We comment on the optimality of the designed topologies resorting to analytical models based on mathematical programming;
- We validate our simulation code against the testbed results and carry out an extensive simulation analysis of the proposed topology control solution in large-scale static and mobile WSNs.

The manuscript is organized as follows: in Section 2 we discuss the state of the art in topology control for wireless ad hoc and sensor networks, highlighting common approaches and differences with respect to ours. Section 3 describes our cooperative

[1] A shorter version of this paper, lacking the analytical study of optimality and the evaluation in mobile scenarios, previously appeared in [7].

solution to provide effective topology control in WSNs by means of controlling the transmission power. Section 4 reports on testbed development, evaluation and validation. In Section 5, two analytical models based on mathematical programming are introduced to assess the optimality of the proposed distributed topology control, whereas Section 6 illustrates the performance of the proposed scheme in large-scale static and mobile WSNs carried out through simulations. Finally, Section 7 ends the paper with brief concluding remarks.

2 Related Work

The general problem of controlling the topology of wireless ad hoc and sensor networks has been widely addressed in the literature. A broad classification of the work in the field distinguishes between homogeneous and non-homogeneous topology control approaches [2]. Work of the former type assumes a common transmission power level for all the nodes in the network, and the main goal is often to find/characterize the minimum power level, or the so called *Critical Transmitting Range, (CTR)*, such that the resulting network graph has specific properties in terms of connectivity. *CTR* is characterized either resorting to graph theory [8], or through probabilistic approaches [9] considering the statistics of nodes distribution and mobility.

Besides theoretical results on the properties of *CTR*, several solutions have been proposed to operationally calculate the *CTR* under different network topologies and connectivity constraints. Narayanaswany et al. propose in [10] a distributed protocol to obtain a minimum transmitting range to ensure network connectivity, whereas in [11] the authors analyze through simulation the trade-off between connectivity and the minimum *CTR*, showing that the *CTR* can be significantly reduced with less strict requirements on network connectivity. On the opposite side, other valuable work has tackled the problem of *CTR* characterization under more critical requirements on network connectivity, to ensure, for example, k-connectivity[2] [12, 9, 13].

Non-homogeneous topology control refers, on the other hand, to those network scenarios where the transmission power levels can vary from node to node. The problem of power assignment, and consequently topology control, in this scenarios is often formally formulated as a *Range Assignment Problem*, whose target is to minimize the sum of the transmission power levels used throughout the network, still matching some type of connectivity constraint [14, 3]. As in the case of homogeneous topology control, the determination of the transmission power vector is often tackled either through analytical approaches [15], or by proposing distributed algorithms [16, 17].

In the field of distributed algorithms, the proposed solutions mainly differ in the type and "quality" of information which is available to drive the transmission power assignment, and in the way the actual power update is accomplished. As an example, reference [18] introduces topology control solutions for ad hoc networks where the nodes can leverage geographical positioning information in the power update phase. Starting from the consideration that in many other practical cases (e.g., WSNs) such information is hardly available, other solutions have been designed leveraging "lower-quality" information [19]. Within this field, neighborhood-based topology control solutions aim at maintaining a given local degree at each node, by leveraging information on the 1-hop neighborhood only. Traditional approaches for ad hoc and sensor networks, e.g., [20, 21, 22, 23, 24], let each node arbitrarily increase its transmission power until

[2]Each network node must be connected to all the other network elements through k disjoint paths.

K neighbors are heard, possibly resorting to the maximum power whenever the threshold is not met. Other solutions [25, 5], instead, define the local connectivity target as a interval of feasible degrees, i.e., requiring that the degree K of each node fulfill the condition $K_{min} \leq K \leq K_{max}$. In [26], the authors introduce a mechanism based on explicit notification of non-connected nodes. The main differences in the topology control technicalities between our approach and the aforementioned neighborhood-based approaches are widely commented in Section 3.

On the other side, we point out here that the vast majority of the topology control solutions available in literature is evaluated resorting to either simulation or mathematical analysis, only. Hence, it is difficult to assess the real feasibility of these solutions to real network scenarios, where many of the assumptions made during the analysis may not hold true any longer. Even though much work has been done on the implementation of real-life testbed for WSNs, to the best of our knowledge, very few papers have appeared on experimental studies of topology (and power) control solutions for sensor networks, with the notable exceptions provided by [27] and [21]. In the former, a distributed power control scheme is proposed and evaluated in real-life networks, with the purpose to maintain the quality of wireless links among sensors above a given threshold. The latter investigates the problems of synchronization and routing topology construction for in-building applications on real WSNs implementations. To this extent, one of the main contributions of the present paper is the implementation and evaluation in a practical testbed of the proposed novel topology control protocol.

3 Protocol Description

In this section, we illustrate our approach for distributed topology control in WSNs, by means of a reference example. We start off by describing the basic elements and then we refine the description to account for the peculiarity of WSNs.

3.1 Topology Control Basics

The protocol we present is composed of two distinct phases: the *Neighbor Discovery* and the *Topology Update*. Both are performed periodically to react to arbitrary changes in topology as induced by node failures. Since the protocol is designed to be extremely lightweight and focuses on large-scale and dynamic environments, we do not require any form of synchronization among nodes that would require additional overhead. Hence, we do not make any assumption on how discovery and update phases are scheduled on different nodes. We just impose that the interval between two subsequent update phases is fixed and it is chosen in a way to guarantee that all beacons from potential neighbors have been received. Randomization may be exploited to determine the instant to broadcast beacon (between two update phases) in order to reduce the likelihood that beacons from different nodes collide.

In the protocol description, we will adopt the assumption that the transmission range of a given communication can be estimated by each node knowing the transmission power level, the reception threshold power and the propagation model. This allows us to use only for description purposes the concept of transmission range. We then comment on practical implementation issues in Section 4.

Neighbors Discovery As mentioned in Section 2, traditional approaches [28] for topology control in ad hoc networks resort to maximum power transmissions during the discovery phase to detect all the nodes potentially reachable. Once this information is acquired, each node tunes its transmission range (or power) to achieve the desired neighbor degree. We argue that this solution is detrimental in that it wastes precious energy resource and it may also lead to non-optimal solutions since transmitting at maximum power is likely to create interference among node transmissions thus preventing some nodes to correctly receive packets from other nodes. This issue is particularly critical in WSNs, where transmitting at maximum power might dissolve the benefits in terms of energy saving coming from the topology control scheme adopted.

Our protocol, instead, takes a different approach: each node starts transmitting at low power and incrementally increases until K neighbors are contacted. To this end, each node periodically broadcasts a $beacon$ message containing its ID, the list of its current neighbors[3] $\mathcal{N}$ and the transmission range ρ (or the transmission power level) used. For instance, considering a generic node s, its beacon message β_s will have the following structure $\langle s, \mathcal{N}_s, \rho_s \rangle$.

When a node r overhears β_s, it saves the ID of the sender s together with its relative distance δ_{s-r}. This information can be estimated at the receiver by considering the ratio between the transmission power at the sender site and the power computed at the receiver site, relying on the relation between the power attenuation and the distance. For wireless links, a signal transmitted with power P_t over a link with distance d gets attenuated and is received with power

$$P_r \propto \frac{P_t}{d^\alpha} \text{ with } \alpha \geq 2$$

where α is a constant that depends on the propagation medium[4], as illustrated in Section 4.

If δ_{s-r} is smaller than the transmission range used by r, ρ_r, s is included in $\mathcal{N}_r$. Otherwise, s cannot be considered neighbor because the link is not symmetric (s cannot hear beacons from r because $\rho_r < \delta_{s-r}$).

Topology Update During the topology update phase, each node computes how many neighbors it has collected during the discovery phase. If they are less than K, it increases the transmission range by a factor ρ_{inc} defined as protocol parameter.

Otherwise, if the number of neighbors is equal or greater than K, the transmission power is regulated to cover at most the distance of the K^{th} neighbor[5]. This way, a node is free to adaptively tune its range to cover exactly K neighbors.

3.2 Cooperation in the Topology Control Protocol

The protocol just described is indeed successful in maintaining the desired neighbor degree on each node and it enables saving a large amount of energy if compared with protocols without topology control [25]. Nevertheless, it still shows some drawbacks that may negatively impact the overall performance. This undesired behavior is depicted in Figure 1(a). There are three nodes, namely A, B and C, which have already reached the desired local connectivity ($K = 2$ in this case). However, there exists a further node D which instead needs to find K neighbors. Unfortunately, regardless

[3]Two nodes are considered neighbors if and only if their relative distance is less than their transmission ranges.

[4]α is typically around 2 in free space and around 4 for indoor environments.

[5]Here, of course, we do not account for the error introduced by estimation protocol. In a real deployment, we would add ε to the K^{th} node distance to tolerate it.

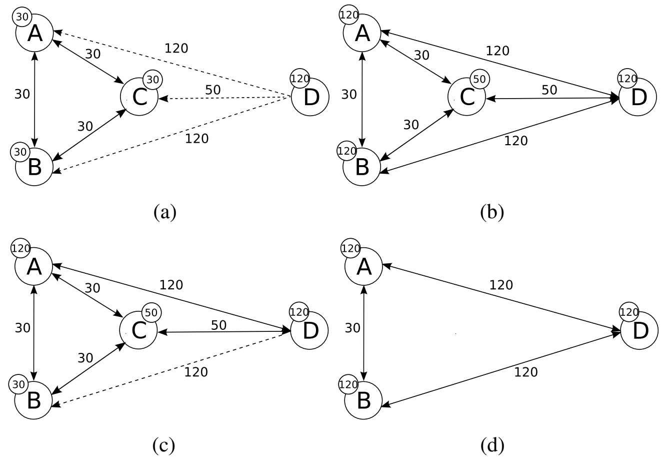


Figure 1: Operation of the topology control algorithm: a simple example ($K = 2$). Values on edges represent distances while the number on each node shows the node's transmission range.

how long its transmission range is, it is unable to connect to any node, since all other nodes have already K neighbors and are therefore unwilling to extend their range to include D. According to the protocol just described, D would end up in transmitting at maximum power, thus consuming high power and creating significant interference to other communications.

A common solution found in literature [5] consists in specifying low and high bounds for node degree ($K_{min} = K$ and $K_{max} > K$). Throughout the paper, we will refer to this solution as to MINMAX approach. MINMAX approach actually solves the problem but at the expense of an increased average number of neighbors (and, consequently, of the transmission power used). Indeed, this mechanism does not distinguish among nodes that do need a connection (*critical nodes* in our terminology) and nodes which do not have this requirement. This is clarified in Figure 1(b), in which both A and B decide to increase their range to connect with D, whereas only one additional neighbor (beside C) is needed by D.

In [26], the authors propose a cooperative approach to overcome this issue. Whenever a node is below the desired local connectivity, it explicitly signals it to surrounding nodes through a special `help` packet. It then uses a `satisfy` packet to notify neighbors whenever a node is no longer critical. We will call this mechanism EXPLICIT . Even if a node has more bi-directional links than needed, it may increase its transmission power to help critical neighbors.

Beside the additional overhead required, this solution suffers from oscillation behavior. Indeed, in the example in Figure 1, A and B would first increase their range to reach D since it has sent a `help` packet. However, later D would send a `satisfy` packet and hence A and B would reduce their power, since they have more than $K = 2$ neighbors. This would lead to an oscillating behavior moving from situations depicted in Figure 1(a) and Figure 1(b). This issue was also confirmed by our experimental and simulation analysis, as detailed in Section 4.3

To avoid this behavior, our protocol leverages the neighbor list provided by each node in its beacons. During the discovery phase, when a node r receives a beacon from s, it computes the size of s's neighborhood ($\mathcal{N}_s$) and if it is lower than K, s is marked as *critical*. In the update phase, critical nodes are included as neighbors and transmission range is modified accordingly. Since cooperation is based on the content of the neighborhood lists, we will refer to our solution as to LIST BASED.

As pointed out above, it may occur that two or more nodes decide to accept a critical node as neighbor when, instead, for instance only one would suffice. Nevertheless, this does not represent an issue: during the next discovery phase the critical node will receive beacons from these nodes and will decide which one is more convenient (i.e. the closest). This way, in the subsequent discovery phase the critical node will broadcast its new neighbor list, containing the neighbors ordered from the closest to the farthest. Consequently, all other nodes can realize that they are not needed and can reduce their range. To avoid oscillatory behavior, we mark a node as critical for two subsequent discovery phases. In such a way, the critical node can receive the beacon from the cooperating node and can perform its choice (if there are more cooperating nodes than needed) in the next phase.

In our example, both A and B would decide to extend their range to reach D. However in the next phase D will beacon its neighbor list ($\mathcal{N}_D =< C, A, B >$), enabling other nodes to detect whether they could reduce their range. In this case, only B is allowed to decrease its power, as it is the third D's neighbor whereas the critical threshold is $K = 2$. C and A, instead, cannot reduce their transmission ranges since they are essential to provide connectivity to D.

Our topology control protocol is also able to cope seamlessly with node failures. Indeed, during the discovery phase each node receives beacons from its neighbors and in the subsequent update phase it adjusts its range according to the data collected in the previous phase. With reference to our example, suppose that C crashes (e.g., because it runs out of battery) yielding to the situation sketched in Figure 1(d). B and D would realize that their number of neighbors is below the threshold $K = 2$. Hence, now B decides, cooperatively, to accept D because the latter is critical ($\mathcal{N}_D =< A >$) since it needs more neighbors. Interestingly, this operation is also beneficial for B as it has too few neighbors as well.

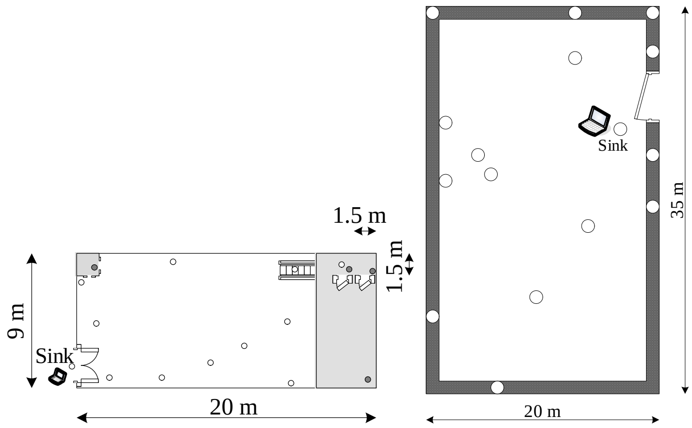
4 Experimental Evaluation

In order to test our protocol on the field, we set up experimental testbeds both in outdoor and indoor scenarios. In the following we highlight the implementation issues we have encountered, and we comment on the performance measures we have gathered through the testbed.

4.1 Testbed Setting

Each experiment adopts 16 XBow MicaZ [6] sensor nodes running topology control functions. MicaZ nodes are equipped with the ChipCon CC2420 radio transceiver [29] which allows to choose among 8 transmission power levels in the interval [-25 dBm, 0 dBm] as specified in Table 1.

In the indoor experiments, the MicaZ nodes have been positioned in a warehouse building (20 m x 9 m) as described in Figure 2(a): 11 sensors are positioned at the ground floor, 4 at the mezzanine and 1 on the connecting stairs. Moreover, one of the ground-floor nodes is inside a separate room. All the nodes directly lay over materials and machines of the warehouse at different heights.



(a) Indoor Scenario. (b) Outdoor Scenario.

Figure 2: Network topologies of the testbed.

Power Level ID	Emitted Power [dBm]
7	0
6	-1
5	-3
4	-5
3	-7
2	-10
1	-15
0	-25

Table 1: CC2420 Transmission Power Levels.

The outdoor experiments have been conducted on top of a flat roof of the same warehouse building. The experiment area is 35 meters long and 20 meters wide. MicaZ are deployed as shown in Figure 2(b), where nodes on the border of the flat roof (including sink) lay on a 1-meter-high parapet, while other sensors are positioned directly on the ground. We decided to place the other sensors on the ground to emulate unfavorable propagation conditions, thus stressing the topology control solutions.

Since it is very impractical to manually download data sensor by sensor at the end of each experiment, we implemented an automatic procedure to collect at a sink node all the data stored during the experiment by all the other sensors. To this end, one MicaZ node in each scenario acts as information sink and is directly connected through a MIB510 Serial Gateway to a PC running Linux distribution Debian with 2.6.18 kernel version. Each sensor collects and stores periodical samples of information during the experiment including the list of perceived neighbors (and the corresponding power levels) and the current transmissions power. Upon completing the experiment, each sensor searches for a path to the sink by using the MintRoute routing protocol [30] and then sends to the sink all these information samples.

The sink sensor passes such information to the PC which runs a Java filter, returning the overall performance measures used to evaluate the topology control solutions. Moreover, the Java tool implements also a query mechanism based on a diffusion protocol to force the sink node to request missing information that may get lost during the collection phase.

	Code Size	RAM Footprint
MinMax	11.2 Kbytes	488 bytes
List based	11.9 Kbytes	744 bytes
Explicit	11.4 Kbytes	488 bytes

Table 2: Binary size and RAM footprint of the topology control protocols.

4.2 TC Implementation Issues

We implemented our protocol and the other approaches described in Section 3 in TinyOS ver.1.x and deployed them onto MicaZ sensors. The corresponding binary sizes (including radio stack, UART, timers and led components) and memory footprints are reported in Table 2.

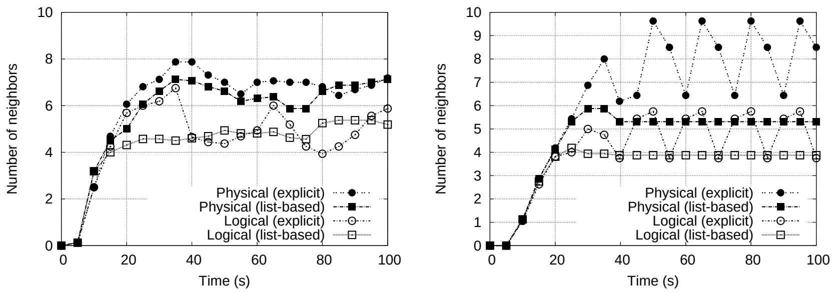
During our experiments, we have observed that the stability of any topology control solution is highly affected by the variability of the wireless link quality. In fact, if link quality varies very often, the perceived number of neighbors is scarcely stable, and the algorithm itself is driven to frequent changes in the transmission power. Therefore, it is of utmost importance to introduce techniques to stabilize the number of neighbors filtering out the fluctuations of the wireless channel. First, we need to define metrics to measure the "quality" of a given link. It is shown in [31] that the Received Signal Strength Intensity (RSSI) of wireless links among MicaZ sensors geared with ChipCon 2420 transceivers provides a consistent estimate of the Packet Reception Rate (PRR). Namely, the authors show that if the RSSI is above -87 dBm, the PRR is above 85%. Below that threshold a gray zone does exist, where the PRR may be extremely variable.

We inserted a control on the RSSI of the received transmissions according to which the information contained in a received beacon message is considered in the topology control procedures only if the RSSI is above the -87 dBm threshold. Moreover, to achieve long-life link stability, we have decoupled in time the topology update and the beaconing phase allowing a topology update every twelve beaconing intervals. The information contained in a beacon is stored and used in the topology control phase only if at least x (parameter) out of the 12 beacons replicas have been received correctly, i.e., with an RSSI above -87 dBm. Beacons contain the transmitter ID, the list of neighboring sensors and the transmission power level, which allows each sensor to locally create a list of neighbors with the corresponding transmission power levels to be used to reach them. Information on the criticality of each neighbors is also stored.

The results obtained from the testbed are validated against TOSSIM simulations in the very same indoor and outdoor network scenarios. We adopted the same empirical approach proposed in [30] to model the link behavior in simulations. Each sensor in the testbed transmits 200 packets to any other sensor which measures the packet reception rate. Such procedure is repeated for all the 8 transmission power levels and for all the 16 sensors in the network. Thus, for each sensor, we obtain measurements at different receivers when using different transmission power levels. We are therefore able to associate to each directed pair of sensors and for each power level a packet reception probability, which is then used in the TOSSIM simulations. Table 3 reports the values of packet reception probabilities for the links of node 1 towards all the sensors in the indoor environment.

		Transmitting Sensor														
		0	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
TX Power Level	**0**	0.9	0.9	0.18	0	0	0	0	0	0	0	0	0	0	0	0
	1	1	1	0.99	1	0.85	0.98	0.15	0.31	0	0	0	0	0	0	0
	2	1	1	1	1	1	1	0.75	1	0.17	0.75	0	0	0	0	0
	3	1	1	1	1	1	1	1	1	0.3	1	0.32	0	0	0	0
	4	1	1	1	1	1	1	1	1	0.35	1	1	0	0	0	0
	5	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
	6	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
	7	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0

Table 3: Empirical measures of PRR at sensor 1 from different transmitters, using different transmission power levels.



(a) Testbed. (b) TOSSIM Simulations.

Figure 3: Average number of physical and logical neighbors (Outdoor).

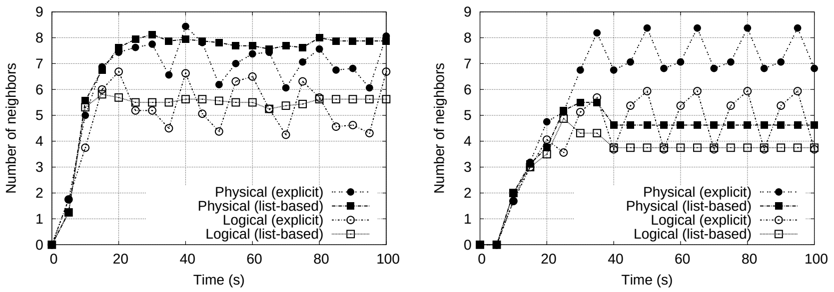
4.3 Performance Evaluation

Every test is composed of two phases: in the first one, nodes are switched on from scratch and run the specific topology control algorithms for a period of 100 s. After that, they move onto the second phase devoted to data collection and data elaboration as described in Section 4.1.

We collected the following performance metrics:

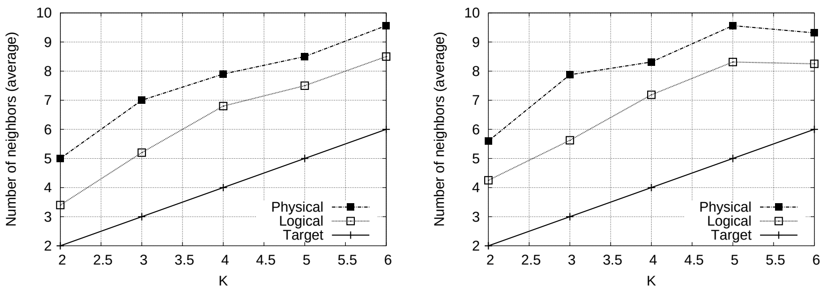
- *local connectivity*: we measure the local connectivity of any sensor in terms of *logical* neighbors, i.e. those neighbors connected through symmetric links, and *physical* neighbors, i.e. all the nodes reached by sensor's beacons (through symmetric and asymmetric links);
- *network connectivity*: we measure the network connectivity as the ratio between the number of vertexes of the largest connected sub-graph and the total number of sensors. When such ratio is 1 all the sensors constitute a fully connected graph;
- average *transmission power* and transmission power distribution.

The first parameter we analyze is the local connectivity provided by the cooperative LIST BASED and EXPLICIT topology control solutions. Figures 3 and 4 depict the average number of logical and physical neighbors in the outdoor and indoor network scenarios, respectively ($K = 3$). Figure 3(b) and 4(b) give the simulation results obtained through TOSSIM in the very same testbed environments (outdoor and indoor). Both testbed and simulation results confirm the oscillatory behavior of the cooperative



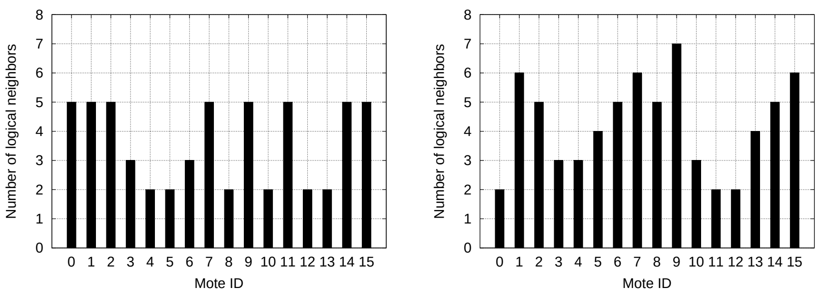
(a) Testbed. (b) TOSSIM Simulations.

Figure 4: Average number of physical and logical neighbors (Indoor).



(a) Outdoor. (b) Indoor.

Figure 5: Physical and logical neighbors against K (testbed).

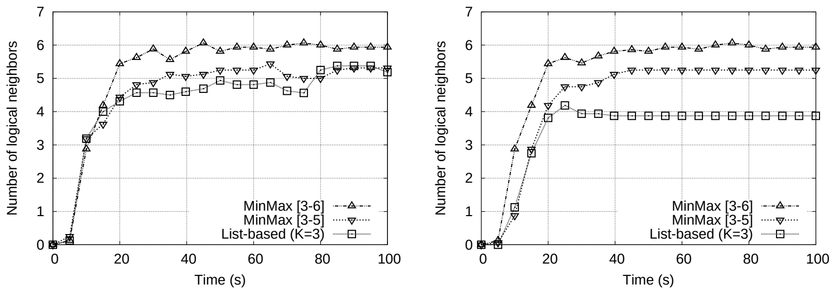


(a) Outdoor. (b) Indoor.

Figure 6: Number of logical neighbors per sensor in case $K = 2$ (testbed).

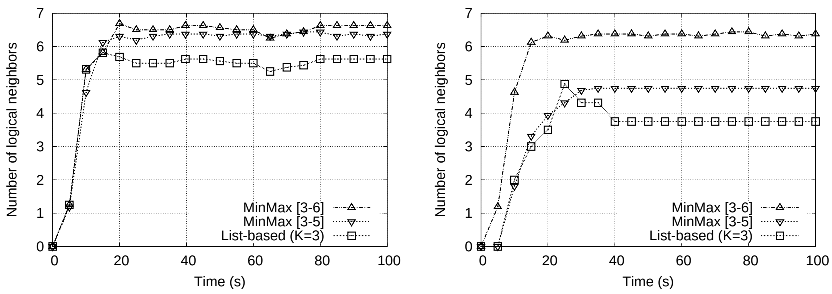
EXPLICIT approach, as expected and described in Section 3.2. We further observe that even if TOSSIM simulations provide the same behavior as testbed measurements, a difference in the absolute numbers holds, due to the non-ideal propagation conditions of the testbed compared to the static empirical propagation model used in the simulations.

Notably, in both scenarios the list-based algorithm provides a number of logical neighbors slightly higher than the target parameter K. In fact, Figure 5 reports the



(a) Testbed. (b) TOSSIM Simulations.

Figure 7: Average number of logical neighbors (Outdoor).



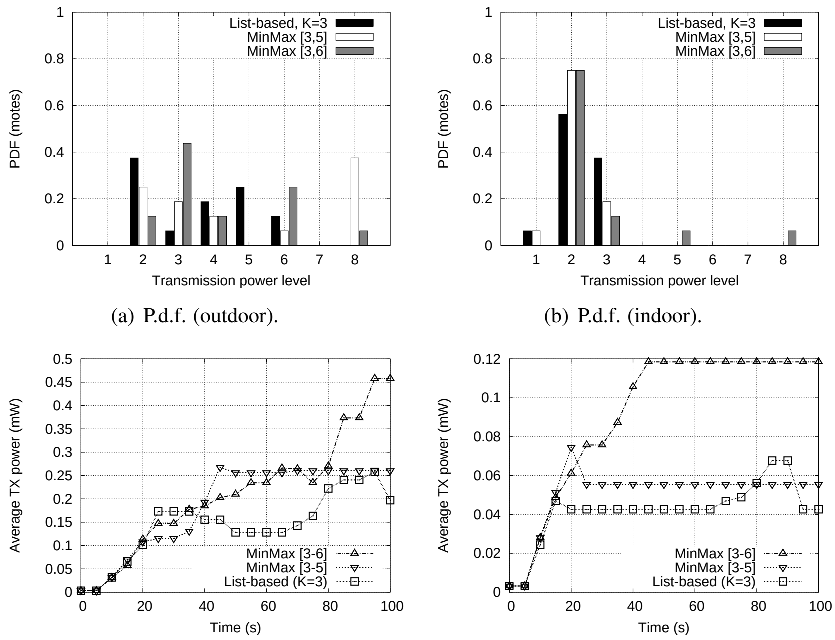
(a) Testbed. (b) TOSSIM Simulations.

Figure 8: Average number of logical neighbors (Indoor).

measured number of logical and physical neighbors against the target value K for the LIST BASED topology control approach in the testbed. Such difference in excess is due to the "price of cooperation", that is, the fact that the cooperative approach forces a subset of nodes to increase their transmission power to help critical neighbors (see Section 3.2). Figure 6 zooms on this effect by reporting the number of logical neighbors per sensor in case the LIST BASED approach is used with $K = 2$. As clear from the two figures, the aforementioned "price of cooperation" leads some sensors to have a number of logical neighbors which is higher than the target value ($K = 2$) in both indoor and outdoor testbed scenarios.

One might argue that non-cooperative approaches based on an interval $[K_{min}, K_{max}]$ of feasible degrees (hereafter referred to as MINMAX protocol) may make cooperation useless. To address this remark, we tested this strategy in the testbed and compared its performance with the LIST BASED cooperative approach. In our experiments, we have set $K_{min} = K = 3$ whereas we tested two values for K_{max} (5 and 6) in the MINMAX case.

Figures 7 and 8 compare the average number of logical neighbors in outdoor and indoor scenarios for the three cases: LIST BASED cooperative, MINMAX $K_{max} = 5$ and MINMAX $K_{max} = 6$. Results obtained through TOSSIM simulation are also reported for the sake of comparison. We observe that the MINMAX protocol leads the nodes to have an average number of neighbors often close to K_{max}. The reason stems



(a) P.d.f. (outdoor).

(b) P.d.f. (indoor).

(c) Average (outdoor).

(d) Average (indoor).

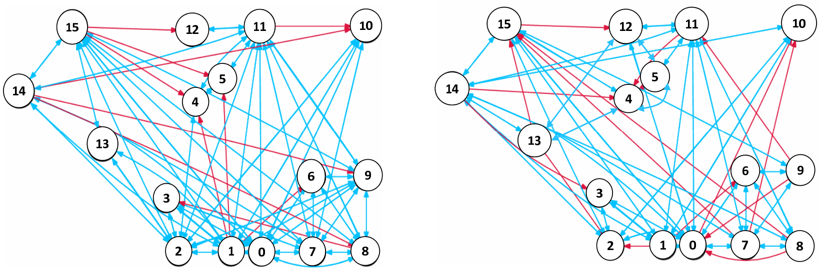
Figure 9: Transmission power (testbed).

from the fact that a node cannot distinguish between critical and non-critical nodes and, hence, it always accepts neighbors until the threshold K_{max} is met. Moreover, in some cases, MINMAX approach provides an average number of neighbors which is even slightly higher than K_{max} (e.g., MINMAX 3-5 in Figure 8(a)); this counter-intuitive behavior has two causes: the specific testbed topology and the quantization of the transmission power levels. In fact, it may happen that one sensor tuning its power level to reach its K_{max}-th neighbor, reaches also other farther away neighbors. In other words, the granularity with which neighbors can be added to the neighbors' list may be coarse. This granularity effect is visible in Figure 6, where the maximum number of logical neighbors per sensors is clearly higher in the indoor testbed scenario (7 versus 5), which features a higher density of sensor nodes.

The overall effect is that nodes consume much more power because the more neighbors they have, the higher their transmission power is, as readily confirmed by Figure 9 which reports the average transmission power over time and the *P.d.f.* of the transmission power levels at the end of the testbed experiments ($t = 100$s).

Figure 10 pictorially compares the connectivity graphs for the outdoor testbed at algorithm convergence in case the LIST BASED and the MINMAX ($K_{max} = 5$) approaches are adopted respectively. Blue Edges with double-sided arrows represent bidirectional connectivity relations, whereas red ones with single-sided arrows stand for mono-directional connectivity. It is visually recognizable the aforementioned effect of higher connectivity degree provided by the MINMAX approach, with a consequent increase in the transmitting (and consumed) power.

Besides local connectivity, it is worth evaluating the connectivity properties of the overall network topology. To this end, we have computed in post processing the per-



(a) MINMAX Algorithm. (b) LIST BASED Algorithm.

Figure 10: Connectivity graph at convergence (Outdoor).

	Time to Connectivity [s]		
	List-based	**MINMAX [3-5]**	**MINMAX [3-6]**
Indoor	25	20	20
Outdoor	15	10	10

Table 4: Time to reach full multi-hop connectivity.

centage of sensors in the largest connected sub-graph by automatically solving max flow problems on the data collected at the sink. We have observed that the network becomes fully connected in all the cases (indoor and outdoor) and for all the algorithms. The time-to-full-connectivity is reported in Table 4. The MINMAX approach allows to have a slightly lower time to connectivity, with the drawback of consuming more transmission power, as shown beforehand.

5 Assessing Topology Control Optimality

In order to check the optimality of the numerical results obtained through the testbed, we propose here a mathematical programming formulation for the topology control problem. Namely, we want to analytically characterize the transmission power assignment which minimizes the total power used throughout the network, such that all the sensors have K bidirectional neighbors, at least. Different from other work in the literature targeting network-wide connectivity [32], the focus here is on local connectivity only. To this extent, we derive two formulations: the first one considers discrete and quantized available transmission power levels of MicaZ sensors (see Table 1), whereas in the second one we relax the assumption on discrete power levels and assume that continuous power levels can be used by sensors.

5.1 Minimum Power Assignment Problem with Discrete Power Levels

The Minimum Power Assignment Problem with discrete power levels (MPAP-D) can be cast as follows; let $\mathcal{N} = \{1, \dots, n\}$ be the set of sensors' indices, and $\mathcal{P} = \{1 \dots, p\}$ the set of available power levels. Moreover, parameters b_{ij}^{hk} are used to express the neighboring relationships among sensors, and are defined as:

$$b_{ij}^{hk} = \begin{cases} 1 & \text{if sensors } i \text{ and } j \text{ are bidirectional neighbors} \\ & \text{when using power levels } h \text{ and } k \text{ respectively} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Parameters b_{ij}^{hk} can be derived experimentally as already described in Section 4.2 by imposing a reception threshold on the transmissions, that is, $b_{ij}^{hk} = 1$ if the following conditions hold:

$$PRR(i,j,h) \geq 0.9 \quad AND \quad PRR(j,i,k) \geq 0.9,$$

where $PRR(i,j,h)$ is the packet reception rate at sensor j out of a transmission from sensor i at power level h.

Decision variables of the formulation will then define the transmission power assignment, i.e.,

$$x_i^h = \begin{cases} 1 & \text{if user } i \text{ transmits at power } h \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The mathematical formulation of MPAP-D is:

$$\min \sum_{i \in \mathcal{N}} \sum_{h \in \mathcal{P}} x_i^h P(h) \tag{3}$$

s.t.

$$\sum_{h \in \mathcal{P}} x_i^h = 1 \qquad \forall\, i \in \mathcal{N} \tag{4}$$

$$\sum_{\substack{j \in \mathcal{N} \\ j \neq i}} \sum_{h \in \mathcal{P}} \sum_{k \in \mathcal{P}} x_i^h b_{ij}^{hk} x_j^k \geq K \qquad \forall\, i \in \mathcal{N} \tag{5}$$

$$x_i^h \in \{0,1\} \qquad \forall\, i \in \mathcal{N}, h \in \mathcal{P} \tag{6}$$

The objective function expressed by Eq. (3) aims at minimizing the sum of the transmission power levels used throughout the network, being $P(h)$ the amount of power transmitted if using power level h. Constraints (4) require each sensor to choose a single transmission power level, whereas constraints (5) express the condition on the minimum local degree for each sensor. Finally, constraints (6) express the integrality of the decision variables.

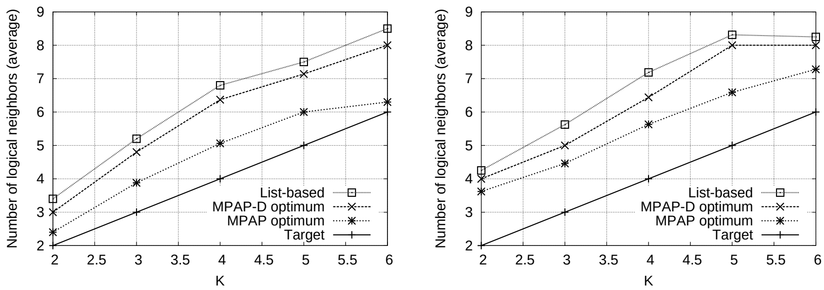
We further observe that constraints (6) are non-linear (bi-linear), but they can be easily linearized in the form:

$$\alpha K(1 - x_i^h) + \sum_{j \in \mathcal{N}, j \neq i} \sum_{k \in \mathcal{P}} b_{ij}^{hk} x_j^k \geq K \qquad \forall\, i \in \mathcal{N}, \forall\, h \in \mathcal{P} \tag{7}$$

where $\alpha \geq 1$. The constraints above activates only when $x_i^h = 1$, requiring user i to have K neighbors, at least.

5.2 Minimum Power Assignment Problem

It is worth studying the loss in optimality due to the quantization in the usable power levels. To this extent, we formulate hereafter the Minimum Power Assignment Problem



(a) Outdoor. (b) Indoor.

Figure 11: Average number of physical and logical neighbors (Outdoor).

(MPAP) if power is continuous. New decision variables are introduced to define the transmission power level adopted by sensor i, namely, $p_i \in Re^+$ for $i \in \mathcal{N}$. The propagation law is modeled through parameters $\alpha_{ij} \in Re^+$ with $i, j \in \mathcal{N}$, which represent the attenuation gain on the link between sensor i and sensor j.

We further need to introduce binary variables to represent neighborhood relations. Namely, variables:

$$y_{ij} = \begin{cases} 1 & \text{if sensor } i \text{ and sensor } j \text{ are bidirectional neighbors} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Leveraging the above mentioned variables and parameters, we can cast a mixed integer linear formulation of the MPAP problem:

$$\min \sum_{i \in \mathcal{N}} p_i - \beta \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}, j \neq i} y_{ij} \tag{9}$$

s.t.

$$p_i \alpha_{ij} \geq \gamma y_{ij} \qquad \forall\, i, j \in \mathcal{N} \tag{10}$$

$$p_j \alpha_{ji} \geq \gamma y_{ij} \qquad \forall\, i, j \in \mathcal{N} \tag{11}$$

$$\sum_{j \in \mathcal{N}, j \neq i} y_{ij} \geq K \qquad \forall\, i \in \mathcal{N} \tag{12}$$

$$P_{min} \leq p_i \leq P_{max} \qquad \forall\, i \in \mathcal{N} \tag{13}$$

$$y_{ij} \in \{0, 1\} \qquad \forall\, i, j \in \mathcal{N} \tag{14}$$

$$p_i \in Re^+ \qquad \forall\, i \in \mathcal{N} \tag{15}$$

The first term of the objective function aims at minimizing the overall adopted transmission power, whereas the second term is introduced to force y_{ij} variables to 1 for the bidirectional neighbors[6]. Constraints (10) and (11) define the bidirectional neighboring relations, where he parameters α_{ij} have been obtained through measurements on the testbed scenarios. Constraints (12) enforces a minimum number of bidirectional neighbors for each sensor, and constraints (14), (15), and (13) set the type of the decision variables involved in the formulation.

[6] β is a normalization factor such that $\beta << P_{min}$.

5.3 Numerical Results and Observations

To get the minimum power assignment matching the local connectivity constraints, we formalized MPAP-D and MPAP in AMPL [33] and solved it through the commercial solver CPLEX [34] for the two topologies of the testbed experiments, indoor and outdoor.

Figure 11 compares the results obtained from the testbed against the optimal solutions of MPAP-D and MPAP in terms of number of logical neighbors, when varying the target parameter K. As clear from the figure, the average number of neighbors provided at convergence by the LIST BASED topology control algorithm is pretty close to the MPAP-D optimal solution, thus demonstrating that the distributed topology control algorithm is able to provide nearly optimal solution.

On the other side, we observe that the average number of logical neighbors obtained solving to optimality the MPAP formulation is slightly lower than the ones provided by the LIST BASED approach and by the MPAP-D. This clearly shows the effect of transmission power quantization which tends to require higher power (and consequently higher neighbors) to match the common local connectivity constraint (K). We further observe that even the solution of MPAP leads to have a number of logical neighbors slightly higher than the target (K) due to the "price of cooperation".

6 Simulation Analysis

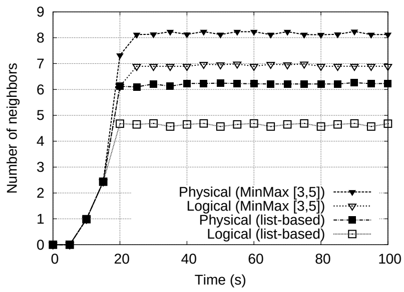
In this section we report on our simulation analysis which complements the experimental and analytical study presented in the previous sections. Results fully confirm the suitability of our protocol to ensure high connectivity with minimal overhead in both static and dynamic scenarios

6.1 Static Network

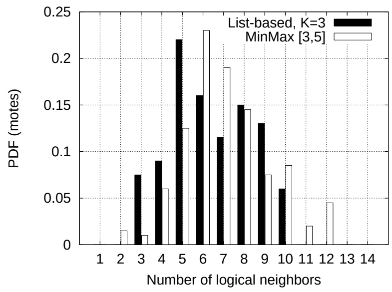
The experimental results presented in Section 4 have been obtained on real life testbeds featuring a small number of sensors. It is worth analyzing whether the performance characteristics of the topology control solutions highlighted so far still hold true for medium/large network scales. Since a real large-scale testbed was unfeasible, we resort to simulation in TOSSIM. First, as shown in Section 4.3, we validated the TOSSIM results against the real testbed. Then, we run a number of experiments on a large-scale scenario with a square network topology (350 m x 350 m), where 200 sensors are randomly scattered. Each result shown hereafter has been obtained averaging over 100 realization of the sensors' distribution. The measured confidence interval for all collected statistics is smaller than 5% in 98% of all cases.

To characterize the wireless links, we have resorted to an empirical approach similar to the one described in Section 4. In details, we have measured the Packet Reception Probability (PRR) of a single outdoor wireless link of increasing length, when adopting different transmission power levels. The measured PRR has been used to characterize the packet reception procedure in the TOSSIM simulations, depending on the simulated distance between sender and receiver, and the transmission power.

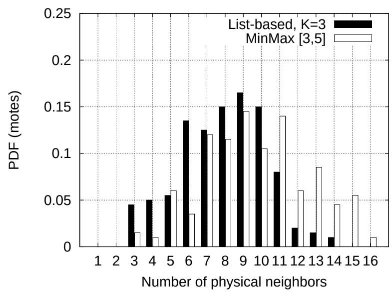
Again, we begin by analyzing the local connectivity provided by different topology control solutions. Figure 12 plots the average number of logical and physical neighbors and their *P.d.f.* in the reference network scenario for the LIST BASED and MINMAX topology control algorithms. As already shown in the small-scale scenario (testbed and



(a) Average number of logical neighbors.



(b) P.d.f. Logical Neighbors.



(c) P.d.f. Physical Neighbors.

Figure 12: Local connectivity (TOSSIM Simulation).

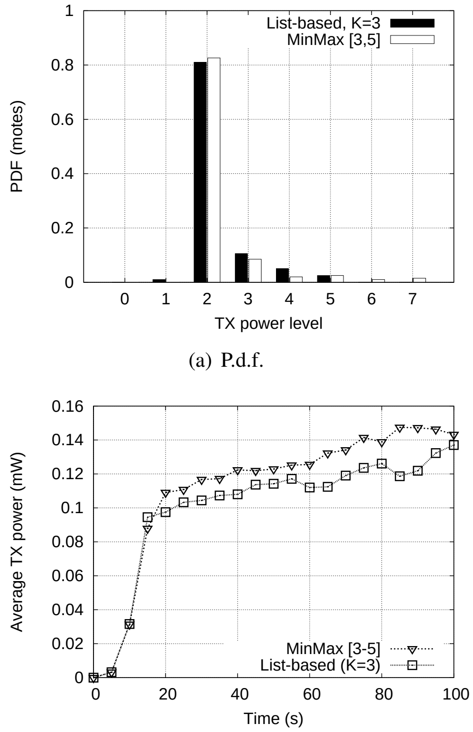
simulations), the MINMAX protocol provides higher average number of logical and physical neighbors with respect to the LIST BASED approach. As a consequence, the amount of consumed power is higher power as confirmed by Figures 13 which reports the average transmission power over time and the *P.d.f.* of the transmission power levels at the end of the simulation ($t = 100$ s).

Interestingly, in the MINMAX case, a small fraction of nodes still have less than $K_{min} = 3$ logical neighbors (see Figure 12(b)). This yields two significant consequences. Firstly, these nodes will transmit at maximum power[7] in the attempt to find other neighbors, thus dramatically increasing their power consumption and introducing high interference. Furthermore, the fact that not all the nodes match the local connectivity constraint leads to failures in the overall network connectivity too. Indeed, with the MINMAX approach and $K_{max} = 5$ the network remains not connected (connectivity degree is 0.97), whereas the LIST BASED approach provides 100% connectivity in the simulation time. It can be further noted that some nodes may have more than K_{max} logical neighbors in the MINMAX case. This is again due to the same effect of the transmitting power level granularity observed and commented in the analysis of the small-case topologies.

6.2 Mobile Network

Thus far, we concentrate our analysis on stationary nodes, being this the most common scenario for WSNs. Nevertheless, we recently observed a rising interest in mo-

[7]This explains why in Figure 13(a) there are a few nodes transmitting at the highest power level.



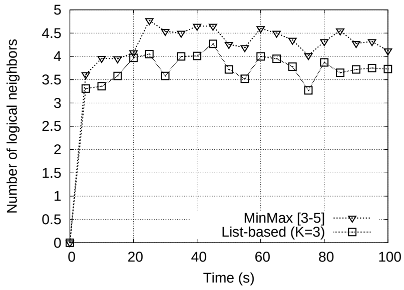
(a) P.d.f.

(b) Average.

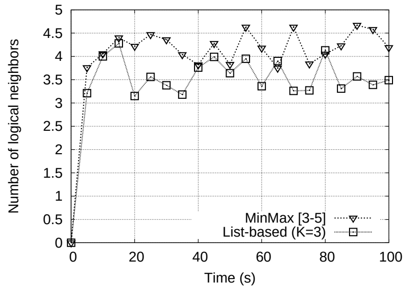
Figure 13: Transmission Power (TOSSIM Simulation).

bile WSNs, e.g., in wildlife monitoring [35], people sensing [36] and vehicular systems [37]. Moreover, sensor mobility is also foreseen in those WSN scenarios where static sensor nodes are complemented by mobile actors, which can move around to collect sensing information or to react to environmental phenomena [38].

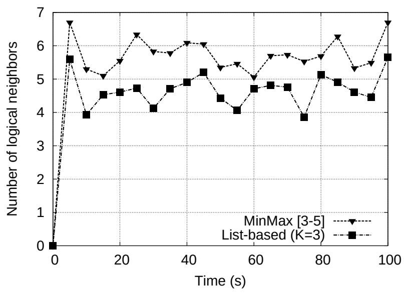
An interesting question is therefore how our cooperative protocol would behave in a mobile scenario. To answer this, we re-use the same settings adopted in Section 6.1 but this time we let some nodes freely move in the area. To this end, we set up the mobile simulation environment in TYTHON [39], which provides a scripting language to manage TOSSIM simulations. The mobility model we chose is the Random Waypoint model [40] as this model has been widely used in the research community and, despite other models are being proposed, it is still considered the state-of-the-art. Furthermore, some studies [41] seem to indicate that the mobility pattern has little influence on the distribution of the critical transmitting range. We consider a mobile environment where we proof-test two mobility degrees for the mobile nodes, featuring speed values of 5 m/s, and 10 m/s respectively. To closely resemble realistic hybrid scenarios wherein a number of static sensors interact with mobile sinks, we assume that only 10% of sensors are moving. Each simulation run is executed for 100 s of simulated time. As in the previous section, we compared the LIST BASED protocol against MINMAX . Figure 14 reports the number of logical and physical neighbors versus simulation time when sensors move at respectively 5 and 10 m/s. As clear from Figure 14(a) and 14(b), the number of logical neighbors provided by the LIST BASED protocol is lower than the one provide by MINMAX for both speed values.



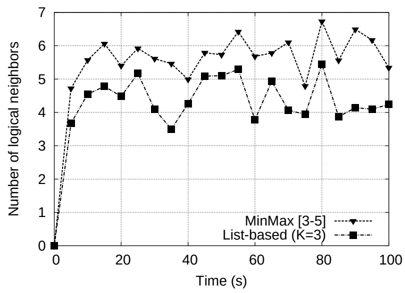
(a) Logical Neighbors (5 m/s)



(b) Logical Neighbors (10 m/s).

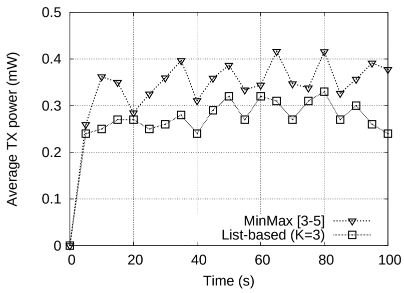


(c) Physical Neighbors (5 m/s).

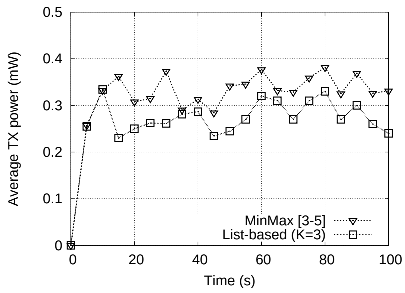


(d) Physical Neighbors (10 m/s).

Figure 14: Local connectivity in the mobile scenario.



(a) 5 m/s.



(b) 10 m/s.

Figure 15: Transmission Power.

The very same behavior can be appreciated when observing the number of physical neighbors, reported in Figure 14(c) and 14(d). Notably, the MINMAX approach forces the sensor to have a higher number of physical neighbors than the LIST BASED protocol. This yields two negative effects. First, some nodes exhibit a very high number of physical neighbors which increase the likelihood of network interference. Second, as plot in Figure 15, these nodes have to resort to high transmission power, thus increasing their energy consumption and reducing their life time.

These results prove the suitability of our cooperative solution even for challenging scenarios as those characterized by mobility, thus making our topology control protocol a good candidate for ensuring network connectivity in modern mobile WSNs. Additional studies, involving on field measurements on mobile devices, are part of our future research agenda.

7 Concluding Remarks

In this paper, we have described a lightweight and cooperative solution to the problem of controlling the local connectivity in wireless sensor networks. We set up and deployed real-life testbeds of small-scale indoor and outdoor wireless sensor network to test the performance of the proposed solution against other common approaches. Mathematical programming formulations of the power assignment problem have been further introduced to test the optimality of the proposed topology control solution. Finally, we complemented the testbed and analytical evaluation with simulations in TOSSIM in large-scale static and mobile wireless sensors networks.

The evaluation carried out through experimental, simulation and analytical approaches shows that the proposed topology control solution outperforms other approaches, providing steady network connectivity while reducing the overall power consumption.

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