Measurement and Characterization of Link Quality Metrics in Energy Constrained Wireless Sensor Networks

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***Abstract*— In wireless sensor networks, a good cost metric encapsulating wireless link quality is essential to an energy-efficient routing topology. For many wireless network scenarios, rapid variation in the channel precludes an efficient mechanism for knowing instantaneous link quality at the time of transmission, thus making it difficult to estimate the instantaneous value of the cost metric. This paper explores what a good cost metric may be and how it can be measured in an energy-efficient way. We present an experimental study of wireless link quality variation over a period of several days in a sensor network placed in two different indoor office environments. The nodes are equipped with low power transceivers operating in the 900 MHz band. Results are documented for several different link configurations, *i.e.*, relative placement of the transmitter and receiver. Based on detailed observations of link quality variation, we form quantitative measures of link quality, and propose a cost metric. We find that reasonably few channel measurements are sufficient to obtain a good estimate of the cost metric, hence even during the initialization phase one can obtain sufficient information about links in order to design an efficient topology. The estimate can be improved further as more measurements are taken during the normal operation of the network.**

I. INTRODUCTION

Wireless sensor network protocol design may be a challenging task due to severe limitations of power consumption and cost along with high demands on functionality and reliability: Typically, the protocol must allow sensor nodes to communicate amongst themselves to self-organize, aggregate and process information, and deliver information to a central point or actuator interface ([2],[3],[4],[5],[6]). The design of a complete protocol suite involves link, medium access, and network layers and is strongly dependent on the application requirements. The problem is made even more challenging by the requirement that nodes often have to survive on a limited battery energy for extended periods of time, up to several years. Since energy is a constraint for many existing and envisioned sensor network applications, energy-efficient protocol design has emerged as an important problem.

The motivation of our work has been the design of a protocol for an energy-constrained wireless sensor network. We concentrate on stationary networks, *i.e.*, where the nodes are not mobile. In the course of designing and implementing a low-power sensor network prototype, we have been able to isolate key questions in energy-efficient protocol design. The scope of this paper is limited to one of the most basic of those questions: How to characterize, measure and utilize link quality. We have conducted experiments on our prototype to obtain insights to answer this question. We believe that our results will also be relevant in the context of sensor networks different from ours, as long as they satisfy most of the assumptions that will be presented in the next section.

It is well known that designing an energy-efficient routing topology in a wireless sensor network requires the use of a cost metric based on wireless link quality. However, it is not well understood what that metric should be. Whatever the form of the cost metric is, it is likely to require nodes to maintain information about the quality of their links to other nodes. This information must be reliable in order to provide a sound basis for network functions such as multi-hop routing. However, for many potential applications of sensor networks, lack of knowledge about the immediate state of the wireless channel that is just about to be used precludes on-the-fly calculation of an accurate link quality estimate.

In a stationary network, the profile of each link may be learned through taking many measurements throughout a day or several days. However, with battery-operated sensor nodes that are required to survive unattended for a long time, the energy cost of such continuous measurement is prohibitive. This motivates us to explore whether it is possible to obtain a good estimate of the true cost metric based on only a few measurements, which may be improved as opportunity arises later. As we shall see, this seems to be possible.

In the following section, we present our assumptions about the network scenario. In section III, we define the cost metric that we call *link inefficiency*. In section IV, we describe the experiment setup in detail, and discuss some experimental observations in V. In Section VI, we propose a method to estimate *link inefficiency* in an efficient way. Finally, Section VII presents our conclusions.

II. Network Scenario

Sensor networks find potential applications in a wide variety of scenarios. Some of the typical envisaged applications are in environment monitoring and surveillance, smart spaces, and security management. Such a network would need to report alarms or warnings to a central point whenever a certain sensed parameter (say, temperature, pressure, motion) exceeds a threshold value. It is important that a valid network topology is available when demand arises.

We assume that due to dense deployment of nodes and the use of a common media for transmission and reception, various multi-hop paths are available from any single node to another node or a central point. The energy needed to reach the central point from a particular node can be vastly different along different multi-hop paths, though. A routing topology designed for maximizing the lifetime of the network must choose paths that cost least in terms of energy. The energy consumed on a link has a strong relationship with the the state of the wireless channel between two communicating nodes. This motivates the need for using link quality as a cost metric in topology establishment and routing.

The intuitive fact that routing based on link quality statistics is more efficient than a straight-forward hop-count based routing algorithm has been documented in recent literature [7]. In [8], it is proposed that each node should try to assess its connectivity so that it can adapt its participation in the multi-hop network topology. There, as in several other recent papers, connectivity is measured in terms of a loss threshold that a higher layer application can tolerate. When a node experiences a data loss rate that is more than the loss threshold, it solicits its neighbors' help and invites them to join the network to improve connectivity. Although the above-mentioned schemes justify the use of link quality as a reasonable basis for topology establishment, they implicitly assume that the nodes have a relatively high duty cycle so that they can determine the recent state of the wireless links to other nodes. For example, in [7], link quality is calculated based on the number of packets received successfully out of the last 32 packets sent. Since reception or promiscuous hearing in the type of sensor network we consider involves expense of significant energy (about $2/3$rd of transmission energy[1]), a knowledge of the current state of the wireless channel may come at a substantial, even prohibitive, cost.

In our energy-limited sensor network scenario, nodes need to save energy by turning their radio off except when they need to communicate. As a result, the nodes have little knowledge of the recent state of their links to others when they need to transmit status packets towards the centralized controller. The requirement of establishing an energy-optimized and reliable topology, coupled with the problem of incomplete knowledge of the state of a wireless link just before it is to be used, motivates us to propose a novel method of using an initialization phase in the protocol suite. During the initialization procedure nodes transmit a known number of packets to their neighbors. Based on received packets from each neighbor, each node obtains link quality information about its neighbors. This provides the basis for establishing an energy-optimized network topology in the beginning. This topology can be fine-tuned through local reconfigurations that are done after long-term periodic link assessments.

III. "Link Inefficiency"– a cost metric

As pointed out above, the network of interest to us is energy-limited. The network lifetime is defined as the smallest time that it takes for at least one node in the network to drain its energy beyond the point where it can function normally. This is essentially the time between two battery changes for nodes in the network. Since replacement of energy sources incurs installation costs and human effort, one should try to maximize network lifetime by trying to equate the nodes' lifetimes. Assuming nodes are equipped with batteries of similar capacity, this can be achieved by making the rate of energy drainage from the nodes similar.

What is then the rate of energy drain of a certain node? We assume that on every link, an ARQ protocol is employed. That is, a node will repeat the transmission of a packet until it is correctly received. Suppose we are transmitting a packet on link i at time t. If we model link i to have a certain packet success probability $\mathrm{PSP}_i(t)$ at time t, such that every transmission is successful with probability $\mathrm{PSP}_i(t)$ independently of the others, then the mean number of transmissions[2] is $\frac{1}{\mathrm{PSP}_i(t)}$. Since the energy used for each re-transmission is similar, the energy to transmit the packet successfully is proportional to $I = \frac{1}{\mathrm{PSP}_i(t)}$. We shall call I the *link inefficiency*. Note that a perfectly efficient link has $I = 1$. I grows as a link gets worse, *i.e.*, the inefficiency increases corresponding to a larger amount of energy spent on that link due to retransmissions.

As we argued above, the expected energy consumption on link i at time t is proportional to the inefficiency at time t, denoted by $I_i(t)$. The total energy consumption on this link during the operation of the network is then proportional to the time average of this quantity, $\overline{I}_i$. We propose $\overline{I}_i$ as a cost metric, and believe that it forms a good basis for energy-efficient topology algorithms.

There is a tradeoff between keeping the energy expense at a minimum, which calls for channel measurement to be completed in as short a time as possible, and obtaining a reliable estimate of link inefficiency, which may require long term measurement. Striking a good balance in this tradeoff requires a good understanding of the behavior of channel

[1] With our node hardware, the energy to receive is typically $2/3$rd of the energy to transmit. A similar ratio holds for many short-range sensor networks.

[2] We assume $\mathrm{PSP}_i(t)$ variation in time is much slower compared to the expected time it takes to successfully transmit a packet, so the indicator random variable $X_i^{(k)}$ of correct reception of the k^{th} repetition of a packet that starts at time t is i.i.d. Bernoulli with parameter $\mathrm{PSP}_i(t)$.

quality in the course of a day. This is the goal of the experiments we describe in the next section.

IV. Experimental Setup

The experimental setup was designed for continuous monitoring of a wireless link between a transmitter and receiver for a long time with respect to channel variation, *i.e.*, several days. The transmitter and receiver were placed in different positions with respect to each other in a typical indoor office environment to observe good, moderate and bad links (precise definitions follow). We used a sensor node hardware developed at Bosch Research, with an 8-bit micro-controller, 16K RAM, and an ultra-low-power binary FSK radio chip. The transmitter and receiver nodes were equipped with quarter-wavelength monopole wire antennas, and the 915 MHz ISM band has been used. The radio was operated at a rate of 19.2 kbaud in Manchester encoded data mode, thus giving a raw data rate of 9.6 kbaud. The transmitter's nominal output power was set to 5 dbm. The center frequency used for the BFSK modulation was 916.3812 MHz, the frequency separation being 64 KHz. The nominal receiver sensitivity at these operational settings was -101 dbm.

In the experiment, a 34 byte data packet was transmitted over the wireless link of interest once every 100 ms. The receiver had a priori knowledge of the packet format and thus was able to compute the number of byte errors as well as single bit errors in the received packets. In addition, it sampled the Received Signal Strength Indicator (RSSI) for every byte of data it received. Averaging these values over an entire packet, it calculated an estimate of the average received signal power for a packet. By further sampling after the packet reception was complete, the receiver also obtained a value for the average noise power immediately after the packet. All the collected per-packet data was transferred by the receiver to a PC over a serial port and logged into a file. Experiments were conducted in office environments at Stanford University and at Bosch Research in Palo Alto, CA.

Packet success rate (PSR) is the ratio of the number of successful packets to the total number of packets transmitted over a certain duration. Packet success can be defined in several different ways which lead to different PSR values. $\mathrm{PSR_S}$ is obtained by declaring a packet successful if the start sequence (2 bytes) is correctly received, and if there is at most a single-bit-error in each of the succeeding bytes. The motivation behind this definition is that such packets can be recovered successfully using a single-bit-error correction mechanism. In our experiments, no error correction mechanisms were used so that the effects of the channel are reproduced faithfully.

An upper bound on $\mathrm{PSR_S}$ is obtained by counting packets whose start sequences are correctly received. Let us call this $\mathrm{PSR_u}$. A lower bound, $\mathrm{PSR_l}$, is given by counting completely error-free packets. Unless stated otherwise, all PSR values mentioned henceforth correspond to $\mathrm{PSR_S}$.

V. Experimental Observations

An immediate marker of link quality is SNR (signal to noise ratio). To present our results, we define a good channel as one that has SNR greater than 25 dB for the most part of the observation period (typically a day). When SNR is larger than 25 dB, the PSR measured is 100% almost all the time, hence good channels are not very interesting in our context. A moderate channel is defined as one where SNR fluctuates between 25 and 15 dB. If SNR is less than 15 dB most of the time, we call it a bad channel.

Figures 1 and 2 plot signal and noise power, packet success rate, and SNR for two typical moderate channels at Stanford and Bosch, respectively. The "noise" includes interference from the environment in addition to receiver noise. Since the receiver noise level is around -101 dBm, most of the measured noise is actually background interference.

PSR is calculated by counting the successful packets in a time window $T = 300$ seconds (and dividing by the number of packets sent during that time). 100% PSR thus corresponds to an ideal 3000 packets received in the last 300 seconds. Note that for our definition of "moderate" based on the SNR, the PSRs are still observed to be close to 100%. Figures 3 and 4 show signal and noise power, PSR and SNR for two representative bad channels. In these plots we can see that the PSR falls sharply whenever the SNR falls below 11 db, the reason of which will be explored in the next section.

A curious phenomenon that is visible in Figures 2 and 4 is the marked reduction in the noise floor at night. This reduction in the noise floor at night, and increase in the following morning was observed as a common feature in all experiments in this particular office environment, irrespective of channel configuration. Moreover, channel quality variation was seen to be almost periodic with a period of 24 hours, that is, SNR and PSR values are similar at the same time on different days.

For moderate channels, the $\mathrm{PSR_u}$, $\mathrm{PSR_l}$ and $\mathrm{PSR_S}$ are all very high and almost indistinguishable. This is not the case for bad channels. Notice in Fig. 4, for example, that there is a significant difference between $\mathrm{PSR_u}$ and $\mathrm{PSR_l}$. Interestingly, $\mathrm{PSR_S}$ is almost identical to $\mathrm{PSR_u}$, which is plotted as a solid line (hence $\mathrm{PSR_S}$ is not visible in the figure). This indicates that most bit errors are isolated and a vast improvement in PSR may be achieved using a simple single-bit error correction scheme.

VI. Estimation of Link Inefficiency

To better understand the implications of our measurements, we model packet transmission as a probabilistic process. Consider k consecutive packets. Let X_i be a random variable which takes on the value 1 if the i^{th} packet is successfully received, and 0 otherwise. Let the X_i's be independent and identically distributed for $i = 1, \ldots, k$. Notice that the expected value of X_i, $\mathbb{E}(X_i)$, is equal to the probability that packet i is successfully received, *i.e.*$P_s(i)$.

The average number of correctly received packets in k transmissions, *i.e.*, PSR, is $\frac{1}{k}\sum_{i=1}^{k} X_i$. When k is large, by the weak law of large numbers, PSR can be closely approximated

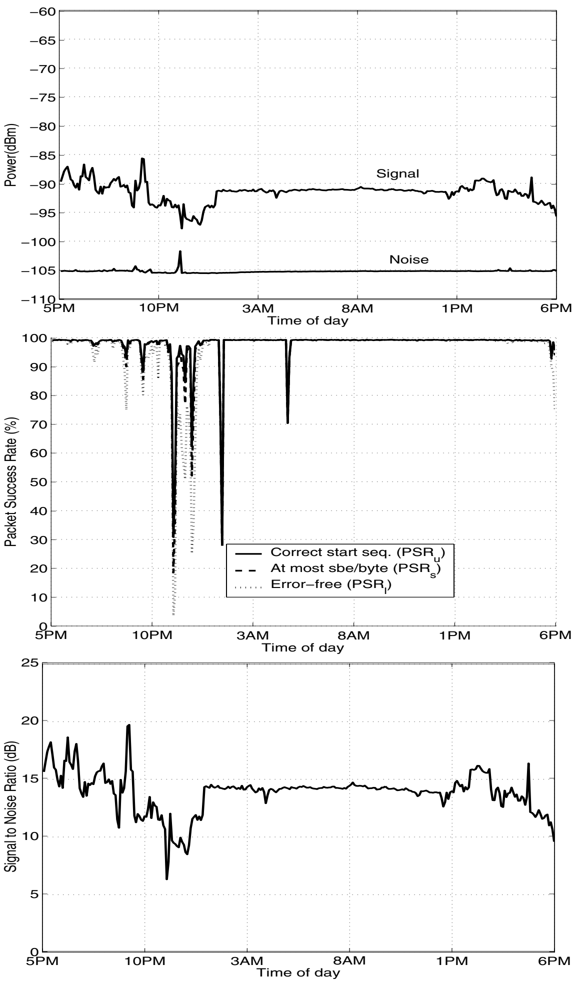

Fig. 1. Moderate channel I: signal and noise powers, measured PSR and SNR

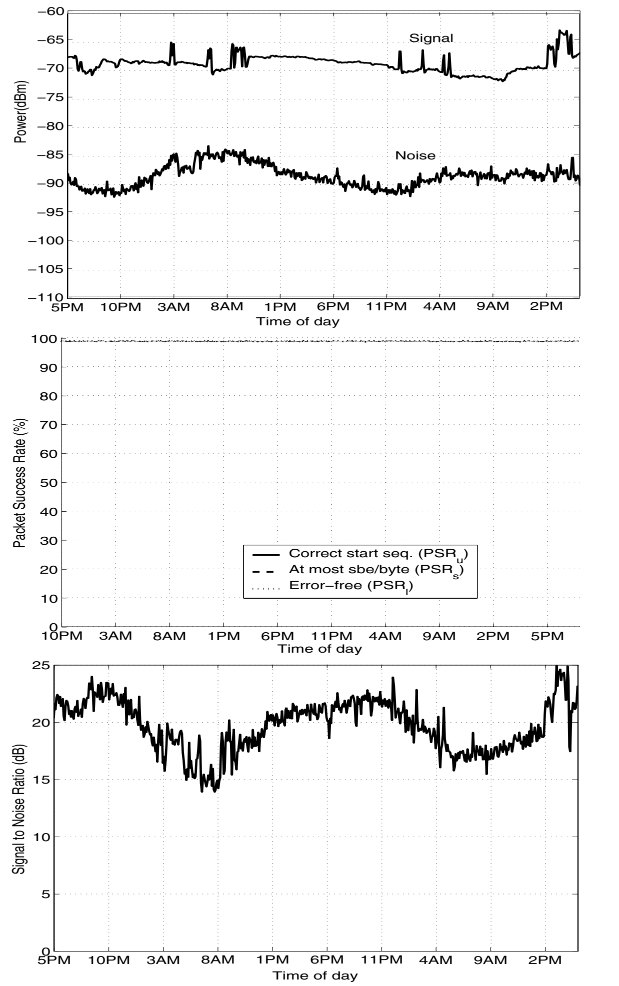

Fig. 2. Moderate channel II: signal and noise power, measured PSR and SNR

by $\mathbb{E}(X_i)$. In the measurements, $k = 3000$ (recall that each plotted PSR value is the ratio of the number of successfully received packets to the total number of packets sent in 300 seconds, which is 3000.) Hence, the measured PSR can be approximatedby $\mathbb{E}(X_i)$, the probability of correctly receiving a packet. Let this be the probability that the first two bytes are received with no bit errors and the remaining bytes with at most one bit error each, as we previously defined as $\mathrm{PSR_S}$.

Suppose packets contain L bytes each. Recalling that a byte is 8 bits,

$$\mathbb{E}(X_i) = ((1 - \mathrm{P_e})^8)^2 (8\mathrm{P_e}(1 - \mathrm{P_e})^7)^{\mathrm{L}-2} \tag{1}$$

where $\mathrm{P_e}$ is the bit error probability. Recalling that the modulation scheme used in our transceivers is binary FSK with non-coherent detection, the probability of bit error, at an SNR of σ_i, is $\frac{1}{2}e^{-\sigma_i/2}$. Assuming SNR is constant at σ_i throughout the i^{th} packet, Equation 1 can be written as:

$$\mathbb{E}(X_i|\sigma_i) = ((1-\frac{1}{2}e^{-\sigma_i/2})^8)^2[(1-\frac{1}{2}e^{-\sigma_i/2})^7(1+\frac{7}{2}e^{-\sigma_i/2})]^{L-2} \tag{2}$$

where we conditioned on the SNR value σ_i. This function is a sigmoid, as seen from its plot in Figures 5 and 6 (the solid-line curve labeled "expected PSR"). The plot indicates that the PSR varies from 0 to 1 over a very small range of SNR (about 6 dB to 12 dB). The PSR versus SNR curve has a knee around 11 dB, beyond which PSR is close to 1, and quite insensitive to the value of SNR. This observation will be very helpful in refining our link quality judgment.

The expected packet success rate is then the expectation of this over SNR, given by $\mathbb{E}_{\sigma_i}\mathbb{E}(X_i|\sigma_i)$. We make the following approximation: since the sigmoid is almost linear on most of its domain, $\mathbb{E}_{\sigma_i}\mathbb{E}(X_i|\sigma_i)$ will be replaced by $\mathbb{E}(X_i|\mathbb{E}(\sigma_i))$. Then the expected PSR is approximately

$$\mathbb{E}(\mathrm{PSR_s}) \approx (1 - \frac{1}{2}e^{-\overline{\sigma}/2})^{16}[(1 - \frac{1}{2}e^{-\overline{\sigma}/2})^7(1 + \frac{7}{2}e^{-\overline{\sigma}/2})]^{32} \tag{3}$$

where $\overline{\sigma}$ is the time-average SNR over the k packets, and we substituted $L = 34$. Figures 5 and 6 contain scatter plots of measured PSR values versus corresponding average SNR values. Figure 5 contains the data from Moderate Channel I and Bad Channel I, while figure 6 contains data from Moderate

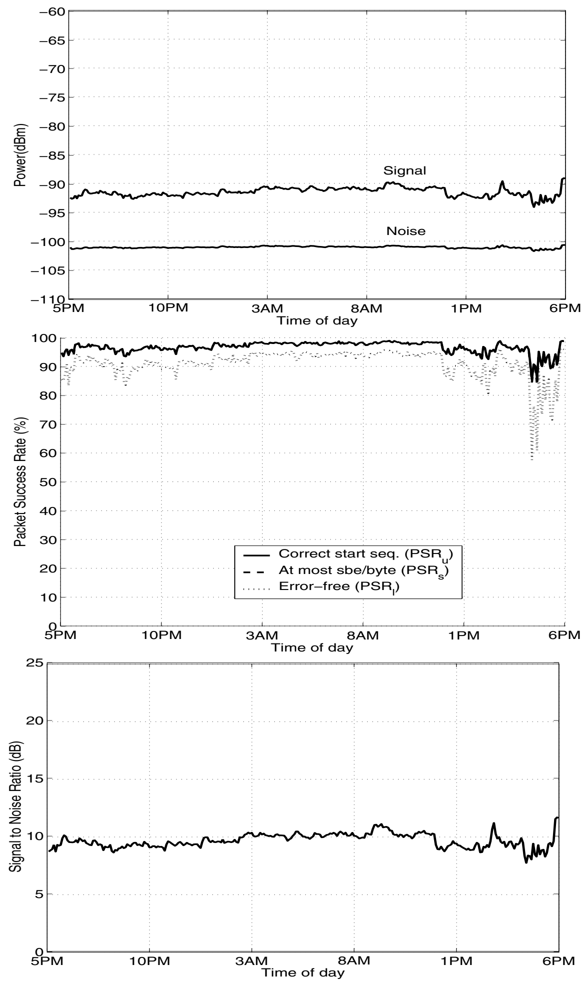

Fig. 3. Bad channel I: signal and noise power, measured PSR and SNR

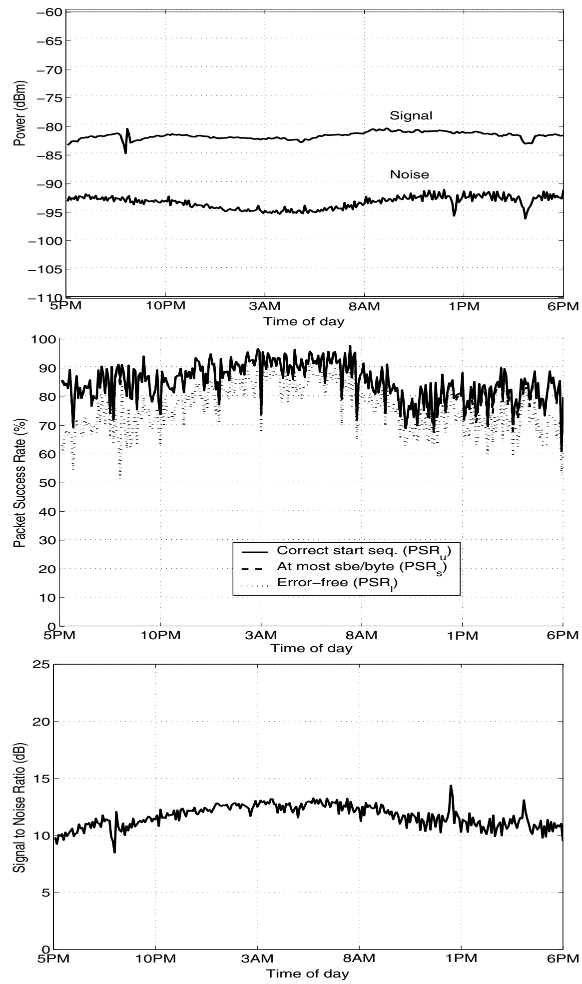

Fig. 4. Bad channel II: signal and noise power, measured PSR and SNR

Channel II and Bad Channel II. The plots have been truncated at an SNR of 20 dB to highlight the $0-20$ dB region (since PSR converges to 1 beyond an SNR of 20 db), hence they concentrate mostly on the scatter points obtained from the bad channels.

Note that both plots follow the expected PSR curve, shifted by a constant amount (1 or 2 dBs). We believe that the main reason for this shift (aside from the approximations we have made) is the unavoidable inaccuracy in the SNR measurement: the RSSI reading on the receiver chip has nonlinearity, and a ± 6 dB variation.

Now we are ready to consider estimating link quality with a finite number of observations of the channel. Suppose a node wakes up at k random times uniformly distributed during a 24-hour period. Each time it wakes up, it samples the same link for T seconds, and records average PSR and SNR at that time. We are interested in finding out how fast the average of those sampled values converges to the true time average taken over a day.

As observed in Section V, typically the quality variation on each link exhibits periodicity, usually with a period of 24 hours. In that case, a node can achieve the same estimate either by taking a certain number of samples during a day or the same number of samples distributed over several days. In the latter case, the estimate takes a number of days to converge to the same reliability, however, depending on the protocol, such spreading out of the measurement can allow the node to make use of the times that it would need to be awake anyway, therefore spend less energy on measurement. If there are significant changes in the behavior of a link from one day to the next (due to a change in the environment, such as a furniture re-placement in an office, for example), these will be slowly reflected in the running average of samples.

Figures 7 and 8 plot the absolute percentage error in estimated link inefficiency and estimated SNR versus the number of random samples k, for Moderate Link II and Bad Link II, respectively, versus the number of samples taken. Corresponding plots for Moderate Link I and Bad Link I are similar to Figures 7 and 8 and therefore they are not shown. The absolute percentage error in the link inefficiency estimation with k samples is

$$|\frac{1}{k}\sum_{t=1}^{k}\frac{1}{\mathrm{PSR}_s(i)^{(t)}} - \overline{I}_i|/\overline{I}_i \times 100 \quad (4)$$

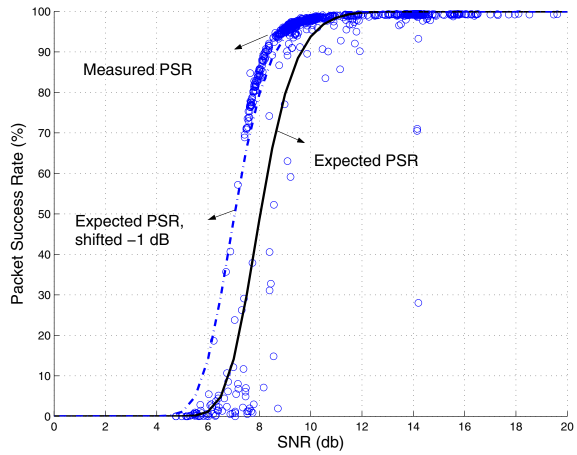

Fig. 5. Measured and expected PSR versus SNR, for Moderate Channel I and Bad Channel I

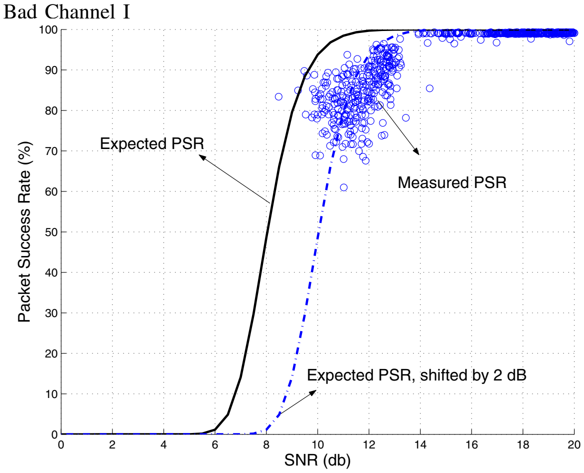

Fig. 6. Measured and expected PSR versus SNR, for Moderate Channel II and Bad Channel II

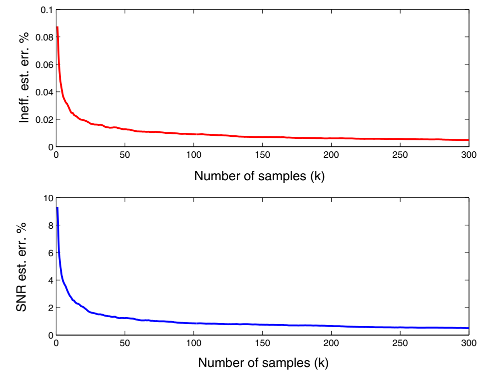

Fig. 7. Average absolute percentage error in estimating link inefficiency (top) and link SNR (bottom) on Moderate Channel II

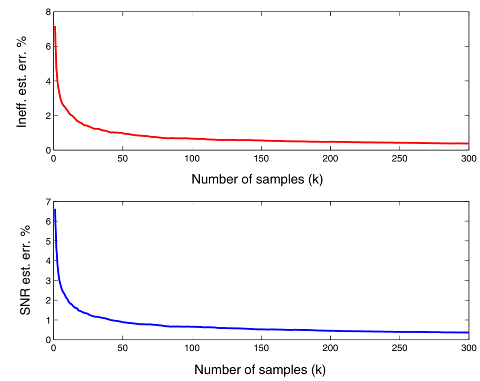

Fig. 8. Average absolute percentage error in estimating link inefficiency (top) and link SNR (bottom) on Bad Channel II

The SNR estimation error is calculated similarly. Each value on the curves is the average over 1000 independent runs of the same experiment, hence closely approximate the expected absolute estimation errors. Note that even with a few samples, the estimation error in link inefficiency is less than a few percent, even for a bad channel. For a good link, the estimation error in link inefficiency is almost zero, since by definition such links have close to 100% PSR all the time.

It seems that around 10 samples are sufficient to get a very good estimate of link inefficiency even for bad links. But is this estimate sufficient as a sole metric to grade wireless links? If we had a perfect estimate of link inefficiency, from the point of establishing an energy-efficient topology, we would not need any more information about that link. However, if we have only an *estimate* of link inefficiency calculated for a small number of samples, as it would be the case during the initial stages of the network's operation, should we trust that estimate as the sole metric? The following is a counter-example: Let there be two links, both of which are affected by a strong interferer for short, periodic bursts. Suppose we happened to sample both links when the interferer was not active, and the measured PSR for both is close to 100%. The measured SNR for one of the links is 17 dB, and the other has SNR=25 dB. Should we grade these links in the same way? It may happen that when the interferer is on and affects both links in the same way, the former link's SNR falls to 7 dB, while the latter still enjoys an SNR of 18 dB. In that case the PSR of the former link will drop drastically, while the other remains at 100%! The true time average of the former link's inefficiency is around 2.5 (assuming the interferer is on half of the time, and referring to Figures 5 and 6, the average PSR is $\frac{1}{2}(1/.25+1/1)$), and the other is close to 1. Hence, in this example, using a PSR estimate based on only a few samples would not give a reliable result.

Let us generalize what we argued by the counter-example above. Referring to Figures 5 or 6, packet success probability is close to 1 when SNR is above a "knee" value of approximately 11 dB. The further to the right of this knee a link's measured SNR, the more tolerance it has to an unexpected interferer. Therefore, in comparing two links with the same high estimated PSR, it is useful to take into account their estimated SNR values. One way to do this is to weigh calculated inefficiency by a decreasing function of $(\mathrm{SNR}{-}11\mathrm{dB})$, *e.g.*, the derivative of (3) with respect to $\bar{\sigma}$ can be used as such function[3]. How much the weight should be can be determined based on the details of the system design and how conservative the designer chooses to be.

When the measured SNR is at the knee point or lower, the measured SNR is inherently unreliable. The reason is, with our techniques (and probably with most other measurement techniques), SNR can only be measured when a packet is correctly received. Hence, the estimated SNR is an average over only successful packets, which form a fraction of all packets (since PSR is low too in this case). Therefore, if SNR is below the knee, the link inefficiency estimate should make use of only the measured PSR.

In summary, we propose the following rule for determining the link cost: Sample the channel SNR. If SNR is below the "knee" point, calculate the instantaneous link inefficiency as the reciprocal of measured PSR for this sample. If the SNR is above the knee, again calculate inefficiency by inverting PSR, however, weigh it with a factor that depends on how far away from the knee SNR is. Then, include this instantaneous inefficiency value in the running average formed by all samples taken so far.

Our observations show that this running average gives a reliable cost metric for grading links, with a surprisingly few number of samples. These samples can be taken during the same day, or at random times over several days, depending on the specific constraints of the protocol, *i.e.*, regarding energy consumption. In a severely energy-constrained network, for example, link measurements can be taken during the times when nodes need to be awake for sensor data exchange. In this way, the nodes can obtain and maintain good estimates of the cost of each link at very little extra energy spent for cost estimation.

VII. Conclusion

Results of an experimental study of wireless links in an indoor sensor network operating in the 900 MHz band have been presented. Based on these measurements, and on a consideration of energy-efficient topology in such networks, *link inefficiency* was proposed as a cost metric based on link quality. We have explored how link inefficiency can be measured in an energy-efficient way, by studying wireless link quality variation over a period of several days for various link configurations (*i.e.*, relative placement of the transmitter and receiver), and in different office buildings. We find that only a few measurements of the channel are sufficient to obtain a good estimate of the cost metric, hence even during the initialization phase one can have sufficient information about links to design an efficient topology. The estimate can then be improved as more measurements are taken during the normal operation of the network.

Acknowledgment

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[3]Note that (3) is increasing and concave for $\bar{\sigma} \geq 10$dB, so its derivative is a positive and decreasing function with respect to $\bar{\sigma}$.

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