An LQI-based Packet Loss Rate Model for IEEE 802.15.4 Links

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***Abstract*—Packet loss rate (PLR) is a crucial and popular link quality metric for wireless sensor networks (WSNs). In this paper, we investigate how to estimate PLR of an IEEE 802.15.4 link from the information that is easily obtained from radio chip. Specifically, we aim to establish a generalized model that connects PLR to link quality indicator (LQI), a physical layer link quality measure, and packet length under diverse environmental conditions. To this aim, an extensive experimental study considering various environmental factors and packet lengths is conducted, from which rich observations are made on the spatio-temporal characteristics of the dependency of PLR on LQI and packet length. Based on the observations, we propose a packet loss rate model as a function of LQI and packet length, that is applicable in all experimented scenarios. Besides, a comparison with a literature LQI-only based PLR model shows that our proposed model has higher accuracy for various packet lengths. Finally, we provide the implications of the empirical study and the guidelines for real-world WSN applications to construct and adapt the proposed PLR model in different environments.**

I. Introduction

Packet loss rate (PLR) of a link is a crucial parameter for the design and adaptation of higher-layer protocols in wireless sensor networks (WSNs). Though long term average PLR can be easily estimated by counting the number of packets transmitted and successfully received, in many cases, e.g., for routing and link performance maintenance, it is crucial to estimate the expected PLR instantly or in short time. In such cases, the literature has resorted to information that can be retrieved easily and locally, which includes, e.g., link quality indicator (LQI), received signal strength indicator (RSSI) and signal to noise ratio (SNR).

In a recent experimental study [1], we reported our findings about how environment impacts the dependency of link PLR on SNR and packet length and proposed a SNR-based PLR model. Among all the experimented scenarios, we notice that in some scenarios such as outdoor open spaces or indoor office environment during non-working hours, a variation in the SNR as small as 2 dB can change a good link to a bad one, and vice versa. This implies that in such scenarios, SNR may not be the best indicator for PLR, especially when the link is in the transitional region. On the other hand, another physical layer link quality measure provided by radio chips, LQI, has received significant attention in the research community in recent years. A number of works argued that LQI shows stronger correlation with PLR than other hardware indicators such as RSSI and hence LQI is a good indicator of PLR [2] [3]. Specifically, Srinivasan *et al.* showed in [4] that average LQI over a large packet window (e.g. 120 packets) can provide accurate link quality estimation.

Some recent works try to model the correlation between link PLR and LQI. The authors of [5] build a piecewise linear model of packet reception rate (PRR, i.e. $1 - \text{PLR}$) as a function of average LQI. Other works [2] [6] suggest that PRR can be approximated by hardware indicators with sigmoid curves. Liu *et al.* [7] use logistic regression to fit the sigmoid curves to the PRR-LQI data points collected from a testbed placed along an office corridor. In [8], Bildea *et al.* model the dependence between PRR and LQI for CC1101 radio links with a Fermi-Dirac function in an indoor environment. Note that, these existing LQI-based PLR models (e.g., [7] [8]) have been proposed based on findings in highly controlled environments (e.g. indoor environment with static surrounding objects).

Despite these efforts, the impact of typical environmental factors on the mathematical mapping from LQI to link PLR still remains unclear, such as the impact of temperature [9], human presence [10], interference [11], climate condition and terrains [12]. Without a comprehensive understanding of such environmental impact, the acquired empirical PLR models are severely limited to specific scenarios. In addition, the impact of packet length on PLR revealed in previous studies [1] [13] are not considered in most existing LQI-based PLR models. Taking both factors, i.e. environment and packet length, into account forms the foundation of the present paper.

The specific objective of this paper is to *establish a PLR model that quantifies the impact of both LQI and packet length on the PLR of an 802.15.4 link under diverse environmental conditions*. To do so, an extensive experimental study under diverse environmental conditions and different packet lengths has been conducted. In particular, we conducted indoor and outdoor experimental campaigns in four locations, considering a variety of environmental factors, such as climate condition during day and night, obstacles, human presence, interference, etc. In addition, various packet lengths were experimented to capture and model the impact of packet length on the PLR-LQI relationship in different environments.

The most important experimental findings include: (1) the PLR-LQI relationship can be significantly different in different environments, and may differ from link to link in the same environment, (2) the PLR-LQI relationship is highly dependent on the packet length, (3) the impact of LQI and packet length on PLR may vary over time due to interference and shadowing effects of humans or other objects. Based on these observations, *we propose a link PLR model as a function of LQI and packet payload size*. We further validate that the proposed model is applicable in all experimented scenarios and for any packet length, while *only the values of model parameters may vary over space and time*. The proposed model is compared with one literature LQI-only based PLR model. The comparison shows that our proposed model has higher accuracy for various packet lengths. Finally, we provide the guidelines to construct and adapt the proposed PLR model in different environments and discuss briefly the comparison between LQI and SNR for predicting the link PLR.

The rest is organized as follows. In Sec. II, we introduce LQI briefly, describe the experimental study, and present the spatial and temporal characteristics of the dependency of link PLR on LQI and packet length under diverse environmental conditions. In Sec. III, we propose a PLR model, validate it, compare it with an existing model, provide guidelines for its application in different environments and discuss briefly about the use of LQI and SNR to predict link PLR. Finally, in Sec. IV, we conclude the paper.

II. AN EXPERIMENTAL STUDY

A. LQI, Packet Length and PLR

LQI is proposed in the IEEE 802.15 standard, but its implementation is vendor-specific. For CC2420, which is probably the most widely adopted radio chip in wireless sensor network research, LQI is measured based on the first eight symbols of the received packet, using a score ranging from 50 to 110. The score value is related to the correlation between phase shifts of incoming data and 802.15.4 symbols [14]. A higher value of LQI indicates higher quality of the received symbols. The corresponding *symbol error rate* directly affects *BER (bit error rate)* and consequently *PER (packet error rate)*, which further subsequently affects PLR because packets with errors will be discarded by the link-layer mechanisms.

As its definition shows, LQI is determined by the quality of the wireless link, which, like all wireless links, is environment-dependent, or in other words, can be highly affected by various environmental factors. The dependence flow between PLR, PER, BER and symbol error rate provides the underlying reason about why LQI has been experimentally shown, e.g. in [2] [3] [4], to be a good indicator for PLR.

It is also worth highlighting that, when relating BER to PER, i.e. $PER \approx 1 - (1 - BER)^l$, the packet length l is a non-dispensable factor. This implies that, in modeling and estimating PLR, packet length must also be taken into account, which affects PLR from an orthogonal angle of the environment.

Based on the above analysis, an extensive experimental study has been conducted to investigate the impact of LQI and packet length on link PLR under diverse environmental conditions. The experiment setup and the results are presented in the subsequent subsections.

B. Experiment Setup

To consider both indoor and outdoor scenarios and cover diverse environmental factors, we have chosen four experiment locations: (1) an Athletic Field, an open field isolated from human activity and absent from (severe) electromagnetic interference, (2) an university Parking Lot, where shadowing effect of obstacles such as cars is notable during the day, (3) an Office Building, a university building with heavy human-related activities during office hours, and (4) Home, an apartment where cross technology interference is ubiquitous.

In the experiments, TelosB nodes are used, each of which is equipped with the CC2420 radio chip compliant with IEEE 802.15.4 and on-board omnidirectional antenna. The radio chip operates in the ISM band of 2.4 GHz at the PHY layer and all experiments use the standard TinyOS 2.1 CSMA MAC layer.

Other experiment details, such as a list of performed experiments, deployment setup, and data collection procedure, can be found in our previous report [1]. We do not repeat them here due to space constraints.

C. Results under Different Environments

In this subsection, we focus on investigating whether / how the PLR-LQI relationship may vary under different environments and/or with different packet lengths.

We first study the *large-scale environmental impact*, i.e. the impact of different experiment locations. Fig. 1 plots the PLR-LQI curves with respect to packet payload size L (in bytes) for a selected link in each of the four experiment locations. Each graph in the figure is plotted based on two consecutive experimental runs (i.e. 192 thousand packets transmitted in approximately one hour) and PLR is computed over every 3000 packets and then averaged for each value of LQI (at a step of 1). In this analysis, all results are generated from experiments of a short time span (e.g., over a one hour window) to minimize temporal effects of the environments.

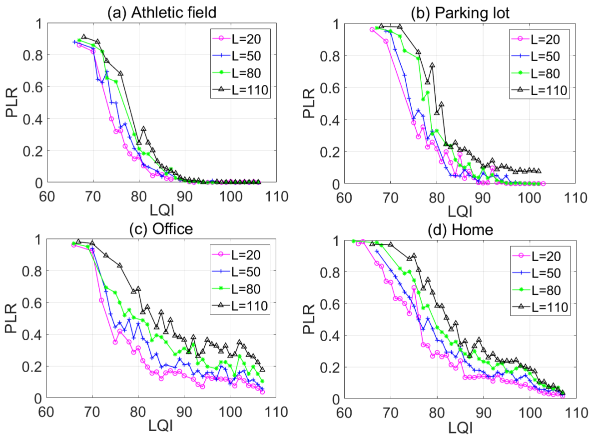

Fig. 1: The dependency of PLR on LQI and packet payload size L (in bytes) in four different experiment locations.

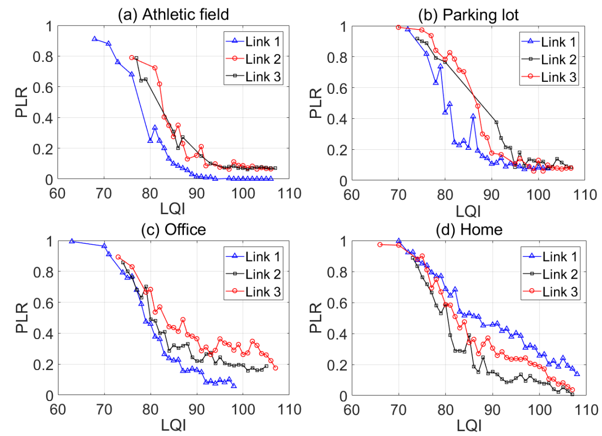

Fig. 2: The PLR-LQI relationship (for 110 bytes payload) of three different links in each experiment location.

Fig. 1 shows that PLR always decreases with LQI while the steepness of the PLR-LQI slope clearly varies with the experiment location. As a result, the width (in terms of LQI) of the transitional region (PLR between 0.1 and 0.9) strongly depends on the location. For example, for 80 bytes payload, the width is approximately 18 in the athletic field (Fig. 1(a)) but 36 in the office building (Fig. 1(c)). We can further observe that the LQI threshold of good links (PLR less than 0.1) varies significantly with the environment. The maximum LQI threshold of good links observed in all experiments is 108 for a link in the office building while the minimum is 81 for a link in the athletic field. These indicate that *the PLR-LQI relationship can be significantly different in different environments*.

In addition, from Fig. 1, we can observe that PLR always increases with larger payload size and there is a clear separation between the PLR-LQI curves of different payload sizes in the transitional region in all experiment locations. The maximum PLR difference between 20 bytes payload and 110 bytes payload is found to be more than 0.4 in all the four graphs. These indicate that *the PLR-LQI relationship is highly dependent on the packet length*. We can also see from the figure that such an impact of packet length varies over the experiment location. For example, only in the athletic field, the PLR-LQI curves of various packet payload sizes almost overlap in the LQI range between 90 and 105.

We then investigate the *small-scale environmental impact*, i.e., whether the PLR-LQI relationship differs from link to link at the same experiment location. We select 3 different links from each location and plot the PLR-LQI curves in Fig. 2.

Interestingly, Fig. 2 shows that, even at the same experiment location (e.g. athletic field), different links can have their PLR-LQI curves significantly different from each other due to small-scale environmental differences. For the athletic field (Fig. 2(a)), a possible reason for the PLR-LQI relation difference is that Link 1 maintains line-of-sight (LOS) between the transmitter and receiver while Link 2 and Link 3 have non-line-of-sight (NLOS) radio communication. The three selected links in the parking lot (Fig. 2(b)) are all NLOS links while the PLR-LQI curves yet still look different from each other. We believe that this difference is likely caused by the different shadowing effects of objects (in this case, cars) on each link. Similarly, the difference of PLR-LQI curve between different links in the office scenario (Fig. 2(c)) and the home scenario (Fig. 2(d)) may largely be due to the different shadowing effects of human, furniture, etc. The observation from Fig. 2 essentially indicates that *the PLR-LQI relation is sensitive to not only the large-scale environmental impact but also small-scale environmental factors.*

D. Results under Different Times

In this subsection, we investigate whether / how the PLR-LQI relationship vary under different times when there may be changes in environmental characteristics. In this investigation, the impact of packet length is also considered.

We first focus on outdoor environments. For the athletic field, we consider the impact of time change over day and night, when climate environmental factors such as temperature and humidity may be different. Fig. 3 provides an example showing the dependency of PLR on LQI and packet payload size for a link in the athletic field during both day and night. We notice that when changing from day to night, the quality of the link improves, i.e. LQI increases and PLR decreases under the same transmission power. However, the dependency of PLR on LQI and packet payload size remains surprisingly almost unchanged, showing no clear temporal variation due to the transition between day and night. This indicates that though the change in

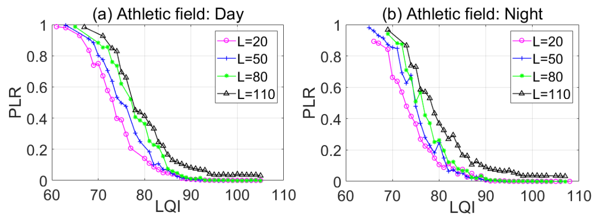

Fig. 3: The climate change from day to night has almost no impact.

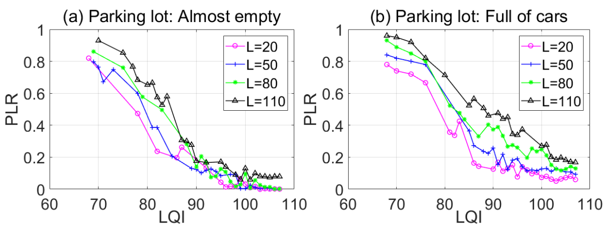

Fig. 4: Temporal variation due to the shadowing effect of cars.

climate conditions (such as temperature and humidity) may impact PLR or LQI individually, it has little impact on the mapping between PLR and LQI.

For the parking lot scenario, we consider the impact of the shadowing effect of objects, i.e. cars. Fig. 4 plots the impact of packet length and LQI on the PLR of a link during day time when the parking lot was full of cars, and during night time when the parking lot was almost empty. As the figure depicts, the width of transitional region of the link during the day (Fig. 4(b)) is larger than that during the night (Fig. 4(a)). As we have showed above that the climate change from day to night induces almost no variation on the relation between PLR and LQI, the major variation here is very likely due to the presence of cars. This suggests that the shadowing effect of objects may strongly impact the dependency of link PLR on LQI and packet length.

We next focus on indoor environments. Here we consider two common human-related factors in such environments: (1) human presence and movement, and (2) WiFi interference. The former imposes shadowing effects on the links; the latter is known to have a strong impact on link quality [11].

We use the testbed in the office building to perform a set of experiments in a weekend, to minimize the interference from other possible sources. We first let a person walk around the transmitter, and then, close to a link, we place a laptop that first streams live videos and then downloads a large file from an access point (AP) using WiFi. During the experiment, we select two different CC2420 channels: Channel 12, whose frequency overlaps with the channel used by the AP, and Channel 26, which is known to be outside the WLAN radio frequency [15].

The impact of people walking on the dependency of PLR on LQI and packet length for an exemplary link is plotted in Fig. 5. We can observe that human presence and walking extend the width of the transitional region of the link (Fig. 5(b)), compared to the baseline case (Fig. 5(a)). We believe this impact is due to the shadowing effect of human, similar to the impact of cars on the PLR-LQI relationship in the parking lot scenario.

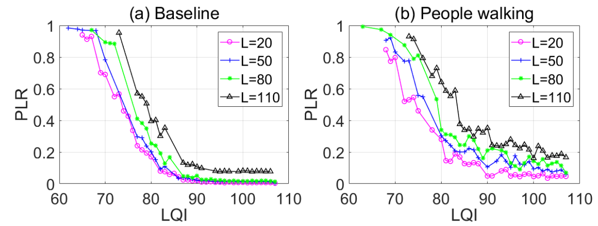

Fig. 5: Temporal variation due to people walking.

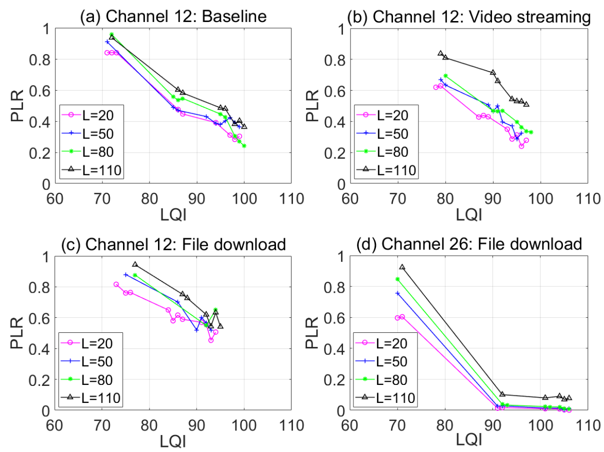

Fig. 6: Temporal variation due to WiFi interference.

Fig. 6 plots the impact of WiFi interference for the link close to the laptop that communicates with the AP. The figure shows that the interference from file download (Fig. 6(c)) has a stronger impact than video streaming (Fig. 6(b)) on the correlation of PLR with LQI and packet length on Channel 12, while the impact of WiFi interference is minimal on Channel 26, as the PLR in Fig. 6(d) is much lower for the same LQI value even during file download.

Bringing the above observations together, we summarize the impact of environmental changes due to time as follows. *The PLR-LQI relationship may vary over time due to environmental changes*, such as interference and shadowing effects of human, obstacles, etc. Interestingly, the normal climate change in temperature and humidity from day to night induces almost no variation on the PLR-LQI relationship. Additionally, *the impact of packet length on the PLR-LQI relationship may also change over time due to the environmental changes*, as the PLR difference between 20 bytes payload and 110 bytes payload of the same LQI value changes when, e.g., cars are present in the parking lot scenario (Fig. 4) or people walk around in the office scenario (Fig. 5).

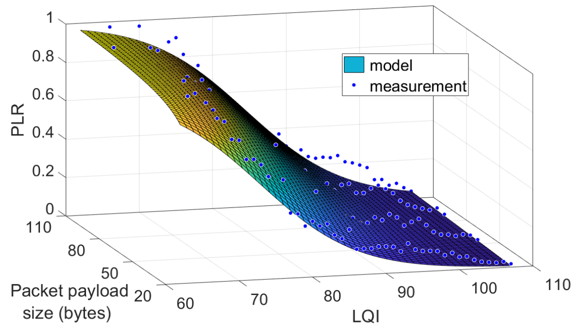

Fig. 7: Modeling PLR of an exemplary link as a function of LQI and payload size ($\alpha = 0.00048$, $\beta = 0.1461$).

TABLE I: Model accuracy of Eq. (1) in different scenarios

Scenarios	Param. α	Param. β	R^2
Open field - LOS	0.0009	0.1618	0.924
Open field - NLOS	0.0008	0.1551	0.913
Parking lot - cars	0.0007	0.1533	0.901
Parking lot - no cars	0.0008	0.1547	0.918
Office - people walking	0.0005	0.1493	0.918
Office - interference	0.0002	0.1407	0.896
Office - weekend	0.0007	0.1521	0.933
Home	0.0005	0.1461	0.925

III. Model, Validation and Implications

In this section, we propose a link PLR model as a function of both LQI and packet length based on the spatio-temporal characteristics presented in the previous section. Also, we validate it under various environmental settings and packet lengths. Furthermore, we compare its performance with a literature LQI-only based PLR model. Finally, we provide the guidelines for applying the proposed model to real-world sensor network applications in different environments, and discuss briefly about predicting link PLR using LQI and SNR.

A. The Proposed Packet Loss Rate Model

To propose the link PLR model, we used Matlab to find the best fit for all data sets and different theoretical models were compared according to the chi-square test.

Eq. (1) is our proposed PLR model for 802.15.4 links, which is a function of LQI and packet payload size.

$$\text{PLR} = \frac{1}{1 + (\alpha/L) \cdot \exp(\beta \cdot LQI)} \quad (1)$$

where LQI denotes the value of LQI, L is the packet payload size in bytes, and α and β are two model parameters. The specific form as shown by Eq. (1) is the result of model-fitting for the data sets from the experiments described in the previous section. Fig. 7 shows an example of modeling PLR for a link in the home scenario. The values of model parameters α and β are found with 95% confidence level.

B. Model Validation

For all the data sets collected under diverse environmental settings, the proposed model (Eq. (1)) always

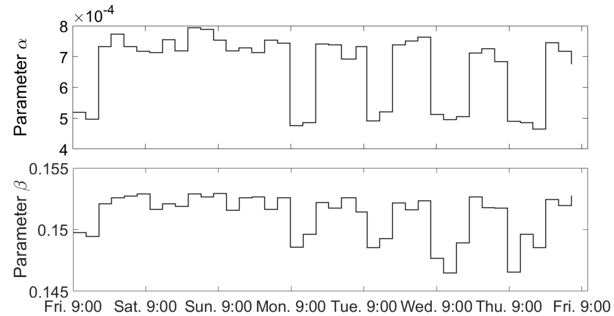

Fig. 8: Weekly variation of model parameters α and β in the office scenario.

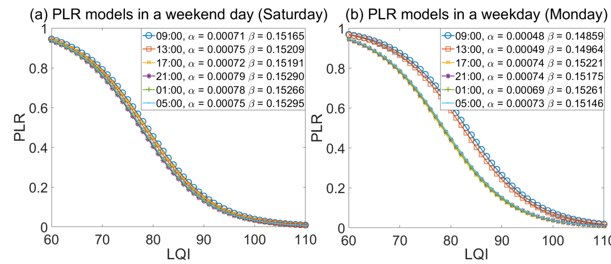

Fig. 9: Daily variation of PLR models in the office scenario.

fits well. In other words, the mathematical function expressing the dependency of PLR on LQI and payload size remains in the same form (Eq. (1)) while the values of the model parameters α and β may vary for different (spatial and/or temporal) environmental settings. Due to space limitation, only two sets of the validation results are presented below.

1) Model validation in different environments: For validation purposes, the collected data set is segmented into model training and validation sets at 0.25-0.75 ratio. Table I lists the typical values of the model parameters of the proposed PLR model that are validated in all experimented scenarios, together with model precision in terms of a standard error measure for model fitting: R^2 (R-squared). R^2 is a value between 0 and 1, with a value closer to 1 indicating a greater fitting of the model to the measurements.

2) Model validation for environmental changes: We take the office environment as an example and apply the model to the data set collected from a 7-day experiment on the testbed in the offices. Fig. 8 plots the weekly variation of the model parameters of a testbed link, where α and β are updated approximately every four hours. Fig. 9 provides the daily model variation (for 110 bytes payload) on Saturday and Monday, respectively.

Both figures show that the model parameters change significantly in the morning when people walked in and in the afternoon when people left the offices, while they only change slightly in rest of the time. Over the whole week, the R^2 values of the proposed models always remain above 0.87. These show that the proposed model is still applicable despite the over-time environmental changes in the offices.

C. Model Comparison

Now we compare our proposed PLR model (Eq. (1)) with a literature LQI-only based PLR model. In [7] [8], LQI has similarly been considered as the only factor that impacts the PRR and the PRR-LQI relationship is approximated as a sigmoid curve, e.g., the Fermi-Dirac function in [8]. Here we transform the PRR-LQI model in [8] to obtain the corresponding PLR-LQI model that has the following form:

$$\text{PLR} = \frac{1}{1 + \exp((a - LQI)/b)} \tag{2}$$

where a and b are two model parameters of this model. Note that packet length is not involved in Eq. (2).

For the comparison, we use the measured PLR-LQI data points under a certain packet payload size (i.e. 80 bytes) to determine, using curve fitting, the values of the model parameters of each model (i.e. Eq. (1) and Eq. (2)), respectively. Then we compute the R^2 values of the two models when the packet payload size changes from 80 to 20, 50, and 110 bytes. This process is performed for the experimented environments and the results are listed in Table II.

We observe from the table that the R^2 values for 80 bytes payload are the highest in most cases for both models. This is because the data set under 80 bytes payload has been used to compute the model parameters for both models. Only in this case, the literature model achieves similar R^2 values as our model. However, when the packet length changes, our model is still able to give good R^2 values (ranging from 0.887 to 0.988) that are much better than what are from the literature model.

This indicates that our proposed model can be well applied for various packet lengths in all experimented environments. It also implies that using our model, the model parameters only need to be estimated one time under a certain packet length for one environmental condition, and after that, they can be directly re-used for other packet lengths without the need of updating the model parameters for this environmental condition. This avoids possibly huge overhead if the LQI-only based PLR model were to be applied where its model parameters would need to be examined or updated for every different packet length. This suggests that our model is more preferred in practice, since the packet length in real-world applications of WSNs may vary for various purposes.

D. Discussion

Finally, we discuss the implications of the empirical study and how to apply the proposed model in real-world sensor network deployments, followed by a brief discussion about which of LQI and SNR is a better predictor of link PLR.

TABLE II: Model accuracy comparison between Eq. (1) and Eq. (2) when packet payload size changes from 80 to 20, 50, 110 bytes

Environ.	Models	R^2-20	R^2-50	R^2-80	R^2-110
Athletic field	prev. model	0.821	0.916	0.988	0.656
	our model	0.908	0.945	0.988	0.918
Parking lot	prev. model	0.781	0.816	0.940	0.809
	our model	0.887	0.910	0.940	0.926
Office	prev. model	0.872	0.955	0.973	0.811
	our model	0.912	0.977	0.974	0.904
Home	prev. model	0.863	0.923	0.964	0.867
	our model	0.903	0.977	0.965	0.945

1) Application of the proposed PLR model: The observed spatial characteristics of the dependency of PLR on LQI and packet length suggests that every link may need its own PLR model for the deployed environment, which could be highly challenging in practice. Fortunately, with our proposed PLR model, the same function can be applied to all links across the network under various environmental conditions spatially and/or temporally, where only two model parameters need to be determined for each link.

Thanks to this finding, the modeling complexity is significantly reduced, enabling the possibility of sensor nodes to construct their own link PLR models. We adopted a similar approach from our previous work [1] and developed an online LQI-based PLR modeling scheme running on sensor nodes. The difference is that for modeling PLR from LQI and packet length, we need to first convert Eq. (1) to the following form:

$$(\alpha/L) \cdot \exp(\beta \cdot LQI) = \frac{1}{\text{PLR}} - 1 \tag{3}$$

Then we can linearize the exponential function at the left side of Eq. (3) by taking the logarithm of both sides and use linear regression to determine the values of the two model parameters. Details of this scheme are not shown here for space limitations. We found that with up to 5 minutes measurement of probing packets (at an interval of 20 ms), we achieved good model accuracy in all experimented environments.

The acquired empirical PLR models need to adapt to environmental changes due to the observed temporal characteristics. In indoor environments, the modeling process can be triggered, e.g., when people enter the offices and start working or when people leave the offices. In outdoor environments, the models need to updated, e.g., when detecting a drastic change in link PLR for the same LQI value.

2) LQI vs. SNR: Despite the research efforts for more than a decade, which of LQI and SNR is better for predicting link PLR is still an unanswered question, reflected by several contradicting statements and results [15]. Fig. 10 shows an example of estimating link PLR using SNR and LQI, respectively. The two graphs are plotted based on the same data set with the same parameter settings for data processing (e.g., the size of the packet window to average SNR or LQI is the same).

Fig. 10 clearly shows that when the link is in the transitional region, PLR changes with LQI much smoother than it changes with SNR, possibly implying that LQI is better than SNR to estimate link quality of intermediate links. Take 50 bytes payload for example. The width of the transition region (PLR between 0.1 and 0.9) in terms of SNR is around 1 dB (compared to the measured SNR range of 15 dB) while the width of the transitional region in terms of LQI is around 18 (compared to the measured LQI range of 45).

In addition, the figure shows that the PLR-SNR curves of different packet payload sizes almost overlap with each other in the transitional region while the PLR-LQI curves are clearly separated, e.g., between the curves for 20 and 110 bytes payload. This implies that from a SNR-based PLR model trained from, e.g., the data depicted in the left graph in Fig. 10, we may not see the possibility of decreasing packet length to reduce PLR, unlike what we can see from the PLR-LQI curves in Fig. 10.

Nevertheless, we still need to answer several important questions before jumping into the conclusion that LQI is a better predictor of link PLR than SNR. For example, if we decrease the size of the packet window to average SNR and LQI at the same time, how would the model accuracy of both models change in different environments? What many measurements are needed under various environmental conditions to generate accurate enough SNR-based and LQI-based PLR models, respectively? Which of the model is more resistant to what kinds of environmental changes? As an ongoing work, we are using the experimental data sets obtained in [1] and this work to investigate these issues and to understand which of SNR and LQI may be a better or complementary predictor for link PLR.

IV. Conclusion

This paper has presented the results of indoor and outdoor experimental campaigns to understand how various spatial and temporal environmental factors impact the dependency of link PLR on LQI and packet length. Based on the observations from this extensive experimental study, a PLR model for 802.15.4 links has been proposed, and validated under diverse environmental conditions and different packet lengths. The comparison with the literature LQI-only based PLR model has showed that, in all experimented environments, our proposed PLR model achieves higher accuracy for various

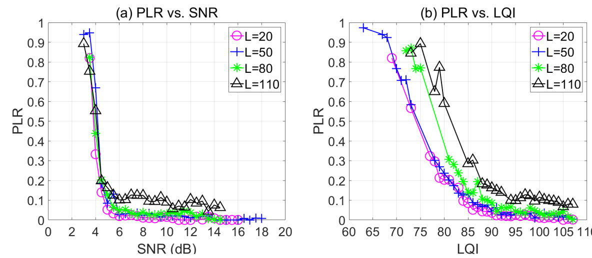

Fig. 10: Estimating the link PLR using SNR and LQI, respectively, for an exemplary link in the office scenario during non-working hours.

packet lengths without the need of updating model parameters. Implications of the experimental results and the guidelines to construct and adapt the model in different environments are provided, enabling the possibility of applying the proposed LQI-based PLR model in real-world sensor network applications.

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