

# SmartConnect: A System for the Design and Deployment of Wireless Sensor Networks

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**Abstract**— We have developed SmartConnect, a tool that addresses the growing need for the design and deployment of multihop wireless relay networks for connecting sensors to a control center. Given the locations of the sensors, the traffic that each sensor generates, the quality of service (QoS) requirements, and the potential locations at which relays can be placed, SmartConnect helps design and deploy a low-cost wireless multihop relay network. SmartConnect adopts a field interactive, iterative approach, with model based network design, field evaluation and relay augmentation performed iteratively until the desired QoS is met. The design process is based on approximate combinatorial optimization algorithms. In the paper, we provide the design choices made in SmartConnect and describe the experimental work that led to these choices. Finally, we provide results from some experimental deployments.

**Index Terms**—Wireless sensor network design; Wireless relay network design and deployment; Field interactive design

## I. INTRODUCTION

Industrial and commercial establishments (such as chemical factories and hotels) deploy a large number of sensors for control or monitoring applications. The sensors are typically spread over a large area and at distances of several tens of meters from the control center. In existing installations, the sensors are connected to the control center by a wireline network, usually a combination of point-to-point and bus networks. Installation and maintenance of such wireline networks incur substantial cost. In addition, it is difficult to expand such wireline sensor networks, for example, to add sensors at some new locations. Due to such reasons, recently there has been a spurt of interest in replacing wireline sensor networks with multihop wireless sensor networks.

There are several sensing applications, particularly in industrial settings, that could employ low power wireless sensors that use the wireless physical (PHY) layers and medium access controls (MAC) being standardized by IEEE 802.15.4 [11], or Wireless HART [2], or ISA 100.11a [3]. Such low power devices can simply be “planted” where needed, and can be expected to work for several months on batteries and harvested energy. Due to their low power operation, the range of such radios is a few meters to a few 10s of meters, necessitating multihopping, and therefore a higher packet loss rate. There are many applications, however, e.g., such as data logging and non-critical control (see [15]), for which such low power and lossy networks are adequate. With such networks in mind, this paper is concerned with the challenges of designing and deploying wireless relay networks for interconnecting sensors (viewed as data sources) with a control center (viewed as a data sink, and also referred to in the paper as a base station). The system that we have developed to address the challenges, and the algorithms and procedures embedded in it, is called *SmartConnect*. In this paper, we present the

design of, and experiences with SmartConnect, a system that iterates by interacting with partial deployments in the field, and uses on-field measurements and statistical models, to suggest improvements, eventually leading to a design that meets QoS requirements.

Given the locations of the sensors and the sink, we are concerned with the problem of placing wireless relay nodes so that the resulting multihop wireless network can carry the sensor data to the sink. There would be placement constraints due to the presence of obstacles (e.g., a firewall, a large machine, or a building), or due to taboo regions; hence we can place relays only at certain designated locations. We therefore consider the situation in which a number of *potential* relay locations is provided to the network designer, but as few relays as possible should be deployed. In addition, since no application can tolerate arbitrary packet delay and loss, the network design has to ensure some level of quality of service (QoS). We require that the network design has to guarantee that the data packets will reach the control station within a *stipulated delay constraint with a high probability*, while taking into account the *highly unpredictable nature of wireless channel*. Further, the wireless network should also preferably have multiple *node disjoint* paths from each source to the sink to provide *resilience to node failures*.

Since there could be hundreds of locations, a design approach based on an exhaustive link quality measurement between every possible pair of locations will be expensive and time consuming. Radio frequency (RF) propagation models are approximate and cannot yield designs that can be expected to work when actually deployed. SmartConnect, therefore, adopts an *iterative field interactive* approach.

The current version of SmartConnect provides a methodology for network design and deployment for sensor networks that carry low rate measurement traffic (“light traffic”), typical of applications such as condition monitoring and non-critical data logging [15].

(i) Given the sensor locations, the potential relay locations, and the location of the sink, a *model* for link quality is used to generate a graph of potential links over the potential relay locations (discussed in Section IV).

(ii) The QoS constraint for light traffic is formulated in terms of a Steiner-type problem of minimizing the number of potential relays to be employed subject to a sensor-sink hop count constraint. This involves the solution of certain Steiner graph design problems for which approximation algorithms (developed by us in related prior work [6]) are utilized (discussed in Section V).

(iii) The proposed relays (typically a very small number) are placed in the field and link quality measurements are made under commands from the SmartConnect console. The graph

design algorithm then uses these measured links and models of the remaining unknown links to propose an improvement to the design (discussed in Section III, with examples presented in Section VII).

(iv) A stochastic model from our previous work [20] provides an approximate analytical model of multihop networks that use the beaconless CSMA/CA as defined in IEEE 802.15.4, to determine the maximum measurement rate that the design can support while meeting QoS.

(v) At this stage, network operation can start. However, since the quality of wireless links can vary over time, the network monitors the packet delivery performance and triggers a topology redesign (that may require relay augmentation, or just re-routing) if the performance degrades below a target level (discussed in Section VIII).

## II. RELATED LITERATURE

Considerable work has been done in the design and deployment of wireless networks in general, and wireless sensor networks, in particular. Ray [17], Li et al. [13], and Huang et al. [10] present tools for node deployment to achieve coverage and connectivity in sensor networks, which are based only on modeling and simulation, and do not take into account the unpredictability of wireless links which require on-field testing of modeled links. SmartConnect adopts a field-interactive design approach, where we iteratively improve upon an initial model based design by making on-field link quality measurements.

Several recent papers address various aspects of wireless link modeling and link quality estimation.

Chipara et al. [9] developed a wall classification based radio coverage prediction model in an indoor WSN, that seems to assume knowledge of the actual path of signal propagation over a link, which is often *not accurately known in a wireless environment due to stochastic fading*. The link model in SmartConnect attempts to capture the average characteristics of the environment by estimating the maximum communication range,  $R_{\max}$ ; deviation in link quality from predicted model due to specific non-homogeneities are accounted for during on-field link learning.

Liu and Cerpa [14] present a three step, *feature based* approach to *short temporal* link quality prediction to better utilize temporally intermediate links for routing purposes. However, their link prediction approach cannot be adopted in an iterative *network design* process, since this approach requires link features (e.g., PRR, RSSI etc.), *which are available only for on-field links*, and not for links between potential locations which are not yet deployed.

Chen and Terzis [8] proposed a Bernoulli trial method to identify spatially intermediate links with high PRR. A key trade-off of the proposed approach is that one requires several trials to identify even a single good (high PRR) location. They also presented a method for *unconstrained* relay placement (i.e., no restriction on the locations of the relays) to connect a set of sensing nodes to a gateway. Their objective in deploying relays is to identify *relatively longer* links (beyond the stable connected range) with high PRR. SmartConnect, on the other hand, addresses a *constrained* relay placement problem, and provides *explicit end-to-end QoS guarantee* that cannot be achieved by just ensuring a high PRR on each link.

Krause et al. [12] study the problem of *sensor placement* to maximize information obtained from the sensors while minimizing *total communication cost*. In SmartConnect, *sensor*

*locations are given*, which is more often the case [8]; we aim at minimizing the cost of deploying additional relays, subject to a target communication cost *per sensor*.

There are also products that deploy relays for sensor connectivity based only on on-field measurements [1]–[5]. But any broken links are corrected and tested only based on the intuitive prediction of the deployment engineer.

Robinson et al. [18] address the problem of deploying a minimum number of mesh nodes to build a *tree* for providing client coverage and mesh (backhaul) connectivity subject to mesh capacity constraints, while accounting for non-uniform propagation characteristics. A Degree Constrained Terminal Steiner Tree algorithm is used to obtain an initial design from the estimated network graph. Once deployed, measurements are made *only on the proposed backhaul links* to ensure mesh connectivity. If a predefined SNR threshold is violated, then the network is redesigned with the refined network graph.

Beyond the apparent similarity of iterative field measurement driven design, there are several key differences between SmartConnect and the problem addressed by Robinson et al.

SmartConnect focuses on providing an end-to-end *QoS guarantee* per source while aiming to minimize the total number of relays, and can provide a *robust design* by allowing for multiple node disjoint, QoS aware paths between each source and the sink. Robinson et al., on the other hand, *do not aim for any explicit end-to-end QoS*, or robustness ( $k$ -connectivity). Indeed, in their *Measure-and-place* algorithm, measurements are made *only on backhaul links*. Thus, any *poor link quality on a client-mesh link would remain undetected* in this approach, and will affect the end-to-end QoS.

Moreover, once the initial design is deployed on field, SmartConnect makes measurements among all possible on-field links, thus identifying the potentially good links which were estimated to be bad, and allowing for convergence of the design procedure in a small number of iterations (often just one or two iterations). Robinson et al. make measurements only on the *proposed* candidate backhaul links, and not on any other links existing on the field. This keeps the number of measurements per iteration small, but in turn, may take several iterations to converge. Also, in their problem, clients cannot act as mesh nodes, whereas in SmartConnect, sources can act as relays.

## III. FIELD INTERACTIVE NETWORK DESIGN

In this section we provide an overview of the network design and deployment approach utilized by SmartConnect. At the beginning of the design process we are given a deployment region with designated sensor locations, the location of the sink, and several potential locations at which wireless relays can be placed.

To design a network connecting the set of sensor sources and the sink, using topology design algorithms, we need a network graph defined over the sensor sources, the potential relay locations and the sink. In very small networks, relays can be placed at all potential relay locations and the qualities of the links between every pair of relay locations could be learnt by on-field measurements. Using our previously developed topology design algorithm [6] on such a network graph of field-learned links would provide a one-shot design satisfying QoS constraints, if such a design is feasible. For a larger network with a large number of potential relay locations, deploying relay nodes at every potential relay location would

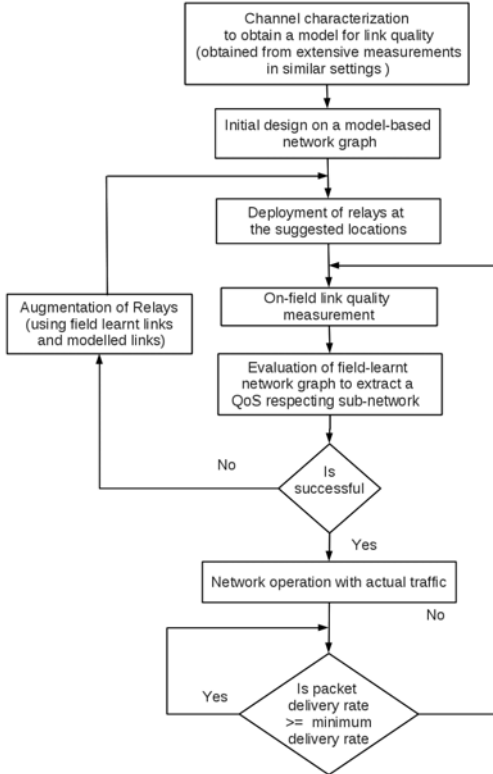


Fig. 1. The phases of SmartConnect’s field interactive iterative network design and deployment.

be impractical. What we need is a model to capture the characteristics of the wireless channel in the deployment environment so as to predict feasible links between the locations of the sources, the relay locations, and the sink; we can then apply the design algorithm on the model based network graph to obtain an initial design satisfying QoS constraints on this graph, and place relays only at the locations suggested by this *initial design*.

While there could be several approaches for modeling the quality of links (e.g., an RF propagation modeling tool could be utilized), we have adopted a simple link quality model. Any two nodes within a distance of  $R_{\max}$  meters are predicted to be in communication range of each other (details of the procedure to obtain such a link model are provided in Section IV). This link model, i.e.,  $R_{\max}$ , can be significantly different for different deployment environments such as an outdoor power distribution yard, or an indoor industrial or commercial establishment, etc. We note that  $R_{\max}$  is just a simple distillation of statistical data collected in a similar environment, and merely asserts that links shorter than  $R_{\max}$  are likely to be good (in a sense to be explained in detail in Section IV).

Statistical link models can only estimate the channel characteristics of the environment, but cannot fully ascertain the existence of the predicted links on the field. Some links could be worse than predicted due to the presence of large obstacles, or even better than predicted, e.g., due to line of sight visibility. *Actual on-field link quality measurement is, therefore, needed* before the network can be put into operation. By actually placing relay nodes at locations provided by the initial design, we can learn the *on-field link quality* of all the links between

the deployed nodes. Upon completion of link learning, we have a network graph of *field-learned links* (acceptable links). This graph is fed to the topology design algorithm for *evaluation* to verify whether the on-field nodes along with the good quality learnt links are sufficient to obtain a sub-network connecting the sensors to the sink, while meeting QoS. If this evaluation of the field-learned network graph is successful, then the design is complete. Only the relays that are part of this topology are kept, and the rest are removed.

If however, the topology design algorithm cannot extract any QoS respecting subnetwork from the on-field network graph on the deployed nodes, the network will need *relay augmentation*. At this stage we have *learnt links* between the nodes on field, and *modeled links* between the rest of the locations. This network graph consisting of modeled and learnt links is now used by the topology design algorithm to obtain a subnetwork that meets the required QoS, which will require the deployment of relays at additional potential locations. Since the locations suggested for relay augmentation are based on modeled links, the newly added links (due to relay augmentation) need to be learnt on field before re-evaluation. As shown in Figure 1, after the initial design, *link learning*, *evaluation* and *augmentation* are repeated iteratively until a QoS respecting network is obtained. This is the crux of SmartConnect’s *field interactive, iterative design*. The iterative process provides a method of partial deployment of networks with modeled and learnt links until a complete deployment meeting QoS requirements on field is obtained. Provided that the link model is not too conservative (i.e., it does not severely underestimate the link quality), if there exists a QoS respecting subnetwork in the actual on-field network graph, this iterative procedure will converge to such a solution on field after a few iterations (a possible problem with an overly conservative link model could be that the topology design algorithm may declare the problem to be QoS-infeasible even if there exists a feasible solution in the actual on-field network graph). A remedy for this situation is discussed in Section VI-B.

Additionally since wireless links are highly dynamic, with significant changes in time of day and surrounding activity, robustness of a deployed network is a challenging issue. To account for these link variations we perform a continuous repair process. As we receive sensor data from the sensor sources, knowing the rate at which data is being sent, we measure its packet delivery rate. This packet delivery rate is continuously monitored at the base station. If it reduces below the delivery rate the network was designed for, then a repair is triggered from the base station. Link learning is initiated, the updated network graph is evaluated, and augmentation is performed if necessary. On arriving at a design that was successfully evaluated, network operation continues till repair is triggered again. This procedure makes the network robust by accounting for link variation over large time duration by repairing as and when necessary. Link variations that stem from, change in activity in the environment, change in obstacle profile or seasonal changes can be handled. The details and implementation of the concepts presented in the current section are discussed in the rest of the paper.

#### IV. WIRELESS LINK MODELING

We assume that our network carries standard size packets (in particular, the packet consists of 90 bytes of payload, together with 20 bytes IP header, 24 bytes MAC header, and

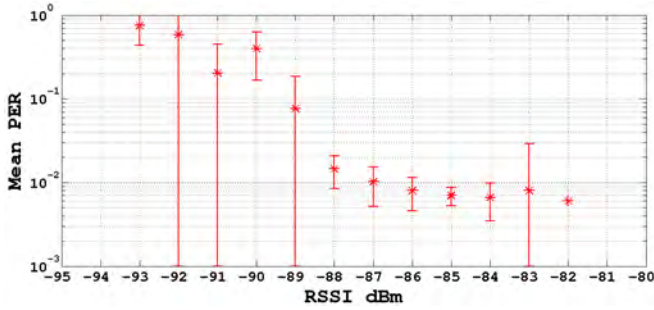


Fig. 2. PER vs RSSI measured between two motes, connected by a standard coaxial cable and standard attenuators. “Over-the-air” packet size: 140 bytes

6 bytes PHY header, for a total of 140 bytes); hence, our measure of link quality is in terms of packet error rate (PER). The packet error rate is determined by the bit error rate, which in turn is governed by the received signal strength, the noise and the interference, and the modulation-demodulation scheme. For the particular radios we have used, Figure 2 shows measured PER (for our standard packet sizes) versus the RSSI (received signal strength indicated by the receiver) in a controlled experiment (see [16], [19]). The PER measurement was conducted by connecting two TelosB motes back-to-back via standard attenuators, and varying the RSSI value. The experiment was repeated for several different node pairs, and the mean PER over all the experiments was obtained as a function of RSSI. Figure 2 shows the mean PER as well as the 95% confidence interval as a function of RSSI. We notice that the PER is reliably below 0.02 or 0.03 for RSSI values larger than -88 dBm, whereas below this RSSI value not only does the PER rapidly increase, but is highly variable *from mote to mote*. We conclude from this experiment that an on-field link should have an RSSI of better than -88 dBm.

Given the above experimental results, for our iterative design process we seek a simple link model, in terms of a link length  $R_{\max}$  such that with a transmitter power of 0 dBm, a receiver at a distance of  $\leq R_{\max}$  is very likely to receive a signal strength better than -88 dBm. The transmitter power of 0 dBm is chosen so as to minimize the requirement of relays.

We now present our approach for choosing  $R_{\max}$ . In this process we have to contend with wireless propagation, a highly unpredictable phenomenon. Classically, for the purpose of analyzing wireless digital communication links, the RF propagation loss is modeled in terms of (i) a nominal path loss model (typically an inverse power law model), (ii) a stochastic shadowing model (which accounts for statistical variation of path loss over different links of the same length), and (iii) a stochastic fading model (which accounts for multipath fading and channel variations).

In choosing  $R_{\max}$ , we define three measures:

$q_{\max}$  The maximum target PER (e.g., 0.05; see the measurement results in Figure 2); equivalently we can think in terms of the minimum RSSI,  $\text{RSSI}_{\min}$ , e.g., -88 dBm.

$p_{\text{out}}$  The fraction of time that the PER on the link is worse than  $q_{\max}$ ; since links do fade over time, outage is inevitable; the probability of a multihop path being in outage increases with the number of hops; hence, we need to have a target outage probability (henceforth denoted by  $P_{\text{out}}$ ).

$p_{\text{bad}}$  is a function of the link length  $R$ , and is defined

as the fraction of links of length  $R$  that do not meet the outage target  $P_{\text{out}}$ ; this measure is relevant since, due to shadowing, there are link to link average path loss variations, even for links of a given length.

We also have a target  $p_{\text{bad}}$ , which we call  $P_{\text{bad}}$ . The consequences of the choices of  $P_{\text{out}}$  and  $P_{\text{bad}}$ , and a methodology for making these choices will be presented below.

Having defined these measures and their targets, we then define

$R_{\max}$  The link length  $R$  at which  $p_{\text{bad}}$  is less than or equal to  $P_{\text{bad}}$ .

Once we identify an  $R_{\max}$  such that targets for all the above measures are met, then in the design steps that involve model based design (see Section III), we just include all links that are of length  $\leq R_{\max}$ . In doing this, the measure  $p_{\text{bad}}$  plays two roles: (i) The larger the value of  $P_{\text{bad}}$ , the larger the probability that the model-based design will not meet QoS on the field. (ii) It also helps to determine the set of potential locations, as follows. Given  $R_{\max}$  and  $P_{\text{bad}}$ , the set of potential locations can be chosen to be such that if we consider the graph on these locations with all edges of length  $\leq R_{\max}$ , and if each such potential edge is removed with probability  $P_{\text{bad}}$ , then with a high probability the remaining graph still has a subgraph that meets our QoS objectives.

Although analytical models (e.g., Rayleigh or Ricean fading, and log-normal shadowing) can be used to relate  $R_{\max}$ ,  $\text{RSSI}_{\min}$ ,  $P_{\text{out}}$ , and  $P_{\text{bad}}$ , these relations are only indicative and cannot be used for reliably characterizing the quality of links in a design process. We, therefore, resort to a measurement-based approach.

- A large number of nodes (50 nodes in our experiments) are scattered throughout the region, so as to obtain links of varied distances.
- Each node, one after the other, broadcasts a large number (5000 packets in our experiments) of “hello” packets. The nodes that receive them, log the received signal strength (RSSI) of each packet along with the details of the sender node.
- We now have a distribution of RSSI for every link in the network. These distributions are distilled into the plots shown in Figure 4 and Figure 5, as explained in the following bullet points.
- From the graph in Figure 2 we see that to obtain a PER of less than or equal to 0.05 with high probability, the RSSI along the link should be greater than or equal to -88 dBm; this is when the link is not in outage.
- The probability that a link is not in outage, say,  $p_{\text{nout}}$ , is the fraction of packets received at  $\text{RSSI} \geq -88$  dBm on the link. The probability that the link is in outage,  $p_{\text{out}}$ , is estimated as  $1 - p_{\text{nout}}$ .
- A link is said to be ‘good’ if its outage probability is less than  $P_{\text{out}}$ , else it is termed ‘bad’.
- The links we have are now binned according to their link length. The link length is rounded off to the nearest meter to make one meter bins. In each bin, we compute the fraction, say,  $p_{\text{good}}$ , of ‘good’ links, and then  $p_{\text{bad}}$  is estimated as  $1 - p_{\text{good}}$ .
- The maximum distance bin in which the probability of a link being bad ( $p_{\text{bad}}$ ) is less than or equal to a threshold  $P_{\text{bad}}$  is chosen as the maximum communication range ( $R_{\max}$ ) for reliable communication.



Fig. 3. A view of the 440 KV power distribution yard, showing the layout of equipment; apart from the transmission towers, several transformers and a firewall can be seen at a distance.

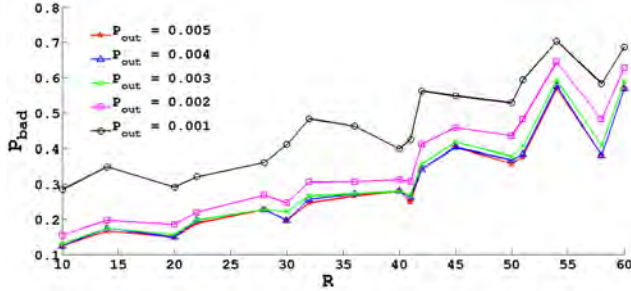


Fig. 4. Measurements taken from a power distribution yard environment (see Figure 3):  $p_{\text{bad}}$ , i.e., the fraction of links whose outage probability is greater than  $P_{\text{out}}$ , vs link length,  $R$ , plotted for multiple values of  $P_{\text{out}}$ .

- The choice of  $P_{\text{out}}$  and  $P_{\text{bad}}$  are based on measurements and is elaborated in the two examples below.

We have carried out such measurements in several environments: 440KV outdoor power distribution yard (since the goal of our project was to create wireless networks for connecting sensors in such yards), our department building (ECE Department, IISc), and a dense wooded area in the IISc campus. We report here results from the power distribution yard and the department building measurements.

In Figure 4, we provide a summary of measurements that we took at a 440KV outdoor power distribution yard. A photograph of a part of this yard is shown in Figure 3. There are several tall towers across which are strung high-tension power cables; there are transformers, circuit breakers, and firewalls separating the transformer bays. The ground is covered with coarse gravel; there are also drainage ditches, and narrow tarred roads criss-crossing the area.

In Figure 4, for each value of  $R$ , between 10 m and 60 m (on the x-axis), we show (on the y-axis)  $p_{\text{bad}}$ , the fraction of links whose outage probability was worse than each of five values of  $P_{\text{out}}$  (0.001, 0.002, 0.003, 0.004, 0.005). In these measurements, the target  $RSSI$  was -88 dBm. As expected, for a fixed value of  $P_{\text{out}}$ ,  $p_{\text{bad}}$  increases with  $R$ . For example, with  $P_{\text{out}} = 0.002$ , for  $R = 30\text{m}$ , about 25% of the links displayed an outage probability worse than 0.002, whereas with  $R = 60\text{m}$  this went up to more than 60%. We notice that there is a sharp increase in  $p_{\text{bad}}$ , for every value of  $R$ , if  $P_{\text{out}}$  exceeds 0.002. From the plot we also see that, at every distance, at least 10% of the links are bad. Lowering  $P_{\text{out}}$  will give a more conservative value of

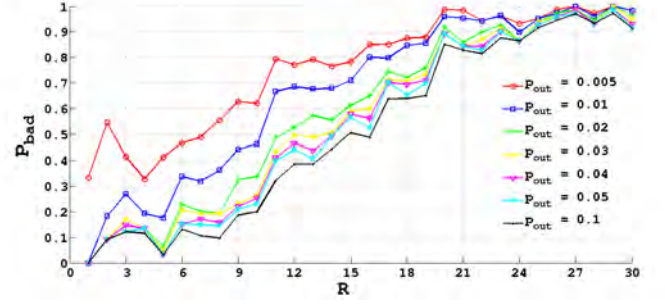


Fig. 5. Measurements taken inside our department building:  $p_{\text{bad}}$ , i.e., the fraction of links whose outage probability is greater than  $P_{\text{out}}$ , vs link length,  $R$ , plotted for multiple values of  $P_{\text{out}}$ .

$R_{\text{max}}$ , for a chosen  $P_{\text{bad}}$ . So the choice of  $R_{\text{max}}$  is a trade-off between  $P_{\text{out}}$  and  $P_{\text{bad}}$ . For a given  $P_{\text{bad}}$ , increasing  $P_{\text{out}}$  may increase  $R_{\text{max}}$ , but affects the packet delivery probability, whereas reducing  $P_{\text{out}}$  reduces  $R_{\text{max}}$ , thus leading to a more conservative (and possibly costly) design. For a given  $P_{\text{out}}$ , increasing  $P_{\text{bad}}$  can increase  $R_{\text{max}}$ , but it also increases the chance that a proposed design requires augmentation, and requires more potential relay locations to begin with. Based on the measurement results shown in Figure 4, we chose  $P_{\text{out}} = 0.004$ ,  $P_{\text{bad}} = 20\%$ , yielding  $R_{\text{max}} = 30\text{m}$ .

Figure 5 shows the summary of similar measurements we made for an indoor deployment inside our department building. The analysis of the figure, as in the previous example, tells us that for a  $P_{\text{bad}}$  of less than 10% we get a value of  $R_{\text{max}}$  of only 3 meters, for any value of link outage. We see that the link outage in the indoor case is much larger than that of the outdoor power distribution yard case. So based on Figure 5, we chose  $P_{\text{out}} = 0.04$ ,  $P_{\text{bad}} = 20\%$ , yielding  $R_{\text{max}} = 8\text{m}$ .

## V. NETWORK DESIGN APPROACH

In each iteration of the design process outlined in Section III, we have a graph on the set of sources and potential relay locations. In some steps, the graph is based only on the model discussed in Section IV, i.e., all pairs of nodes separated by less than  $R_{\text{max}}$  meters are assumed to have a good link between them, or based on measurements, or both. In [6] and [7], we have elaborated how, given a network graph defined on the source nodes, the potential relay locations, and the Base Station (BS), a candidate topology satisfying the QoS constraints is extracted. The basic network design problem that we want to address can be stated as follows: Given a network graph  $G = (V, E)$ , where  $V = Q \cup P$ , is the set of vertices consisting of source nodes  $Q$  (including the base station) and potential relay locations  $P$ , and  $E$  is the set of all feasible links, obtain a subnetwork that connects the source nodes to the base station with the requirement that

- 1) A minimum number of relay nodes is used.
- 2) There are at least  $k$  node disjoint paths from each source node to the BS.
- 3) The maximum delay on any path is bounded by a given value  $d_{\text{max}}$ , and the packet delivery probability (the probability of delivering a packet within the delay bound) on any path is  $\geq p_{\text{del}}$ .

The following assumptions are made regarding the network traffic, and the nature of the wireless medium.

- 1) The traffic generated by the sensor nodes is *very light*; so there is *rarely* more than one packet in the network at any point of time so that, with a high probability, the network is contention free. Such a situation can arise in many applications where successive measurements being taken are well separated in time so that the measurements can be “staggered”, and they do not occupy the medium at the same time, e.g., applications such as data logging, and non-critical preventive control (see [15, p. 9]).
- 2) As mentioned in Section IV, since there is a non-zero PER on each link, packet losses due to random channel errors have been considered, so that a random number of retransmissions are required until each packet is delivered across each link, or is dropped due to excessive retransmissions.
- 3) Also *slow fading* is permitted so that the packet error probabilities on the links vary slowly over time, leading to possible *link outage* (See Section IV).

We approach the problem by designing the network for the, so called, “lone packet model”, thus reducing the problem to one of graph design, and then using an analytical model to evaluate the maximum data rate that the network can support while meeting QoS. Also note that in order to meet the QoS constraints for a positive traffic arrival rate, it is *necessary* to satisfy the QoS constraints under the lone-packet model. As it turns out, even this simplified version of the problem is NP-Hard. Therefore, one cannot hope to solve the more complex general problem with positive arrival rate unless one has a satisfactory solution to this basic lone-packet design problem.

We outline below, how, under a lone-packet model, we can reduce the QoS constrained network design problem into a graph design problem.

#### A. Mapping of QoS to Hop Constraint

Under the assumptions stated earlier, it can be shown by an elementary analysis that the QoS constraints, namely, maximum end-to-end packet delay,  $d_{\max}$ , and packet delivery probability,  $p_{\text{del}}$ , can be mapped to a hop count bound  $h_{\max}$  on each path from each source to the BS according to the following equation (the details of the analysis are provided in [7]):

$$(1 - P_{\text{out}})^{h_{\max}} (1 - \delta(q_{\max}))^{h_{\max}} D_{q_{\max}}^{(h_{\max})}(d_{\max}) \geq p_{\text{del}} \quad (1)$$

where,

$q_{\max}$ : The target maximum PER on a link

$D_q(\cdot)$ : The cumulative distribution function of packet delay on a link with PER  $q$ , given that the packet is not dropped;  $D_q^{(h)}(\cdot)$  denotes the  $h$ -fold convolution of  $D_q(\cdot)$ . Under the lone packet model,  $D_q(\cdot)$  is obtained by a simple analysis of the backoff and attempt process at a node, as defined in the IEEE 802.15.4 standard for beaconless mesh networks.

$\delta(\cdot)$ : The mapping from PER to packet drop probability over a link. Note that even when there is no contention, packets could be lost due to random channel errors on links (i.e., non-zero link PER). A failed packet transmission is reattempted at most three times before being dropped.

$P_{\text{out}}$ : The maximum probability of a link being in “outage” (see Section IV)

The first term in Equation (1) lower bounds the probability that a path is not in outage, and the second term lower bounds the packet success probability on a path, given the path is not in outage. Finally, the last term indicates the probability of *in-time* delivery given that the packet was not dropped.

Since the packet drop probability, given the path is not in outage, is quite small (in fact, it is upper bounded by  $q_{\max}^n$  on each link, where  $n$  is the total number of failed transmission attempts before a packet is dropped;  $n = 4$  for IEEE 802.15.4 CSMA/CA MAC [11]), the packet delivery probability is essentially dominated by the path outage probability, and the probability of *in-time* delivery, given the packet is not dropped. In some of the deployment environments that we encountered, especially indoor environments, the probability of link outage turned out to be quite large; for instance, it turned out that even for small link lengths ( $\leq 8$  meters), about 20% of the links had outage probability in excess of 5%, and the situation was even worse for longer links. In view of this, we adopt the following design strategy: given  $q_{\max}$ , we choose  $h_{\max}$  so as to make  $D_{q_{\max}}^{(h_{\max})}(d_{\max})$  close to 1, say 0.9999. We thus ensure that when the path is not in outage, we deliver the packets *in time* with very high probability. Then the achievable  $p_{\text{del}}$  gets governed only by the  $P_{\text{out}}$ .

With the above mapping from  $p_{\text{del}}$  and  $d_{\max}$  to  $h_{\max}$ , our original QoS constrained network design problem can be reformulated as the following graph design problem:

Given the network graph  $G = (Q \cup P, E)$  consisting of the set of source nodes  $Q$  (including base station), the set of potential relay locations  $P$ , and the set of all feasible edges  $E$ , extract from this graph, a subgraph spanning  $Q$ , rooted at the BS, using a minimum number of relays such that each source has at least  $k$  node disjoint paths to the sink, and the hop count from each source to the BS on each path is  $\leq h_{\max}$ . In [7], this is called the *Rooted Steiner Network- $k$  Connectivity-Minimum Relays-Hop Constraint* (RSN $k$ -MR-HC) problem.

For the special case of  $k = 1$ , in [7] this is called the *Rooted Steiner Tree-Minimum Relays-Hop Constraint* (RST-MR-HC) problem.

#### B. Network Design Algorithms: The Basic Principle

The details of the network design algorithms for the RST-MR-HC and the RSN $k$ -MR-HC problems are discussed in [6] and [7].

Both the algorithms basically perform a series of shortest path computations from each source to the sink, starting with an initial feasible solution, and adopting a certain combinatorial relay pruning strategy to prune relay nodes from the feasible solution sequentially, each time computing a new shortest path involving only the remaining nodes, in an attempt to minimize relay count, while still retaining hop count feasibility.

#### C. Network Performance Analysis

The final step of our design approach is to use an analytical model to obtain the maximum packet rate that each sensor can generate so that the QoS target is not violated for the packets generated by any sensor. For this we utilize a fast and accurate analytical model for multihop CSMA/CA networks that we have reported in [20]. Our approach models CSMA/CA as standardized in IEEE 802.15.4, buffers at each transmitter, and packet error rates on each wireless hop.



Fig. 6. SmartConnect architecture: Iterative deployment involves command-response interaction between nodes on the field and the SmartConnect system via the SmartConnect-WSN gateway; message interaction between the SmartConnect graphical user interface (GUI) and SmartConnect-WSN gateway takes place over TCP/IP.

## VI. IMPLEMENTATION, PRACTICAL ISSUES, AND TESTING

### A. SmartConnect: System Implementation

The components of the SmartConnect network design and deployment architecture and the interactions between them are depicted in Figure 6. The SmartConnect GUI runs the algorithms for network design and analysis at the back-end, and has a console for configuration, field interaction, and information display. The SmartConnect GUI is connected over TCP/IP to the SmartConnect-WSN gateway. The SmartConnect-WSN gateway is a Linux host connected to a base station mote over USB.

The SmartConnect GUI automates the entire design and deployment process by requiring the user to provide minimal inputs. Active participation from the user is solicited only at the time of placing relay nodes on the field. Apart from using the design algorithm to provide relay locations for deployment, the user can intervene with their own intuitively provided relay locations or modify those provided by the design algorithm. The user can also view predicted and field learnt links from each node, as well as the full network graph on which the algorithm is working in each iteration. In our implementation the wireless nodes including the base station mote were TelosB motes with a 2.2 dBi external omnidirectional antenna for increased radio range.

### B. SmartConnect: Some Practical Issues

**Communication Before Network Set-Up:** In the design phase of the deployment we have source nodes and relay nodes at predicted locations on field. There is no existing reliable network connecting the nodes on the field to the sink. At this stage, for sending commands and receiving data from the nodes we need a protocol for topology-free routing. The commands sent from the base station to the nodes during link learning, and the data sent from nodes to the base station containing link data are all sent using a form of flooding implemented in TinyOS called dissemination [4].

When the initial design is deployed on the field, the design is based only on modeled links. In such a deployment dissemination could fail due to one or more ‘bad’ links disconnecting a section of the network. We thus cannot assure reliability of the commands being sent out to the nodes. Since our communication range is conservative in most cases the number

of relay nodes placed on field are in excess of what are needed and used. We depend on this aspect of our design to provide a communication framework before the actual network comes into place. Barring very small number of exceptions, we found that in most test cases we could successfully reach all nodes in the network.

**Stopping with declaration of infeasibility:** The topology design algorithm uses either, a model based network graph (for the initial design) or a hybrid network graph of modeled links and field-learnt links (relay augmentation) to propose relay locations. The link model we use is conservative so as to reduce the number of iterations the design would require (discussed in Section IV). So, when a model based network graph is fed to the topology design algorithm, it could declare the design infeasible (initial design/augmentation not possible) even though, on field measurement of link quality, the design could be feasible. This could happen during initial design, or when augmentation is needed. To still be able to attempt a design, even when the design algorithm declares infeasibility, SmartConnect allows the user to intuitively place relays at any potential relay location, and proceed with the design process. On evaluation of the field-learnt network graph the design may or may not be successful. The user is allowed to continue augmenting the network and evaluating until relays are placed at all potential relay locations.

### C. Testing

After network design and validation, a test phase is conducted to verify whether the delivery probability and delay promised by the design are being met by the network. In this phase the network is essentially in operation, but the data being relayed by the network are pseudo-sensor data. In the specific case that we are addressing, the data from each sensor is collected infrequently. The time duration required to receive from each sensor source depends on the number of hops it is from the base station and is in the order of only a few milliseconds. This allows us to collect data from each source in a Time Division Multiplexed (TDM) manner. A time frame is created with one slot given to each source. Each source sends in its time slot, thus maintaining light traffic in the network. This requires us to have a time sync protocol in place, so the time frames of all nodes are synchronized. The time sync protocol used in our implementation is FTSP (flooding time synchronization protocol) provided by TinyOS.

## VII. EXPERIENCES WITH EXPERIMENTAL DEPLOYMENTS INSIDE OUR DEPARTMENT BUILDING

SmartConnect has been used to make test deployments in three very different environments: inside our department building, on the lawns of our building, and at a large power distribution yard (recall Figure 3). We found that by far the most challenging environment was the building. Hence, we report here our experience with a test deployment in our department.

### A. Indoor Deployment 1

We use this test deployment, to test the basic working of the iterative design and the approximation algorithms. GUI snapshots are shown at each design phase.

This deployment environment is a high ceilinged building, constructed from stone blocks, and built around the time of the World War II. It has thick stone walls (0.66 m outer walls,

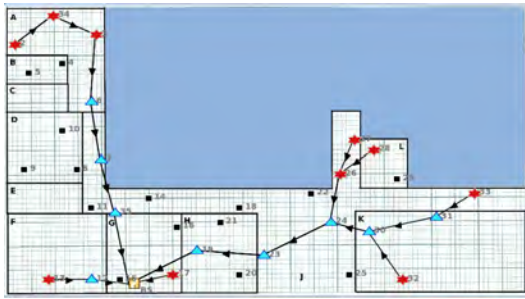


Fig. 7. Indoor deployment 1: Initial design on the model based network graph. 10 sources; the initial model-based design suggests 9 relays; the paths in the initial design are shown.

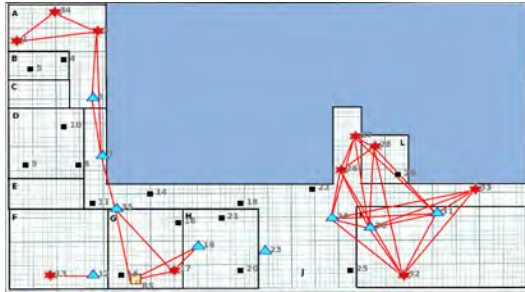


Fig. 8. Links learnt after deploying the relays suggested by the initial design. All good links learnt are shown.



Fig. 9. Augmentation step suggests the placement of Relays 15, 16, 18, and 22. The additional good links learnt now yield a connected network.

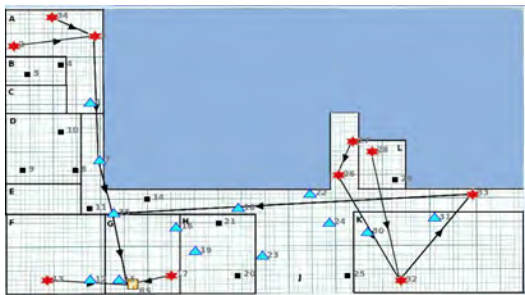


Fig. 10. Final network design based only on the good links learnt in the field. Just two of the relays deployed in the field (namely, 7, and 35) end up being needed.  $\lambda_{max}$  of the network is 0.103 pkts/s.

and 0.66 m thick walls between rooms), 5m high ceilings, heavy wooden doors, cubicle separators, tables and other office equipment. As described in Section IV a communication range model was obtained for the environment before the deployment. Owing to heavy attenuation by walls and doors with very few corridors, link outage in the environment was

Sensor source ID	Measured $P_{del}$	Predicted $P_{del}$
2	0.9751	0.9119
3	0.9857	0.9448
34	0.9791	0.9163
13	0.9997	0.9518
17	1.0000	0.9880
26	0.9191	0.9122
27	0.8548	0.9120
28	0.9389	0.9155
32	0.9581	0.9259
33	0.9911	0.9345

TABLE I  
INDOOR DEPLOYMENT 1: DELAY BOUNDED PACKET DELIVERY RATE IN THE FINAL DESIGN SHOWN IN FIGURE 10.

large, resulting in an  $R_{max}$  value of only 8 m.

The deployment parameters of this test deployment are as follows. Field area of  $1650 m^2$ , 24 potential locations, 10 sensor sources, 200 ms delay constraint, Communication range of 8 m and a path redundancy of 1. The target, delay bounded, packet delivery ratio  $p_{del}$  for this network deployment was 73% which would allow a network of at most 6 hops obtained from the  $p_{del}$  inequality (1)

Figure 7 shows a GUI snapshot of the initial design on the model based network graph. The sensor sources are indicated by red stars, the black squares are potential relay locations, the yellow house is the sink, and the blue triangles are relay nodes. The design algorithm suggested relay locations are indicated by blue triangles and the paths shown are QoS abiding paths on the model based network graph. We see that the initial design suggested nine relays (numbered 6, 7, 35, 12, 19, 23, 24, 30, and 31). The GUI snapshot also shows the paths that each source should use.

After placing relays at locations suggested by the topology, link learning was done with the nodes on field. The field-learnt links between these nodes are shown in Figure 8. Each red line on the graph is a bidirectional ‘good’ link. A link is said to be bidirectional if link outage constraints are met when measured in either direction. We see from the figure that the learnt-links network graph was not even fully connected. Evaluation of this field-learnt network graph failed, and a second iteration was required with the design algorithm suggesting augmentation of relays (four relays, numbered 15, 16, 18, and 22). Figure 9 shows the field-learnt links after augmentation and the second iteration of link learning (the augmented relays are highlighted with a circle). This graph on evaluation was found to meet QoS. The final design is shown in Figure 10. Some observations from this design are that; of all the relays suggested, only two relays (numbered 7 and 35) were used by the design (relays 6, 12, 15, 16, 19, 18, 23, 22, 24, 30, and 31) were removed after the design); some sources are also acting as relays in the design; the link between nodes 33 and 35, even though very long, was learnt to be ‘good’ on field since it had a clear line of sight path.

Once the design was complete, we ran the analytical model described in [20], and found that to meet the QoS requirement; the maximum packet generation rate from any sensor, for a Poisson packet generation process, i.e.,  $\lambda_{max}$ , is 0.103 pkts/s; i.e., about 1 packet every 10 seconds from each sensor, which is quite adequate for applications such as condition monitoring.

Finally, field testing was performed by sending pseudo-sensor data packets over the network. Results are provided in Table I. Predicted  $p_{del}$  for each source node in the table was found by using field-learnt link outage values in the same



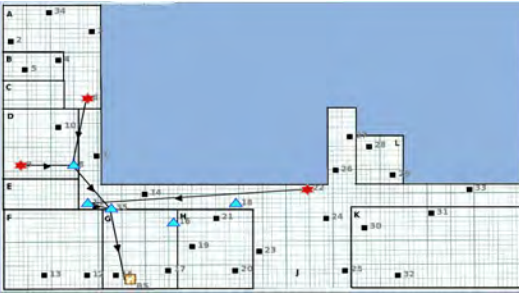


Fig. 11. Indoor deployment 2: Three sensors; five relays proposed by the initial design (namely, 8, 11, 35, 16, 18); finally just three relays (8, 11, and 35) are used.  $\lambda_{max}$  of the network is 0.118 pkts/s.

Sensor source ID	Measured $p_{del}$	Predicted $p_{del}$
6	0.8971	0.8830
9	0.8961	0.8930
22	0.9075	0.9300

TABLE II  
INDOOR DEPLOYMENT 2: DELAY BOUNDED PACKET DELIVERY RATE IN THE FINAL DESIGN SHOWN IN FIGURE 11.

$p_{del}$  inequality.

We see that Node 27 has a delivery probability 6% lower than the predicted value. Due to the dynamic nature of this environment, after deployment, some links turned out to be worse than measured. This could be due to the movement of people around some nodes or opening/closing of doors. In this example the predicted and the measured delivery probabilities are still better than the target  $p_{del}$ , which we recall was 73%. However, this need not continue to hold over time, as long term variations in the statistics of the links affects delivery rates. This motivates the need for a repair phase (refer to the last block of the flow diagram in Figure 1) that is triggered by a drop in delivery rate to handle long term variations and make the network robust. The procedure adopted to do this along with some experimental results are discussed in Section VIII.

### B. Indoor Deployment 2

The results of another smaller deployment made in our department building is presented here. The design parameters of this deployment were the same as the previous example, except that 3 sensor sources were deployed here and the target  $p_{del}$  for this deployment was 77% allowing at most a 5 hop network (1).

Figure 11 shows a snapshot of the final network design. This network required only one iteration of design and evaluation. Of the five relays suggested by the initial design three of them (namely, 8, 11, and 35) were used and the other two (namely, 16, and 18) were removed. On completion of the design, we ran the analytical model as in the previous example, and found that to meet the QoS requirement; the maximum packet generation rate from any sensor, for a Poisson packet generation process, i.e.,  $\lambda_{max}$ , is 0.118 pkts/s. The results of field testing on the network are shown in Table II. Notice that for Node 22, even though the measured  $p_{del}$  was worse than the predicted  $p_{del}$ , both were still much better than the target, i.e., 77%.

## VIII. ROBUST NETWORK DESIGN

The SmartConnect design approach accounts for short term link variations (over channel coherence times) via the wireless



Fig. 12. Set of 24 locations where nodes were placed and link learning performed periodically to evaluate network robustness

Expt. no.	Source IDs	Initial relay set	Augmentation required at cycles	Final relay set	no. of topology redesigns
1	12, 10, 16 21, 6, 4	no relays were used	17	11	2
2	18, 20, 15 13, 9, 4	14, 3	src 13 is isolated at stage 12	X	X
3	22, 16, 6 16, 18, 8	11, 2	17	11, 2, 9, 5	4
4	19, 22, 12 23, 15, 21	16, 5	27	16, 5, 5	4
5	20, 12, 10 15, 3, 7	11, 9	22, 32	11, 9, 2, 5	3
6	22, 23, 24 16, 9, 8	5	6, 27	5, 11, 21, 3	4
7	18, 19, 11 5, 6, 4	no relays were used	none	no relays were used	2
8	20, 21, 4 8, 19, 18	11	17	11, 9	1
9	18, 12, 23 24, 8, 4	10, 5	6, 17	10, 5, 22 3, 11, 9	4
10	12, 22, 16 11, 3, 6	no relays were used	17	5	3

TABLE III  
RESULTS FROM THE EXPERIMENT TO STUDY TEMPORAL ROBUSTNESS OF THE NETWORK DESIGN; SEE TEXT FOR DETAILS.

link model. A sensor network would, however, be expected to operate over a long period of time; at least months, and even years. Over such long periods, due to changes in the propagation environment (e.g., for in-building networks, new furniture, partitions, etc.), the quality of the links in the original design could significantly vary causing a decrease in packet delivery rates. The on-field iterative approach we have adopted, permits us to easily address the problem of network robustness under long term variations in the links; see the design flow chart in Figure 1.

After the initial design has been done, network operation starts, and the network monitors the packet delivery rates. Repair of the network is initiated when the delivery rate of data reduces below what it was designed for. At this point the links between the nodes in the field are learnt again, and if possible the topology is redesigned with no addition of relay nodes. If this is not possible then, exactly as in the initial design process, the modeled links are included and a proposal is made for augmentation with additional relays. At each augmentation stage, the relays that are augmented are kept on the field.

With this approach in mind, it is interesting to ask the following questions:

- 1) How often is topology redesign required?
- 2) Does it happen that after some time no further relay augmentation is required?

In order to study these questions we carried out an experiment in which a set of 24 locations were identified inside

a section of our department building (Figure 12). Unlike the deployment experiments reported in Section VII, we confined these locations to our laboratory (about 600 square meters) in order to be able to leave the relays undisturbed for several days. With the nodes at these 24 locations, link learning was performed periodically with a gap of 4 hours, 20 times over a span of 3 days, and another 20 times over a span of another 3 days, a week later; a total of 40 evaluation and possible redesign cycles.

With the link quality data collected, we could then study the effect of link variations on networks designed over these 24 nodes. We considered 10 sets of 6 nodes as sources, and designed networks (for a target delay of 200 ms) connecting these sources to a base station, using the proposed iterative design approach in the first evaluation cycle. Using the collected link quality measurements we could track the evolution of the delivery probabilities over these 10 different networks, and (virtually) carry out topology redesign and relay augmentation. A redesign was triggered when the delivery rate from any source (as estimated from the measured qualities of the links being used in each design) dropped to below 73% (which is the least delivery rate expected for a 6 hop network with outage  $\leq 5\%$  along each link (discussed in Section V-A)). The performance deterioration would then be attempted to be resolved by topology redesign or by relay augmentation.

We report our results in Table III. The second column of this table shows the 10 different sets of nodes that were sources in the 10 experiments (the numbers relate to Figure 12). The third column shows the set of relays used in the initial design. In the fourth column we show the indices of the 40 evaluation cycles at which relay augmentation was needed. The next column shows the final set of relays, and the final column shows the total number of times redesign (with or without relay augmentation) was done over the 40 evaluation cycles. Out of the 10 experiments, in Experiment 2 we had one source that was poorly located so that in the 12th evaluation cycle, it had no useful links to any other node, thus effectively isolating it. At this point the only alternative is to create more potential locations, a feature that SmartConnect does not as yet include.

From Table III, we see that a maximum of 4 topology redesigns were required over the 40 cycles. So a topology redesign was required around once in 2 days. In cases 1, 3, 7, 8, 9, and 10, after at most the 17th evaluation cycle there was no further need to add relays, even when the network was evaluated after a full week for another 3 days (in fact, case 7 never required a relay augmentation). In cases 4, 5, and 6, no further relay augmentation was required at least over the last 8 evaluation cycles (the last 13 cycles for cases 4 and 6). Thus, it appears that we eventually converge to a deployment where no further relay augmentation will be needed, and topology redesigns over the existing nodes alone will suffice to take care of long term variations. Note that, in this approach, we are essentially over-deploying relays to create redundant links for robustness of the deployed network. But it is also important to notice that in most cases the difference in the size of the initial relay set and final relay set is not large (the worst case being Experiment 9 where four relays had to be added to the original two) indicating that the number of extra relays required to take care of time varying link qualities is quite small.

## IX. CONCLUSION

We have presented SmartConnect, a tool for assisting in designing and deploying multihop relay networks for connecting wireless sensors with a control center, for noncritical monitoring and control applications. We described the core idea of field interactive iterative design, and the associated procedures and algorithms. The SmartConnect system has been fully implemented and can be used for network design in a variety of environments.

The core topology design algorithm, that SmartConnect currently uses, assumes a light traffic model, so that at any time, with a high probability just one packet is traversing the network. In our ongoing work, we aim to extend SmartConnect to be able to design relay networks for more general sensing loads.

**Acknowledgment:** This work was supported by the Department of Electronics and Information Technology (under the Automation Systems Technology (ASTEC) program) and by the Department of Science and Technology (under a J.C. Bose Fellowship).

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