Single Reception Estimation of Wireless Link Quality

Henry-Joseph Audéoud, Andrzej Duda, Martin Heusse

Single Reception Estimation of Wireless Link Quality

Henry-Joseph AUDÉOUD, Martin HEUSSE, and Andrzej DUDA
Univ. Grenoble Alpes, CNRS, Grenoble INP, LIG, 38000 Grenoble, France
Email: henry-joseph.audeoud@univ-grenoble-alpes.fr, martin.heusse@univ-grenoble-alpes.fr, andrzej.duda@univ-grenoble-alpes.fr

***Abstract*—Quick and accurate estimation of link quality, and more specifically packet loss probability, is the key element for efficient and effective communications in wireless multi-hop networks. We focus on IEEE 802.15.4 and we posit that losses only occur when noise and interference last long enough and are strong enough relatively to the received signal, to hinder packet reception. So, the key information for any ordered node pair is the signal to noise plus interference ratio distribution, which we obtain by combining the observed noise plus interference power at the receiver with the received signal strength.**

In this paper, we propose two novel schemes for the estimation of PER: Burst-NISI and Sample-NISI. Burst-NISI is based on high frequency measurements of the power level of ambient noise and interference around a given node. Sample-NISI sporadically samples the power level of ambient noise and interference when the radio operates according to a duty cycle.

Using a large scale experimental platform, we show that our packet error rate estimation schemes are accurate for any packet length and diverse experimentation sites with different settings, for which the prediction is within 10 percentage points of the PER value measured *a posteriori*.

***Index Terms*—Wireless Sensor Networks, IEEE 802.15.4, wireless link quality estimation, IoT-lab**

I. INTRODUCTION

The estimation of link quality in terms of the Packet Error Rate (PER) in multi-hop wireless sensor networks (WSN) is essential for their correct operation. Ideally, the estimation should be accurate, stable, immediate, and energy efficient [1]. Accuracy is required because it determines the soundness of the routes used by the data traffic and stability avoids frequent changes of these neighbors. Quick estimation of link quality enables swift adaptation and allows efficient bootstrapping of new nodes entering the network.

There are two main approaches to quantify link quality: i) based on signal characteristics measured upon packet reception, such as the Radio Signal Strength Indicator (RSSI) or the Link Quality Indicator (LQI), and ii) packet counting. RSSI or LQI are correlated with PER but they are not sufficient for obtaining an accurate PER estimation [2], [1]. Counting correctly received packets gives a statistical estimation of PER, however, it requires a large number of packet transmissions to be reliable [2], [1], so it incurs significant overhead to find the quality of the links to all neighbors.

In this paper, we explore the idea of deriving a PER estimation from the distribution of the Signal to Interference plus Noise Ratio (SINR) and the measurement of RSSI for a given packet reception. We define the Noise and Interference Strength Indicator (NISI) that quantifies the power level of ambient noise and interference mostly due to co-located IEEE 802.11 networks around a given node. Nodes measure the empirical distribution of NISI and with RSSI for a received packet, they can predict PER of future transmissions for a given modulation and coding scheme.

We propose two specific estimation schemes: Burst-NISI and Sample-NISI. In Burst-NISI, a node measures the NISI distribution by switching its radio on and recording the ED (Energy Detection) value as often as possible. Then, it combines the NISI distribution with RSSI measured upon packet reception to obtain a precise estimation of the SINR distribution. Finally, it applies a theoretical model to estimate PER.

To address the energy and computational constraints of embedded systems, we also propose Sample-NISI, a modified scheme based on sporadic sampling of NISI in background when the radio operates according to a duty cycle. When a node wakes up and does not detect any transmission, it records the value of NISI to obtain its distribution. Upon the reception of a packet, the node measures RSSI and applies a similar theoretical model as in Burst-NISI to obtain the PER estimation.

We have experimentally validated the proposed schemes on the IoT-lab testbeds [3]. The PER estimation is in most cases within 10 percentage points of the measured value. To ensure that the results do not depend on specific environmental conditions, we have carried out experiments on three different testbeds (three different IoT-lab sites) and for nine different IEEE 802.15.4 channels. We have also checked that the results are accurate for various packet sizes.

Both schemes present an important advantage with respect to packet counting: besides the background measurements of the ambient noise and interference, a single packet reception allows to obtain an accurate estimation of link quality for a given channel and the estimation takes into account the variations of the local interference and noise.

Even if we present the estimation schemes in the context of IEEE 802.15.4 networks with the typical interference generated by co-located IEEE 802.11 networks, the principles of the schemes stay valid for other types of networks and interferers.

In the rest of the paper, we discuss wireless link quality estimators and related work in Section II, and evaluate the in-

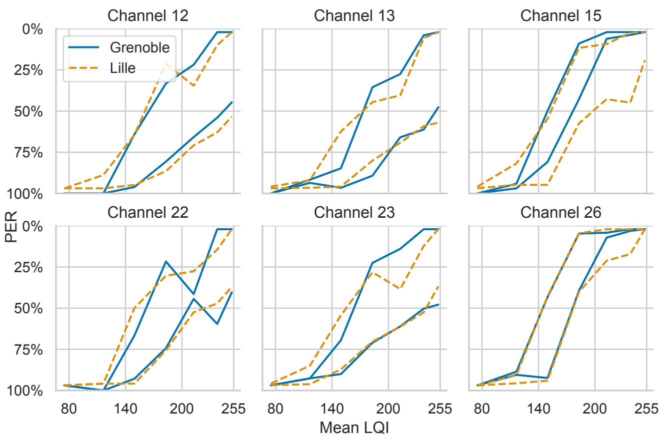

Fig. 1. Quantile regression (5th and 95th percentile) of PER with respect to LQI.

terference in the 2.4 GHz ISM band in Section III. Sections IV and V present the proposed schemes for link quality estimation: Burst-NISI and Sample-NISI, respectively. We then present the results of the experimental link characterization on several sites of the IoT-lab testbed in Section VI. Section VII concludes the paper and presents some future work.

II. Related Work

We start with a review of main link quality estimators, and discuss the schemes proposed in the literature. Finally, we tackle the problem of estimating interference of other networks.

A. Common wireless link quality estimators

*a) **RSSI (Received Signal Strength Indicator):*** Upon packet reception, the radio chip provides a measure of the received signal power. Like many others [1], we have recognized in a previous paper [4] that high reception power implies good reception quality. However, it is hard to discriminate between good and bad links for a lower level of the received signal power.

*b) **LQI (Link Quality Indicator):*** The IEEE 802.15.4 standard [5] is evasive on the exact definition of LQI: "*a characterization of the strength and/or quality of a received packet*". Its interpretation may vary from one radio chip to another, which may explain the great diversity of opinions on the usefulness of LQI.

We have previously studied the AT86RF231 radio chip on the IoT-lab testbed [4] and obtained encouraging results on the ability of LQI to predict the link PER. In Figure 1, the precision of the PER estimation is good on channel 26 (the inter-percentile interval is thin). However, on channels 22 and 23, the inter-percentile interval is wider and a $\overline{LQI} = 255$ no longer guarantees PER of $0\,\%$. On these channels, we also observe more noise (see Figure 2). In fact, LQI is computed only for a few symbols at the start of the reception of a packet [6] and it says little about the reception quality of future packets. Baidoo-Williams at al. [7] remark that LQI estimation could rely on the combination of RSSI with knowledge from the packet decoder about successful packet receptions. However, this only works for successfully decoded packets and does not provide information about transmissions not intended for the specific receiver.

*c) **SNR (Signal to Noise Ratio) and SINR (Signal to Interference plus Noise Ratio):*** The indicators allow to estimate the Bit Error Rate (BER) and PER. However, no radio hardware directly provides a measure of SNR or SINR, although LQI may be related to them, depending on the implementation. Their estimation requires the knowledge of noise and/or interference power as well as RSSI. Our proposed methods aim at computing SINR based on measurements on nodes.

B. Evaluating Link Quality

Much research concerned the estimation of link quality, however, the proposed schemes do not meet the requirements for a fast and accurate estimation in WSN.

Baccour et al. [1] review the main results on characterization of link quality and schemes for its estimation. RSSI only characterizes the received signal strength and does not take into account neither noise nor interference, so it only partially reflects the link quality. LQI is better because it does depend on noise and interference, but it is computed only on a few symbols at the beginning of the reception, so it poorly captures the channel conditions during the whole transmission. Moreover, nodes need to perform several measurements to obtain a good link quality estimation, which means many packet receptions if they need to quantify the links with all neighbors.

Link quality estimation by packet counting may rely on active probing [8], however, probing packets consume additional energy, especially if a node needs to send them to all neighbors. The same problem arises when nodes use overhearing to estimate link quality: Liu et al. [9] designed a passive meter that overhears frames to update link status. Hermeto et al. [10] proposed a passive scheme to avoid costly estimation of PER of unicast links by ranking links based on counting broadcast frames. Nevertheless, all such methods require a large number of transmissions to be reliable. Zhang et al. [11] established a model that connects PER to a measure of LQI for a given packet length under diverse environmental conditions.

The Expected Transmission Count (ETX) is an example of other types of link quality estimators that nodes can directly use without estimating PER. It corresponds to the number of retries each data packet may experience before it is successfully acknowledged by the receiver [12]. ETX is related to the inverse value of $1 - \mathrm{PER}$ for the data and acknowledgment packets. Its estimation requires several packet transmissions to obtain statistically significant estimation. This constraint is particularly limiting for WSN in which sending numerous probes to estimate ETX of all links may be inacceptable.

C. Estimating interference of other networks

Our scheme aims at taking into account the interference of other technologies, especially IEEE 802.11. Shin et al. [13] proposed an analytical model (backed by simulations) to evaluate the effect of mutual interference between both technologies. They showed that the interference with IEEE 802.15.4 becomes negligible if the ratio of the distance between transmitters is above 8 (8 vs. 1 m). Petrova et al. [14] experimentally studied PDR obtained for various IEEE 802.15.4 packet lengths in presence of IEEE 802.11g/n traffic. They showed that the channel frequency and modulation of IEEE 802.11 are both significant. Angrisani et al. [15] also studied this issue on a real testbed and found a correlation between PER and SIR (Signal to Interference Ratio), however, they did not compare the results with any theoretical formula. Brown et al. [16] proposed a statistical model to predict losses based on the observation of the interference. Their model is simpler than ours: it considers the interference as an ON/OFF process that destroys a transmission as soon as there is an overlap. We show below that the impact of noise and interference is not so drastic and we need their better fine-grained quantification.

III. Evaluating noise and interference

To estimate noise and interference in the 2.4 GHz ISM band, we have used the IoT-lab testbed [3]: we ran experiments with many nodes in RX (reception) mode on the Grenoble, Lille, and Lyon premises. We sample the raw radio power received by nodes: we call this value the Noise and Interference Strength Indicator (NISI)—it corresponds to the value of Energy Detection (ED)[1] measured by the radio chip between frame receptions. The results appear in Figure 2: NISI depends on the channel and the considered site. Moreover, there is a clear correlation with common IEEE 802.11b/g/n channels.

To apprehend the impact of IEEE 802.11 on IEEE 802.15.4 and its key factors, we present their transmission and reception characteristics in Table I. If we consider that the attenuation for both signals is the same, which is typically the case if the distances between the transmitters and the receiver are identical, the IEEE 802.15.4 signal would then face a SIR of $-10\,\text{dB}$, which makes communication impossible even with the effective spread spectrum factor of 8 (+9 dB). As IEEE 802.11 networks are less dense (or have a higher link budget by 6 – 10 dB [17]), it is fair to consider the case in which the IEEE 802.11 interferer is farther than the IEEE 802.15.4 transmitter or behind a wall or a door, which can attenuate the signal power by 6 – 15 dB [18]. Attenuation decreases the level of interference and makes IEEE 802.15.4 communication possible.

IV. Burst-NISI: PER estimation from high frequency NISI measurements

In this section, we present Burst-NISI, a scheme that estimates $\widehat{\text{PER}_\text{B}}$ based on bursts of high frequency measurements

[1]According to the IEEE 802.15.4 standard [5]: "*the Energy Detection (ED) value is an estimate of the received signal power within the bandwidth of the channel*"

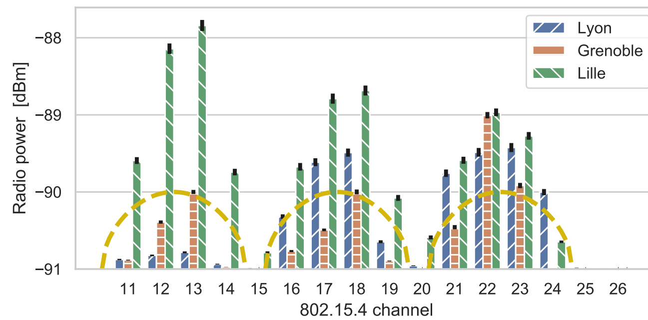

Fig. 2. Mean NISI measured by IEEE 802.15.4 sensors on the IoT-lab testbeds in Grenoble, Lille, and Lyon, with confidence intervals. Dashed curves represent the most used IEEE 802.11 channels (1, 6, and 11). We can clearly observe interference with the 802.11 traffic.

TABLE I
IEEE 802.15.4 vs. IEEE 802.11.

	IEEE 802.15.4	IEEE 802.11n	ratio
Channel width	2 MHz	20 MHz	−10 dB
Transmission power	0 dBm	∼20 dBm	−20 dB
SIR (same attenuation for both signals)			−10 dB
SIR (−6 – −15 dB attenuation for IEEE 802.11)			−4 – +5 dB

of noise and interference. We measure NISI on each receiving node by putting the node radio in RX mode and recording the ED value as often as possible, which results in a series of samples $\text{NISI}[i]$ at instants t_i, $i = 1, \ldots, I$ every $T_s = t_{i+1} - t_i = 166\,\mu\text{s}$. In our experiments, $I = 8300$, representing 1.38 s of airtime. We consider this burst of measurements as a representative of typical NISI.

To compute the probability of successful reception for a frame received with given RSSI, we assume that the frame arrives at the instant corresponding to sample index i_0, the bit error probabilities are independent of each other, and the BER is the same for all bits during T_s:

$$\text{PER}[i_0] = 1 - \prod_{i=i_0}^{i_0+M} \left(1 - \text{BER}\left(\text{RSSI} - \text{NISI}[i]\right)\right)^{b_s}, \quad (1)$$

where RSSI and $\text{NISI}[i]$ are in dBm, $b_s = R \times T_s$ is the number of bits per sampling period, R is the IEEE 802.15.4 data rate, and the relation $\text{BER}(\text{SINR})$ is defined in the IEEE 802.15.4 standard [5]:

$$\text{BER}(\text{SINR}) = \frac{8}{15} \times \frac{1}{16} \times \sum_{k=2}^{16} -1^k \binom{16}{k} e^{\left(20 \times \text{SINR} \times \left(\frac{1}{k} - 1\right)\right)}.$$

Finally, we derive $\widehat{\text{PER}_\text{B}}$ for any possible arrival instant by averaging $\text{PER}[i_0]$ for all positions i_0:

$$\widehat{\text{PER}_\text{B}} = \frac{1}{I - M} \sum_{i_0=1}^{I-M} \text{PER}[i_0]. \quad (2)$$

Algorithm 1: Node operation for packet reception under Sample-NISI. Lines 7–10 differ from standard duty cycles—they correspond to the measurement of RSSI and collecting the NISI histogram.

```
1  K: number of measurable NISI levels
2  F_k: array of size K initialized at zero
3  On every radio duty cycle do
4      switch radio on
5      if synchronization header received then
6          receive packet
7          measure RSSI, record packet duration D
8      else /* collect F_k histogram */
9          k ⟵ measured NISI
10         F_k ⟵ F_k + 1
11     switch radio off
```

We evaluate the accuracy of Burst-NISI in the next section and show that it results in good estimation of PER. However, we can hardly apply it to a low power node in real world deployments. Actually, it requires the radio to be permanently switched on during long periods of time, which consumes considerable energy and requires enough computational power to process measurements.

V. Sample-NISI: PER estimation for energy constrained nodes

To be able to embed the estimation of PER in an energy constrained node, we propose Sample-NISI, a modified scheme that takes advantage of sporadic NISI measurements to compute estimation $\widehat{\mathrm{PER}_\mathrm{S}}$.

The duty cycle is a common technique to reduce energy consumption at the MAC layer. For packet reception, it consists of periodically switching radio on at given instants when the node expects to receive a packet from one of its neighbors. If it receives the synchronization header (SHR), it keeps the radio in RX mode to receive the frame. If it does not detect SHR, it measures NISI and updates F_k corresponding to the histogram that captures the noise and interference distribution:

$$\mathbb{P}(\mathrm{NISI} = k) = \frac{F_k}{\sum_{l=1}^{K} F_l},$$

where K is the number of measurable NISI levels.

Algorithm 1 describes the operation of a node under Sample-NISI. At each duty cycle, when a node wakes up for reception, it can sample NISI without consuming much additional energy.

To compute estimation $\widehat{\mathrm{PER}_S}$ for a given frame of duration D received with a given value of RSSI, based on the distribution of NISI captured by histogram F_k, we use the law of total probability:

$$\widehat{\mathrm{PER}_S} = \sum_{k=1}^{K} \mathrm{PER}\left(\mathrm{RSSI} - \mathrm{NISI}\right) \times \mathbb{P}(\mathrm{NISI} = k), \qquad (3)$$

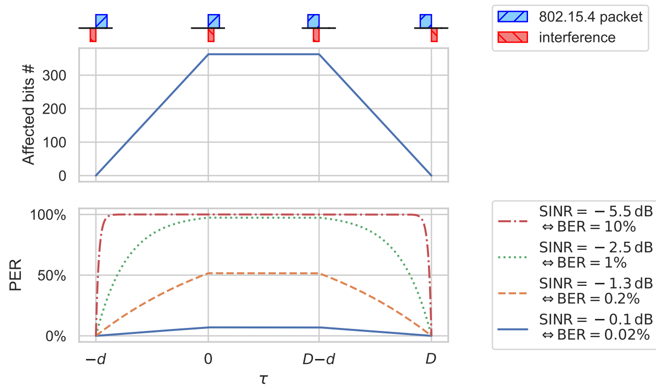

Fig. 3. Interference between an IEEE 802.15.4 frame of duration $D = 4.10\,\mathrm{ms}$ and interference of duration $d = 1.45\,\mathrm{ms}$. τ is the difference (in time) between the beginning of the frame and the interference. The impact of the interference is longer than their respective durations and a high interference level quickly results in almost $100\,\%$ PER during the whole timespan.

where function $\mathrm{PER}\left(\mathrm{SINR}\right)$ for given SINR is derived from Equation 1:

$$\mathrm{PER}\left(\mathrm{SINR}\right) = \frac{1}{d + D} \int_{-d}^{D} \left(1 - \left(1 - \mathrm{BER}(\mathrm{SINR})\right)^{N(\tau)}\right) \mathrm{d}\tau, \qquad (4)$$

where $N(\tau)$ is the number of bits effectively affected by the interference. We compute $N(\tau)$ from the difference τ between the beginning of the typical interference and a given frame with respective durations: D of the IEEE 802.15.4 frame and d of the interference:

$$\mathrm{N}(\tau) = \begin{cases} R(D-d)\left(\frac{\tau}{d}+1\right) & -d \le \tau < 0 \\ R(D-d) & 0 \le \tau < D-d \\ R(D-d)\left(-\frac{\tau}{d}+\frac{D}{d}\right) & D-d \le \tau < D \\ 0 & \text{elsewhere.} \end{cases}$$

Estimation $\widehat{\mathrm{PER}_S}$ relies on d, the duration of typical interference. A wrong value of d may compromise accuracy. In this paper, we have measured d experimentally and adopted the fixed value of $d = 1.45\,\mathrm{ms}$ that matches one IEEE 802.11 beacon of size $180\,\mathrm{B}$ sent at $1\,\mathrm{Mb/s}$ corresponding to the most present interfering traffic we observed during experiments.

Figure 3 gives the graphical representation of N and PER with respect to τ. In a nutshell, when the signal faces interference, the effect of the latter lasts longer than the interference duration: it could mask only one symbol, but it still may result in a wrong frame check sequence (FCS) so the entire frame would be dropped. Beyond the interference, we consider that the SINR is high enough to warrant a negligible BER, which is not true for the case of packets with RSSI near the sensitivity threshold, which we discuss below.

A node can continuously update the F_k histogram of NISI in the background and use it in the PER estimation of links to all neighbors. Sample-NISI then only requires the reception of a single packet to estimate PER from the associated value of RSSI. The scheme gives the estimation of PER for any packet

TABLE II
PARAMETERS OF THE EXPERIMENTS ON THREE DIFFERENT SITES.

IoT-lab	Lyon	Grenoble	Lille
Sensor	IoT-lab (ARM Cortex) M3 nodes		
Sensor radio hardware	AT86RF231 IEEE 802.15.4 chip at 2.4 GHz		
# nodes	18	30	30
TX power	$-12\,\mathrm{dBm}$	$0\,\mathrm{dBm}$	$0\,\mathrm{dBm}$
Data packet size (MAC layer)	33 / 84 / 126 B	84 B	84 B
Mean # of neighbors	5.0	3.0	7.4

sizes—the packet duration is an input parameter to Sample-NISI that takes an important role, in particular for marginal links, which corroborates recent experimental findings [11].

Note that the continuous updating of the F_k histogram is a means of adaptation to changing channel conditions in the local radio environment. If we need to enhance adaptation even more, nodes can update the distribution by weighting the new samples more than the older ones, e.g., with an exponentially weighted moving average (EWMA).

Sensitivity limitations

The IoT-lab M3 nodes we used in our experiments have a minimal measurable radio power level (both for NISI and RSSI) of $-91\,\mathrm{dBm}$. This value is much higher than the sensitivity of $-101\,\mathrm{dBm}$ found in the datasheet, which is itself well above the theoretical limit [19].

So, with this hardware, we do not have any details on NISI and RSSI in the range between -91 and $-101\,\mathrm{dBm}$: all NISI mesures accumulate in the $-91\,\mathrm{dBm}$ histogram bin. This fact limits the range of the RSSI values for which our method is applicable. However, a large fraction of packets are lost in this range of reception power [4], so that the majority of the corresponding links have a high PER and thus should be avoided except, as a last resort.

VI. EXPERIMENTAL VALIDATION OF THE SCHEMES

We have validated the proposed schemes in an extensive measurement campaign involving hundreds of wireless links on several sites of the IoT-lab testbed. The sites are in different cities and occupy areas of various sizes. They are subject to different levels of noise and interference mainly generated by surrounding IEEE 802.11 networks. For each of these links, we measure RSSI and NISI to compute the PER estimation as well as we measure the mean PER based on counting received packets.

Table II shows the key parameters of the experiments. Due to the small size of the Lyon testbed, we reduce the transmission power on this site to avoid having only excellent links. During the experiment, each node sends 90 broadcast packets on each frequency channel. We measure NISI on each receiving node in two different ways: in one burst, at the beginning of the experiment to obtain data for validation of Burst-NISI, and by discrete sampling, interspersed with packet transmissions to validate Sample-NISI.

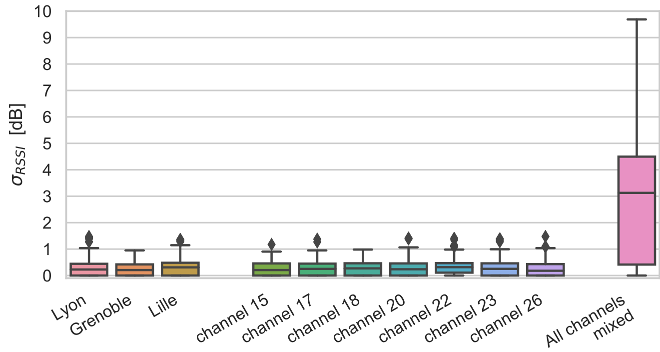

Fig. 4. Standard deviation of RSSI computed separately for each link (transmitter, receiver, channel) and grouped by site and by channel. We note that it is less than $1\,\mathrm{dB}$ almost everywhere. The right-most box-plot represents however the standard deviation computed for each couple (transmitter, receiver), independently of the channel, which shows that we have to consider the channels separately.

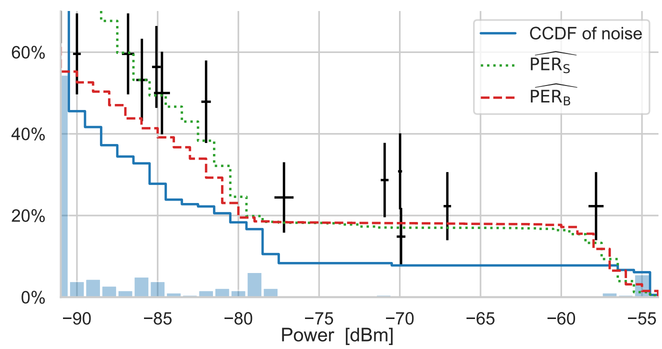

Fig. 5. Link PER vs. RSSI: PER measurements by counting packets, PER estimation with Burst-NISI and Sample-NISI. The black crosses represent the measured RSSI and PER of the links: the horizontal position and length represent the mean and the standard deviation of RSSI and the height represents PER with its confidence interval. Dashed red lines correspond to the PER estimation using Burst-NISI and dotted green lines represent the PER estimation using Sample-NISI. We also draw the normalized F_k histogram, i.e., the distribution of NISI (blue bar plots) and its complementary cumulative distribution function (CCDF), i.e., the proportion of the NISI values above a given RSSI value associated with this distribution.

A. Estimation of RSSI

We first consider the RSSI estimation of each link (i.e., for each transmitter, receiver, and channel). Figure 4 shows the standard deviation of the observed RSSI values on individual links. The standard deviation is less than $1\,\mathrm{dB}$. Compared with the precision required for the estimation of PER, we can conclude that one packet is sufficient to obtain a useful estimate of the effective RSSI over the considered link. As the RSSI value varies from one channel to another, we estimate the link RSSI separately on each channel.

Because of channel fading, the RSSI may still vary along the time. However, the network is not highly mobile and not placed in a highly mobile environment, which makes the fading less concerning. Moreover, the knowledge of the behaviour of one link may be refined and updated at each new reception on that link.

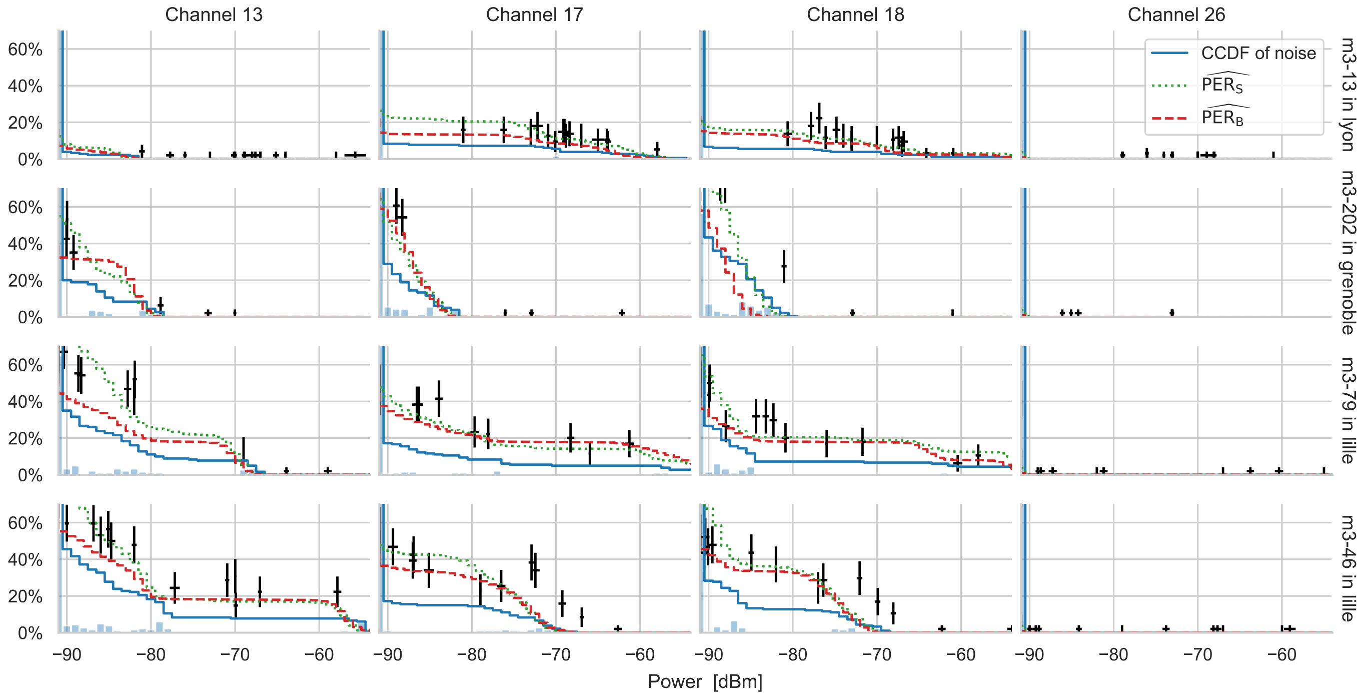

Fig. 6. Link PER vs. SINR: PER measurements by counting packets, PER estimation with Burst-NISI and Sample-NISI for a selection of receivers. Legend for the graphs as in Figure 5. The estimation is sufficient to distinguish the situation in which 1) there is almost no noise and PER is $0\,\%$ for every signal power level except for the lowest value of $-91\,\mathrm{dBm}$ (as for node 13 in Lyon on channel 26) or 2) when noise implies non-zero PER even for strong link power (e.g., node 79 in Lille on channel 17).

B. Ground truth PER measurements

We measure mean PER by counting packets for all links in our selection of nodes by sending tens of thousands packets on each site. As expected, many links have very good quality and we observe a PER of $0\,\%$ in many cases. Thus, to compute the PER confidence interval, we cannot use the common assumption based on the normal distribution. We have decided to use the Wilson score [20] instead, as it is more suitable in this case.

C. Experimental results

We start by observing the relationship between link SINR and PER. Figure 5 presents a set of measured values for channel 13 of node 79 in Lille. This graph shows the correspondence between the PER and the SINR. We observe the distribution of NISI, depicted by the histogram and its complementary cumulative distribution function (CCDF), i.e., the proportion of the NISI values above a given RSSI value associated with this distribution. We also observe the experimentally measured PER and RSSI values of each link of which node 79 in Lille is the receiver, traced as black crosses. Then, we observe the two estimators $\widehat{\mathrm{PER}_\mathrm{S}}$ and $\widehat{\mathrm{PER}_\mathrm{B}}$, computed from the NISI samples.

We can observe that the measured value of PER is clearly related to (but does not superpose on) F_k CCDF. Moreover, the estimated PER values by both proposed schemes correspond fairly well to measured PER: the difference between them is tiny compared to the precision of the RSSI measurements and the required precision of the PER estimation.

Figure 6 presents all the results with one row of plots per receiver. We also separate data per channel (in columns) because of the difference of noise levels shown in Section III. Both estimators successfully take into account the presence or absence of perturbations: on noisy channels like channel 13, they increase with F_k CCDF, whereas on channels with almost no noise like channel 26, they stay at $0\,\%$. In some graphs, the accuracy of the estimation with Burst-NISI differs from the one estimated by Sample-NISI (e.g., channel 13 of the node 79 in Lille, for low power values). The reason for the difference is that the burst of NISI measurements in Burst-NISI is not necessarily representative of the long-term NISI distribution, whereas Sample-NISI takes advantage of the F_k histogram of NISI samples gathered over time, more representative information of the typical values of NISI as they are constantly updated.

Figure 7 summarizes the estimation accuracy for all data recorded during our experiments. To obtain the accuracy, we compute the absolute difference between PER estimated by Sample-NISI and PER measured during the experiments. We draw the distribution of the accuracy using letter-value plots [21]. To analyze the effect of the different parameters, we group the values according to various criteria.

Three plots on the left show that the accuracy is similar for all sites. According to Equation 4, PER depends on the IEEE 802.15.4 packet length, integrated in the PER estimation

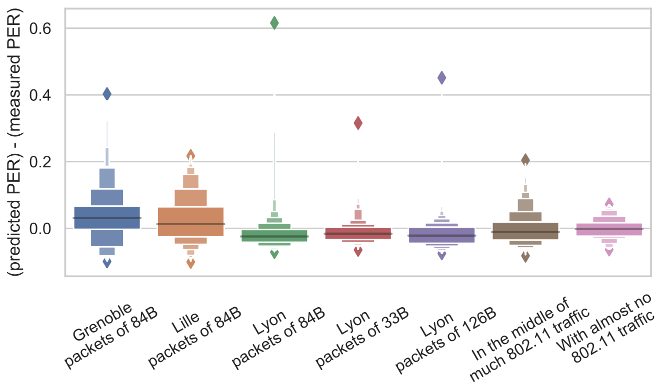

Fig. 7. Letter-value plot of the accuracy distribution for Sample-NISI. The absolute value of accuracy is most of the time less than 10 percentage points.

via the packet duration, so Sample-NISI has the same accuracy for small (33 B), medium (64 B), or long packets (126 B) in the same environmental conditions. Moreover, two plots on the right indicate that the estimation correctly captures the different noise power levels (or interference levels) encountered on the various radio channels.

VII. Conclusion and Future Work

Link quality estimation is subject to a subtle trade-off between accuracy and energy consumption since PER estimation based on active or passive packet counting may consume energy that nodes could otherwise dedicate to application traffic.

Sample-NISI uses all the information readily available during the regular operation of any sensor network: every time the radio wakes up, if it receives a packet from a neighbor, it records associated RSSI to refine the PER estimation of the link. If it does not detect the packet preamble, it refines the F_k histogram of NISI. This approach is compatible with any radio duty cycling mechanism like TSCH, beacon-enabled IEEE 802.15.4, or preamble sampling (such as Contiki MAC). Moreover, a node can use any packet from a neighbor to estimate link PER: it merely needs to measure RSSI and it obtains the same accuracy for any kind of packets (i.e., unicast data frames of any size, routing protocol broadcast packets, etc.). Besides background measurements of NISI, Sample-NISI only requires a single packet reception to estimate PER.

Regarding the estimation of the average interference duration, we intend to investigate an embedded estimation process for finding d, e.g., with two consecutive NISI samples. We also plan to investigate how nodes can take advantage of selecting different neighbors for different packet sizes as Sample-NISI intrinsically gives different PER values for different packet lengths.

Acknowledgments

This work has been partially supported by the French Ministry of Research projects PERSYVAL-Lab under contract ANR-11-LABX-0025-01 and DiNS under contract ANR-19-CE25-0009-01.

References

[1] N. Baccour, A. Koubâa, L. Mottola, M. A. Zúñiga, H. Youssef, C. A. Boano, and M. Alves, "Radio Link Quality Estimation in Wireless Sensor Networks: A Survey," *ACM Transactions on Sensor Networks*, vol. 8, 2012.

[2] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian, and E. J. Coyle, "A Kalman Filter Based Link Quality Estimation Scheme for Wireless Sensor Networks," in *Proc. GLOBECOM*. IEEE, 2007, pp. 875–880.

[3] FIT IoT-LAB, "IoT-LAB: a Very Large Scale Open Testbed," www.iot-lab.info.

[4] H.-J. Audéoud and M. Heusse, "Quick and Efficient Link Quality Estimation in Wireless Sensors Networks," in *14th Annual Conference on Wireless On-demand Network Systems and Services (WONS)*, Isola, France, Feb. 2018.

[5] *IEEE Standard for Low-Rate Wireless Networks*, Institute of Electrical and Electronics Engineers, 2006.

[6] *AT86RF231/ZU/ZF datasheet*, Atmel, 2009.

[7] H. E. Baidoo-Williams, O. Chipara, R. Mudumbai, and S. Dasgupta, "PHY-Layer Link Quality Indicators for Wireless Networks Using Matched-Filters," *CoRR*, vol. abs/1508.04524, 2015. [Online]. Available: http://arxiv.org/abs/1508.04524

[8] C. Vallati, E. Ancillotti, R. Bruno, E. Mingozzi, and G. Anastasi, "Interplay of Link Quality Estimation and RPL Performance: An Experimental Study," in *Proc. ACM PE-WASUN Symposium*. ACM, 2016, pp. 83–90.

[9] D. Liu, Z. Cao, Y. Zhang, and M. Hou, "Achieving Accurate and Real-Time Link Estimation for Low Power Wireless Sensor Networks," *IEEE/ACM Trans. Netw.*, vol. 25, no. 4, pp. 2096–2109, 2017.

[10] R. T. Hermeto, A. Gallais, K. V. Laerhoven, and F. Theoleyre, "Passive Link Quality Estimation for Accurate and Stable Parent Selection in Dense 6TiSCH Networks," in *Proc. ACM EWSN*, 2018, pp. 114–125.

[11] Y. Zhang, S. Fu, Y. Jiang, M. Ceriotti, M. Packeiser, and P. J. Marrón, "An LQI-Based Packet Loss Rate Model for IEEE 802.15.4 Links," in *Personal Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2018.

[12] D. S. J. De Couto, D. Aguayo, J. Bicket, and R. Morris, "A High-Throughput Path Metric for Multi-Hop Wireless Routing," *Wireless Networks*, vol. 11, Jul. 2005.

[13] S. Y. Shin, H. S. Park, and W. H. Kwon, "Mutual Interference Analysis of IEEE 802.15.4 and IEEE 802.11b," *Computer networks*, vol. 51, 2007.

[14] M. Petrova, L. Wu, P. Mahonen, and J. Riihijarvi, "Interference Measurements on Performance Degradation between Colocated IEEE 802.11g/n and IEEE 802.15.4 Networks," in *Sixth International Conference on Networking (ICN)*, 2007.

[15] L. Angrisani, M. Bertocco, D. Fortin, and A. Sona, "Experimental Study of Coexistence Issues Between IEEE 802.11b and IEEE 802.15.4 Wireless Networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, Aug. 2008.

[16] J. Brown, U. Roedig, C. A. Boano, and K. Römer, "Estimating Packet Reception Rate in Noisy Environments," in *39th Conference on Local Computer Networks Workshops*. IEEE, 2014.

[17] E. Morin, M. Maman, R. Guizzetti, and A. Duda, "Comparison of the Device Lifetime in Wireless Networks for the Internet of Things," *IEEE Access*, vol. 5, Nov. 2017.

[18] EURO-COST231 Revision 2, "Urban Transmission Loss Models for Mobile Radio in the 900 and 1 800 MHz Bands," Sep. 1991.

[19] S. Lanzisera and K. S. J. Pister, "Theoretical and Practical Limits to Sensitivity in IEEE 802.15.4 Receivers," in *Proc. 14th IEEE ICECS Conference*. IEEE, 2007, pp. 1344–1347.

[20] E. B. Wilson, "Probable Inference, the Law of Succession, and Statistical Inference," *Journal of the American Statistical Association*, vol. 22, 1927.

[21] H. Hofmann, H. Wickham, and K. Kafadar, "Value Plots: Boxplots for Large Data," *Journal of Computational and Graphical Statistics*, vol. 26, 2017.