Quantifying the Channel Quality for Interference-Aware Wireless Sensor Networks

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ABSTRACT

Reliability of communications is key to expand application domains for sensor networks. Since Wireless Sensor Networks (WSN) operate in the license-free Industrial Scientific and Medical (ISM) bands and hence share the spectrum with other wireless technologies, addressing interference is an important challenge. In order to minimize its effect, nodes can dynamically adapt radio resources provided information about current spectrum usage is available.

We present a new channel quality metric, based on availability of the channel over time, which meaningfully quantifies spectrum usage. We discuss the optimum scanning time for capturing the channel condition while maintaining energy-efficiency. Using data collected from a number of Wi-Fi networks operating in a library building, we show that our metric has strong correlation with the Packet Reception Rate (PRR). This suggests that quantifying interference in the channel can help in adapting resources for better reliability. We present a discussion of the usage of our metric for various resource allocation and adaptation strategies.

Categories and Subject Descriptors

C.4.3 [**Performance of Systems**]: Measurements Techniques. Reliability, Availability, and Serviceability

General Terms

Experimentation, Measurement, Performance, and Reliability.

Keywords

Channel Quality, Interference, ISM Bands, Dynamic Resource Adaptation, Wireless Sensor Networks.

1. INTRODUCTION

Wireless technologies have grown exponentially during the last decade and are progressively cast around for more applications. Many standardized technologies operate in crowded license-free Industrial Scientific and Medical (ISM) frequency bands. Wireless networks in these bands are now ubiquitous in residential and office buildings as they offer great flexibility and cost benefits. However, despite the extensive research, the issue of reliability of wireless networks remains a challenge. Medium access techniques such as TDMA and FDMA cannot be readily applied in the context of ISM bands [1], as they are not designed to tolerate inter-network interference. Instead, distributed multiple access schemes based on *carrier sense*, such as CSMA, are widely employed along with Spread Spectrum modulation techniques which provide some robustness as well as generate lower levels of interference. Although this bottom-up approach to unlicensed spectrum usage exacerbates the challenges to achieve reliability and predictability in low-cost wireless solutions, there are many gains for end users [2] and extensive opportunities for innovation [3]. It has also incubated new research directions, such as dynamic spectrum allocation for future wireless systems [4]. Inspired by this paradigm, we investigate mechanisms for interference avoidance within ISM bands for low-power radios.

Wireless Sensor Networks (WSN) are seen as a viable alternative for monitoring, control and automation applications, provided they are made appropriately reliable and delays are bounded. To this end, interference and coexistence pose a major challenge. In this paper, we present the *Channel Quality* (CQ) metric that provides a quick and accurate estimate of interference by capturing a channel's availability over time at a very high resolution. This metric is useful towards achieving better reliability and lower latency through dynamic radio resources allocation.

Interference from coexisting networks in ISM Bands is typically referred as Cross Technology Interference (CTI). Even though CTI represents a well known problem [5–8] it has not been adequately addressed in WSN. This problem is hard to resolve for two reasons: a) efficient cooperative schemes for spectrum access are not possible with currently deployed technologies and b) there are large RF power and spectrum footprint asymmetries. CTI could be avoided by sophisticated communication protocols that are sensitive to instantaneous spectrum occupation. However, low-cost hardware and limited energy-budget of the nodes make the typical spectrum sensing techniques as proposed for non resource constrained systems [9] unsuitable for WSN.

This paper has the following contributions:

- A novel channel quality metric that is based on channel availability and is agnostic to the interference source.
- An analysis of the parameter space and validation of the metric's performance with real-world interference traces.

The rest of this paper is organized as follows. Section 2 provides further motivation for this work and in Section 3 we derive the expression for our CQ metric. Section 4 describes how we use the energy detection (ED) feature in IEEE-802.15.4 compliant radios to measure evolution of signal (interference) strength in 802.15.4 channels, our experimental setup and our data collection experiments. We then discuss results of our evaluations and conclude the paper in Section 5.

2. MOTIVATION

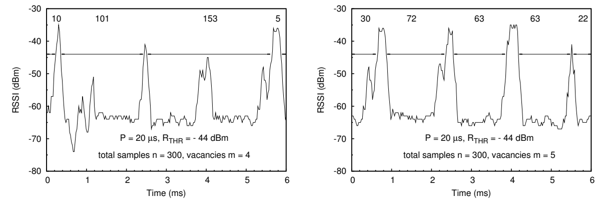
Any given network configuration at deployment phase, like channel selection, is typically not enough as the network may experience communication interruptions or simply fails at some point. We need WSN that seamlessly adapt resources and self-organize to maintain their integrity in a changing environment. Several recent studies have addressed burstiness and interference in wireless links. Srinivasan et al. proposed a metric to quantify link burstiness and show impact on protocol performance and achievable improvements in transmission cost [10]. Also, Munir et al. investigated scheduling algorithms to improve reliability and provide latency bounds [11]. However, these solutions can not react to instantaneous changes in the channel condition. They rather select routes and channels using long-term observations.

There are aggressive techniques to deal with interference in wireless systems. Successive Interference Cancellation (SIC) has been partially demonstrated for 802.15.4 in Software Defined Radios [12]. Nevertheless, there are practical limitations to advance with it. For example, it is known that SIC requires highly linear amplifiers in the receiver (large dynamic range) and also excellent adjacent channel suppression, because residual energy put in the front-end causes it to underperform and desensitizes the radio. Both of these requirements lead to expensive solutions. Furthermore, it is questionable whether SIC's demand for signal processing could outweigh its benefits compared to other approaches, in view of available technology, inexpensive hardware and energy budget constrains. Finally, these ideas are not trivially applied to CTI because a large heterogeneous set of possible signals to disentangle further complicate SIC-based solutions.

Alternatively, we advocate modest improvements in low-power receiver architecture can enable energy efficient spectrum sensing, which is necessary for nodes to form smart reactive networks that eliminate the need for highly complex radios. Spectrum occupation can change rapidly in time and space, yet under unfavourable channel conditions nodes adapt resources or find better channels to maintain communications. Dynamic resource adaptation can lower latency bounds and boost reliability but in order to encompass this information into protocols one needs accurate spectrum sensing. In this paper we show that sufficiently accurate spectrum sensing is feasible with sensor nodes.

Currently, the radio transceivers in WSN nodes are mostly based on the IEEE-802.15.4 standard that is intended for low-power operation. On reception, off-the-shelf radios require around 50 mW and consume 200 – 2000 μJ per packet received. This power is drawn by the PLL synthesizer, digital demodulator, symbol decoder and RF analog blocks for signal filtering, amplification and down-conversion among other functions, typically in this order. Recent incursions in 0.18 μm CMOS process of PLL realizations [13–16], targeted for these systems, report fairly appealing figures: power consumptions below 3 mW and lock-in times less than 30 μs. Since the PLL synthesizer is known to be by far the most power-hungry block in the receiver, these results suggest that the next generations of WSN radios would require, at least, one order of magnitude less chip energy per bit received.

Now, in order to support ED spectrum sensing only the PLL synthesizer, analog RF blocks plus AGC are necessary, while the demodulator can be turned off. Interestingly, among other optimizations, this further reduces energy consumption while the receiver is used exclusively to detect the RF energy in the channel, but we have not yet found any 802.15.4 radio chip providing this flexibility.



(a) Scenario 1 (b) Scenario 2

Figure 1: Channel vacancies: two scenarios with the same Channel Availability (CA).

3. CHANNEL QUALITY METRIC

The sources of interference in wireless networks are typically very diverse. Interference causes a decrease in the Signal-to-Noise plus Interference Ratio (SNIR) which can result in packet losses. Any device that produces RF signals with spectral components within or near the receiver passband is a potential interferer. Average energy in a channel has been used as an indicator of channel usage in the previous literature [17–20]. Unfortunately, this metric is unable to distinguish between a channel where the traffic is bursty with large inactive periods and a channel that has very high frequency periodic traffic with the same energy profile. Clearly, the first scenario is preferable. It may well be the case that the traffic in the second case consists entirely of short-duration peaks resulting in much lower average energy but unusable channel. Motivated by this observation, we propose a metric that is based on the fine-grained availability of the channel over time and ranks in a more favourable way channels with larger inactive periods or vacancies.

Consider the energy levels (or RSSI) in some channel are measured periodically with period P. Suppose, the acceptable noise level and interference threshold is R_{THR}. Therefore, the channel can be considered idle when $RSSI < R_{THR}$. For example, Figure 1 shows RSSI samples over time along with idle intervals, which we refer to as *channel vacancies* (CV). Let m_j denote the number of CV consisting of j consecutive idle samples and n the total number of samples. Then $m_1 + m_2 + \ldots + m_n = m$ is the total number of observed CV. Notice that j consecutive clear channel samples imply that the channel was idle for at least $(j-1)P$ time units. We define the average *Channel Availability* (CA) as:

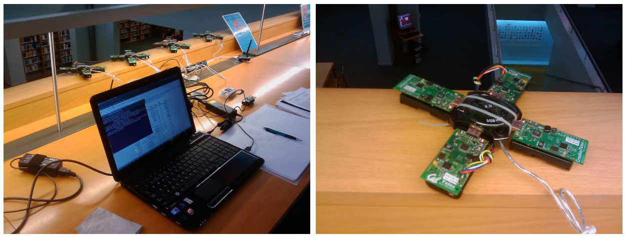
$$CA(\tau) = \frac{1}{n-1} \sum_{j|(j-1)P>\tau} j m_j \tag{1}$$

where $\tau > 2P$ is the time window of interest, which could be the duration of packets. As we argued earlier, a channel where $m_{2j} = k$ is more desirable than a channel where $m_j = 2k$, although jm_j is the same for both cases. Therefore, we want to rank a channel with larger vacancies higher even though the sum of the idle durations might be the same. Hence, we define the *Channel Quality* metric as:

$$CQ(\tau) = \frac{1}{(n-1)} \sum_{j|(j-1)P>\tau} j^{(1+\beta)} m_j \tag{2}$$

where $\beta > 0$ is the bias. CQ in equation (2) take values between 0 and n^{β}, where the larger values indicate better channels. Observe that this expression is agnostic to the interference source.

Figure 1 shows the amount of channel vacancies in two scenarios with a similar channel availability ($CA_a = 0.88$ and $CA_b = 0.83$) computed with a $R_{THR} = -44$ dBm. Due to collisions, the probability of correct reception is higher in the scenario shown in Fig-



(a) (b)

Figure 2: The experimental setup used to collect energy level traces on IEEE-802.15.4 channels deployed at the Library of the Faculty of Engineering at the University of Porto (a) and detail of TelosB motes arranged in a USB hub (b).

ure 1(a) than in the one depicted in Figure 1(b).

4. EVALUATION

In this section, we first describe our experimental set-up used for data collection followed by an analysis of our metric when applied to the data. We devise off-line experiments and implement them in Python [21] scripts to be run over the traces. This has the advantage of producing a naturally controlled environment, e.g. isolating channel effects that are present in an online experiment. We show that our metric is highly correlated with PRR.

4.1 Experimental Setup

In order to experimentally investigate our proposal we need traces of interference signals that help understand channel degradation in real-world settings. More specifically, we want to find out how our metric can help identifying a usable channel and eventually establish which alternative techniques can be applied to employ it effectively. Therefore, we have designed an experimental setup to study interference in the 2.4 GHz ISM band. This band is available globally; there are thousands of certified devices on the market that operate in it and coexistence problems are well known [5, 6], which ultimately facilitates the task of collecting interference traces. Our setup has no limitations to study any kind of interference, but given that Wi-Fi has been identified as the most critical interference source to affect WSN [6] and it is also widely available, in this paper we report experiments with traces where interference stems solely from Wi-Fi networks.

In our setup, we employ a set of 17 TelosB sensor nodes to scan all sixteen IEEE-802.15.4 channels simultaneously. In order to do simultaneous channel readings, we use one of the motes to transmit a scanning beacon on channel 26, which instructs all other nodes to switch to their respectively assigned channels and begin scanning. The motes are connected via USB hubs to a laptop as shown in Figure 2. We sample the RSSI from the CC2420 transceiver at 40 kS/s [22], and store the data in a memory buffer. After completing 5600 samples in approximately 130 ms, i.e., the largest possible amount of samples that can be stored in the constrained memory of TelosB nodes, all nodes return to listen on channel 26 and wait for the next scanning beacon. Scanning beacons are sent every 8 seconds, which guarantees enough time to dump all the RSSI readings to a file. Having one node per channel enables us to increase the pace at which data is collected and makes the logging operation easier.

A large density of Access Points capable of producing notorious spectrum occupation is mainstream in many metropolitan areas today and particularly in university campus. However, it is the density of users and the overall volume of data been transferred that actually produces congestion. Thus, we used our ensemble to collect measurements in our laboratory, which has moderate traffic on a few 802.15.4 channels. Then we conducted a measurement campaign at the Library of the Faculty of Engineering of the University of Porto, where we found very heavy traffic from 802.11 Wi-Fi networks. In our experiments, signals are well above the noise floor (10 - 70 dB), but more relevant is the time distribution of burst patterns that varies from a few microseconds to tens of milliseconds. To examine our metric proposal we then perform off-line experiments, upon a set of traces from a four hour capture.

4.2 Sampling Time

One of the questions we seek to answer is *how long* should we sample a channel in order to have a meaningful CQ value. Sampling too shortly leads to uncertainty about the near future state of the channel. Notice that the *clear channel assessment* (CCA) used in Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) mechanism would not help here given the asymmetric scenario in transmission power and spectral footprint [see 8]. Basically, such asymmetries in the PHY layer among different radios, make the distributed coordination approach fail. WSN nodes employ orders of magnitude less RF power than other channel contenders, which makes them more vulnerable to packet corruption since it is improbable that other nodes would detect an ongoing transmission and thus defer theirs. For this reason, it is necessary to sample for longer time, definitely larger than a CCA accounting for 8 symbol periods or 128 μS, in order to capture a sequence of events large enough to estimate the probability of successful packet reception.

On the other extreme, sampling too long introduces a cumulative effect that misses the dynamics of the channel availability and leads to poor prediction of the next state of the channel. The more distant in time the events are the more likely is that their probabilities are independent and therefore does not help to estimate the channel condition either. Furthermore, during the sampling period the radio is turned on which consumes energy.

In practice, this means that we need to find a compromise for the sampling time that is intrinsically dependent on the system observed. In order to understand this compromise, we progressively compute the CQ, up to 120 ms, over all traces. Figure 3 illustrates the results. The R_{THR} threshold value is primarily chosen based on the RSSI levels of packets from other nodes we are interested in receiving.

Actually there is an SNIR margin, specific for each radio and related to the *Co-Channel Rejection Ratio* (CoCRR), which needs to be considered here. In the CC2420 radio, this value corresponds to 3 dB for a target $PER = 10^{-3}$, and must be accounted to fine-tune R_{THR}.

Since we are not interested here in any specific packet duration, we chose $\tau = 0.2$ ms, small enough so that most CV contributions count in Equation 2. Notice that the sum is computed over CV larger than τ only. For practical reasons, we perform data binning on all CV observations, i.e., all values which fall in a small interval, $bin = 0.5$ ms, are represented by the same value. This quantization affects the absolute values obtained in Equation 2. Suppose an empty channel with one single vacancy of length $j = n - 1$. As mentioned in Section 4.1, we are sampling at approximately 40 kS/s, i.e., we take one RSSI sample every 25 μS. Therefore, we divide j by a factor $k = 20$ and thus, $CQ < (\frac{j}{k})^{\beta}$. This curve is the upper bound for absolute values shown in all graphs in Figure 3. Similarly, the values represented in the abscissas are divided by 40 to obtain the corresponding scanning time in milliseconds.

One common trend in all graphs is that CQ stabilizes after some

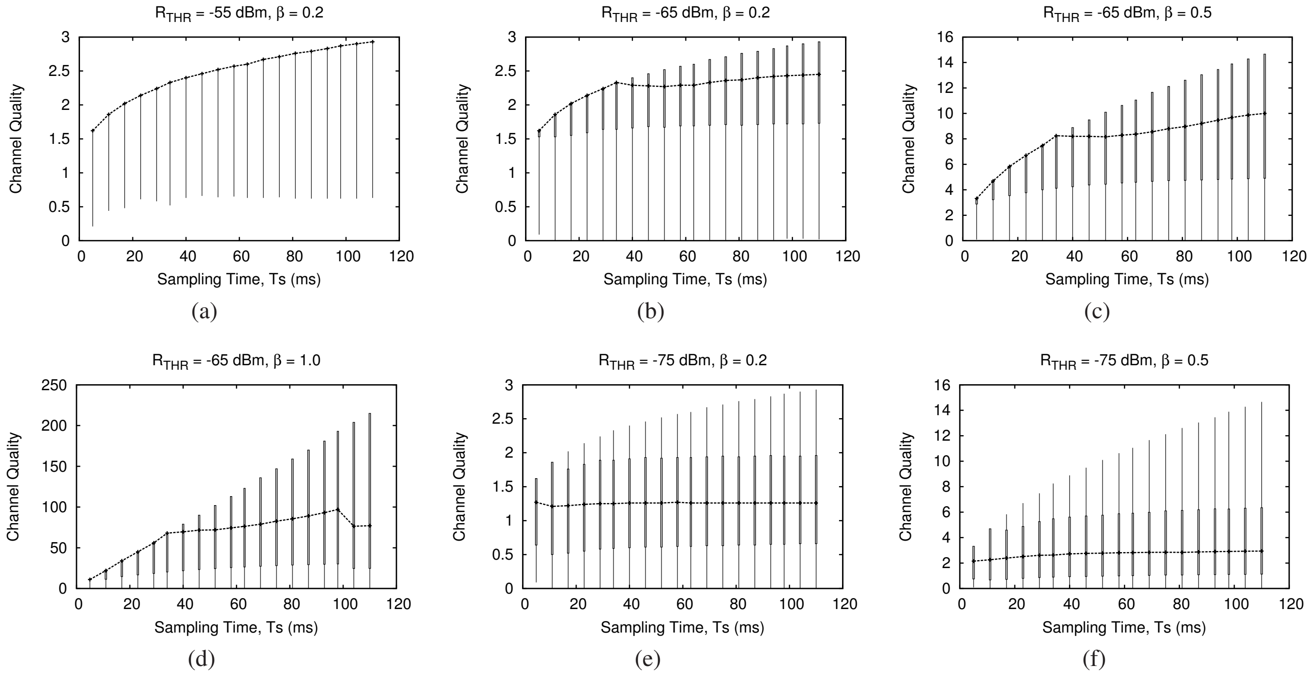


Figure 3: CQ computed over all traces for different sampling times. Curves represent the median, boxes represent the interquartile range (IQR), and bars stand for the rest of the values.

time, provided there is sufficient interference. This indicates that Equation 2 converges toward a value that is proportional to an average number of vacancies during the sampling period and, clearly, also depends on β and the values of j.

Figure 3 shows that for lower R_{THR} values, which corresponds to heavier interference, the median of CQ stabilizes faster. On the contrary, if the channel is mostly idle, CQ grows with very high probability (e.g., if $R_{THR} = -55$ dBm as in 3(a), CQ grows as $(2 \cdot T_s)^{0.2}$ and the IQR shrinks over the maximum). An intermediate case, as when CQ is computed for -65 dBm, see 3(b)-3(d), demonstrates that the metric typically grows to a certain value until it finally stabilizes. Hence, these sampling times are much smaller than the timescale of the interference pattern present in the channel. Based on this behaviour, an optimum sampling time would be as long as it is necessary to have the median of CQ stabilized.

In a system where this metric is computed online the sampling time, represented by n in Equation 2, could be dynamically maintained at this turning point where the median of CQ stabilizes, or below a certain maximum value. We defer the development of a control algorithm for this purpose to future work. For the rest of our experiments we use a hand-picked scanning time of 40 ms.

4.3 Correlation with PRR

Packet Reception Rate (PRR) is a well known reliability metric. When PRR is high, the wireless channel and the link are optimum. However, PRR reflects all forms of signal distortion in the wireless channel, including interference. Thus, a medium or low PRR does not provide enough information to identify factors responsible for poor performance and yet intermediate quality links, that display a medium PRR, may account for up to 50% of all links observed in WSN testbeds [10]. Moreover, PRR and other useful metrics, such as packet's RSSI and LQI, require packet transmissions. Instead, our CQ metric specifically accounts for interference and has no side effect on the channel, as it relies exclusively on the receiver channel energy detection, and therefore scales with node density and channel usage.

We now investigate how the channel availability as described by our CQ metric is related to the probability of successful packet receptions. For this experiment we use a third of each RSSI trace, lasting 130 ms, to compute the metric and the remaining to check for the presence of interference that may lead to packet corruption. If the energy levels in the channel remain 3 dB below the RSSI of packets (CoCRR mentioned in 4.2), during the duration of each packet, then the packet is considered successfully received.

Multiple packets are transmitted over each trace and the average is computed to derive the PRR. Packets are transmitted periodically and transmissions are separated by an Inter-Packet Interval time (IPI) of 2 ms. In this way, we conduct an experiment with more than 240.000 off-line packet verifications on traces obtained from the deployment at the library.

As shown in the previous section, Equation 2 provides a range for CQ values that depends on n and β. However, in order to compare among CQ values computed with different parameter values we rewrite CQ as:

$$CQ(\tau) = \frac{1}{(n-1)^{(1+\beta)}} \sum_{j|(j-1)P>\tau} j^{(1+\beta)} m_j, \qquad (3)$$

CQ in Equation (3) now take values between 0 and 1, regardless of n and β values. For example, if we compute Equation 3 with $\beta = 0.3$ for an IEEE-802.15.4 ACK frame lasting 352 μs, in the scenarios shown in Figure 1, we obtain $CQ_a = 0.65$ and $CQ_b = 0.50$. The difference between CQ_a and CQ_b is three times higher than the difference between CA_a and CA_b (obtained using Equation 1 in Section 3), and it therefore highlights the difference in quality between the two channels.

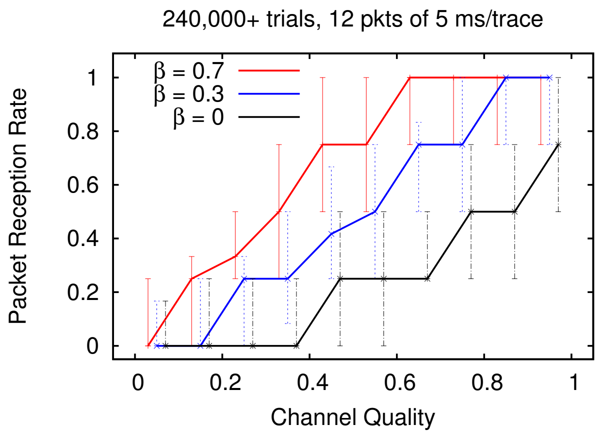


Figure 4: PRR and CQ computed according to Equation 3

Figure 4 shows the correlation between CQ and PRR. The curves correspond to the CQ median and the error bars represent the interquartile range computed over the entire set of traces, at $R_{THR} = -65$ dBm. We compute CQ for bias (β) values 0, 0.3, and 0.7 to highlight that $\beta = 0.3$ linearises the curves and better expand useful range of CQ values.

Higher values of β increase the weight of larger CV in the definition of the CQ. Therefore, having $\beta = 0.7$ will promote the selection of channels with larger CV. On the other hand, observe how for $\beta = 0$, which is equivalent to compute the average channel availability as described by Equation 1, CQ values increase up to 0.4 but almost no packets are received, since vacancies are not large enough. In this case, CQ values grow faster than PRR which indicates that average channel availability does not capture well-enough the complexity of the channel, as we discussed in Section 3. Being able to tune β, as shown in the graph in Figure 4, helps us in maximizing the correlation among PRR and CQ. This makes our metric an accurate indicator of the channel condition, which is an interesting result. In our experiments, we find the β value that maximises the correlation among CQ and PRR to be approximately $\beta = 0.3$. Similar to the scanning time, finding the optimum β value, for an arbitrary interference scenario, is outside the scope of this paper.

4.4 Discussion

In this section we revisit some resource adaptation techniques and discuss how they could be dynamically applied to leverage our CQ metric for interference-aware communication protocols.

Lin et al. demonstrated a novel pairwise transmission power control for WSN that performs significantly better than node-level or network-level power control methods [23]. They improve PRR and energy consumption by dynamically adapting the RF transmission power to maintain the minimum level required to guarantee a good link. This is a clever approach to compensate for the non-linear pathloss. However, it does not account for two important aspects: a) the irreducible error floor [24, Ch. 6] produced by fading can not be removed by increasing transmission power and b) it does not address external interference. A solution to both these problems is dynamic frequency and power adaptation, simultaneously.

In this regard, one can augment such pairwise power control mechanism with CQ, directly establishing a dynamic lower bound for the RF power to use in the transmitter, previous to actual transmissions. Besides, since a maximum transmission power can not be exceeded, an alternative such as a moving to a different channel may be inferred immediately. Starting from the RSSI samples in memory, we could ask the question: which signal level would result in a CQ value that satisfies a given requirement for channel usage under the current interference level?

In general, protocols designed for multichannel operation can maintain good links by using well ranked channels by distributed CQ computations among neighbour nodes, provided a control channel among them is stable. Additionally, these CQ values could aid route changes when an interferer's spectral footprint is very large, as in 802.11n, to take advantage of the irregular coverage, common in some indoor environments.

Successful transmissions in the scenarios in Figure 1 also depend on the packet size. Certain packet size would maximize throughput or minimize the time to deliver a data object over the channel, for a given interference level. Observe that shorter packets have better chances of avoiding collisions (and hence retransmissions) but also result in higher overhead due to fixed packet headers and delays due to acknowledgement timeout. One could look into the relationship between these optimum packet sizes and the CQ values computed on the channel. Based on observed CQ values protocols can then tune packet size to save energy or transfer data in a minimum time.

FEC techniques pose a trade-off between data recovery capacity and its inherent payload and computation overhead. Recently, Liang et al. demonstrated the Reed-Solomon (RS) correcting codes performs well while recovering packets affected by 802.11 interfering signals [8]. Since interference levels may vary extensively it is interesting to see if this solution can benefit from simple CQ based optimizations.

On the other hand, energy cost to compute the CQ metric must be further explored in view of overall energy balance in dynamic link adaptation. In future work we plan to extend our experiments and later implement the metric on WSN hardware.

5. CONCLUSIONS

We introduced a new channel quality metric that is based on the availability of the channel over time. The metric is useful for interference aware protocols in WSN. We described our experimental setup for collecting real-world interference traces in the 2.4 GHz ISM band. Using this data, we showed that our metric has strong correlation with PRR. Thus, our metric's characterization of a channel is reliable and applicable in practice. We also discussed dynamic resource allocation techniques for interference-aware protocols in WSN for which our metric can prove to be useful. We are currently working on a software implementation of CQ for WSN hardware to further validate its performance in online experiments.

6. ACKNOWLEDGEMENTS

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