Modeling Packet Loss Rate of IEEE 802.15.4 Links in Diverse Environmental Conditions

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***Abstract*—Modeling and prediction of Packet Loss Rate (PLR) of wireless links using hardware information is essential for the design of higher-layer protocols in Wireless Sensor Networks. While many previous studies revealed the spatio-temporal variation of various link quality metrics, how environment impacts on the mapping between PLR and hardware indicators still remains unclear. Without a comprehensive understanding of such environmental impact, the acquired empirical PLR models are severely limited to specific scenarios. In this paper, we present the results of indoor and outdoor experimental campaigns focusing on the impact of various environmental factors (e.g., obstacles, human activities, climate conditions) on the dependency between the link PLR, signal to noise ratio (SNR) and packet length. Rich observations are made on the spatio-temporal characteristics of the PLR-SNR relationship and our analysis shows that link PLR can be modeled, in all experimented scenarios, as an exponential function of SNR and packet length with two model parameters that may vary over space and time. Besides, implications of the observations are summarized, providing guidelines to construct and adapt PLR models in different environments.**

I. Introduction

Link quality estimation has been an important problem in Wireless Sensor Networks (WSNs) for about a decade. In particular, modeling and prediction of link Packet Loss Rate (PLR) using the information from radio hardware (e.g., RSSI, received signal strength indicator, or SNR, signal to noise ratio) has received significant attention in the research community [1] [2]. It is essential for the design of higher-layer protocols in WSNs, e.g., routing, deployment planning, link performance maintenance, as the PLR of wireless links has a fundamental impact on the network performance metrics such as delay, reliability and lifetime.

Related work. The quality of low power 802.15.4 links is known as unstable since it is easily affected by a variety of environmental factors. Many previous studies revealed the spatio-temporal variation of link quality metrics, such as RSSI, noise power and PLR, due to the impact of temperature [3], human presence [4], external interference [5], climate condition and terrains [6]. Some other researchers focus on the environmental impact on the relationship between PLR and hardware indicators. Lin *et al.* found that the RSSI threshold of good links is slightly different on a grass field, in a parking lot and in a corridor [7]. Zuniga *et al.* showed that the extent of transitional zone in terms of distance depends on the environment (e.g., outdoor, indoor, obstacles) [8].

Some recent works try to model the link PLR using mathematical expressions, and to study how environment impacts on the models. For example, Bas *et al.* model PLR with respect to distance in indoor and outdoor environments as exponential functions but with different parameter constants [9]. We know, however, that PLR is not well correlated with distance, especially in the transitional region [10]. In [11], Bildea *et al.* model the dependence between RSSI and packet reception rate (i.e. $1 - \mathrm{PLR}$). Nevertheless, the model is only applicable to CC1101 radio links in an indoor environment. Most of these works have studied different aspects of the environmental impact on the prediction of PLR using hardware information. However, to truly apply PLR modeling and prediction to real-world applications in different environments, we still lack a comprehensive and quantitative understanding of the relation between the link PLR and hardware indicators under diverse environmental conditions. This is the focus of this paper.

Motivation. This work is motivated by one of our recent studies [12], in which we presented the joint impact of radio stack parameters on the packet delivery performance over a 802.15.4 link based on the experiments conducted in an office corridor. We modeled the link PLR as an exponential function of SNR and packet payload size and further demonstrated the potential of applying the model to optimize link performance by achieving a good tradeoff between delay, reliability and energy consumption.

However, we need to answer several fundamental questions before we are able to apply the acquired empirical PLR model to real-world deployments. The main questions are: (1) How does the PLR model change in different environments, e.g. in an open field or in offices? (2) Is the PLR model different for different links? (3) Does the PLR model change over time, e.g. during day and night or due to human-related activities?

Contributions. To answer these questions, we conducted indoor and outdoor experimental campaigns in four different locations, considering a variety of environmental factors, such as climate condition during day and night, obstacles, human presence, interference, etc. Our results show that the correlation of PLR with SNR and packet length can be significantly different in different environments, especially in the transitional region. The PLR-SNR relationship may differ from link to link in the same environment, while there may exist a spatial correlation between nearly links. Moreover, the PLR-SNR relationship may vary over time due to interference and the shadowing effect of humans or other objects. Nevertheless, the mathematical mapping between PLR, SNR and payload size remains in the form of exponential function in all experimented

TABLE I: Experimental setup

Location	Experiments	Setup	Description
Athletic Field (outdoor)	OPEN-SPATIAL	a star topology of 10 nodes	two-hour experiments to understand the spatial characteristics of PLR models of LOS (line-of-sight) and NLOS (non-line-of-sight) links in an open field
	OPEN-TEMP	a pair of sender and receiver nodes	24-hour experiments to understand the temporal characteristics of PLR models of LOS and NLOS links in an open field
Parking Lot (outdoor)	PLOT-SPATIAL	a star topology of 10 nodes	two-hour experiments to understand the spatial characteristics of PLR models of LOS and NLOS links in an urban parking lot
	PLOT-TEMP	a pair of sender and receiver nodes	24-hour experiments to understand the temporal characteristics of PLR models of LOS and NLOS links in an urban parking lot
Office Building (indoor)	OFFICE-1WEEK	indoor testbed of 32 nodes	a 7-day experiment with sender rotating between several nodes to understand spatio-temporal characteristics of PLR models in an office environment
	OFFICE-PEOPLE	indoor testbed of 32 nodes	two-hour experiments to understand the impact of people walking on the PLR model, performed in a weekend to minimize other interference sources
	OFFICE-WLAN	indoor testbed of 32 nodes	two-hour experiments to understand the impact of WiFi interference on the PLR model, performed in a weekend to minimize other interference sources
Home (indoor)	HOME	a star topology of 10 nodes	24-hour experiments to understand the spatio-temporal characteristics of PLR models in a home environment

scenarios while the values of the model parameters may change from link to link and vary over time.

The major departure this paper takes from prior work is that we study the environmental impact on the quantitative mapping between PLR, SNR and packet length, rather than that on individual link quality metric: it seeks to discover how the correlation of PLR with SNR and packet length changes with a variety of environmental factors. Based on the rich experimental results, we summarize a set of observations regarding the spatio-temporal characteristics. Furthermore, we provide implications for applications to build PLR models and to maintain model accuracy over time, making it possible to model and predict PLR of radio links in different environments. These constitute the major contributions of the paper.

The rest of the paper is organized as follows. In Section II, the experimental setup is described. The spatial and temporal characteristics of the dependency between PLR, SNR and packet length are presented in Section III and Section IV, respectively. Section V discusses the implications of the experimental results. Finally, in Section VI, we conclude the paper.

II. Experimental Setup

The findings reported in this paper were gathered in indoor and outdoor experimental campaigns. To cover various environmental factors, we have chosen four different experiment locations: (1) an Athletic Field, an open field isolated from human activity and absence of 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, we used TelosB nodes, equipped with the CC2420 radio chip compliant with IEEE 802.15.4, and on-board omnidirectional antenna. The CC2420 is the most widely used chip in sensor network research, also allowing us to leverage past experience in the literature. 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.

Most of our experiments use a star topology with one centralized sender node broadcasting packets and other nodes as receivers logging metadata of received packets. Such topology allows us to investigate the spatial characteristics of the PLR-SNR relation. For experimental setup, we utilize a testbed in the Office scenario and several ad-hoc deployments in other scenarios. The indoor testbed consists of 32 TelosB nodes mounted on the walls and ceilings, spreading over an entire office floor. In outdoor scenarios, we use a smaller ad-hoc deployment of 10 nodes due to safety reasons, where each node is attached to a 1-meter tall wooden stand. The same ad-hoc deployment is used in Home since 10 nodes are enough to cover the entire space. In all experiments, each node is connected to a Raspberry Pi for logging purposes.

To study the correlation of link PLR with SNR and packet length, the sender node broadcasts 3000 packets at a 20 ms interval between messages with a specific radio transmission power and packet length. The receiver nodes measure and log the metadata (e.g., RSSI) of received packets and the noise power when there is no packet transmission. One experimental run includes, in total, the transmission of 96 thousand packets under 8 different power levels from 3 to 31 and 4 different payload sizes from 20 to 110 bytes. Each experiment consists of a number of experimental runs to achieve statistical confidence as well as to investigate the temporal variations in a daily or a weekly cycle. Note that for some long-term experiments in public locations, we are only allowed to deploy two nodes at carefully selected locations for safety reasons. The details of all experiments are described in Table I.

III. Spatial Characteristics

In this chapter, we report the spatial characteristics of the dependency between PLR, SNR and packet length in different environments. To minimize temporal effects, all results are generated from experiments of a short time span (e.g., over a one hour window).

A. PLR-SNR Relationship in Different Environments

The first question that we try to answer is whether the correlation of PLR with SNR and packet length changes in different environments. Figure 1 plots the PLR-SNR curves with respect to packet payload size L (in bytes) for a selected link in each of the experimented environments. Each graph in

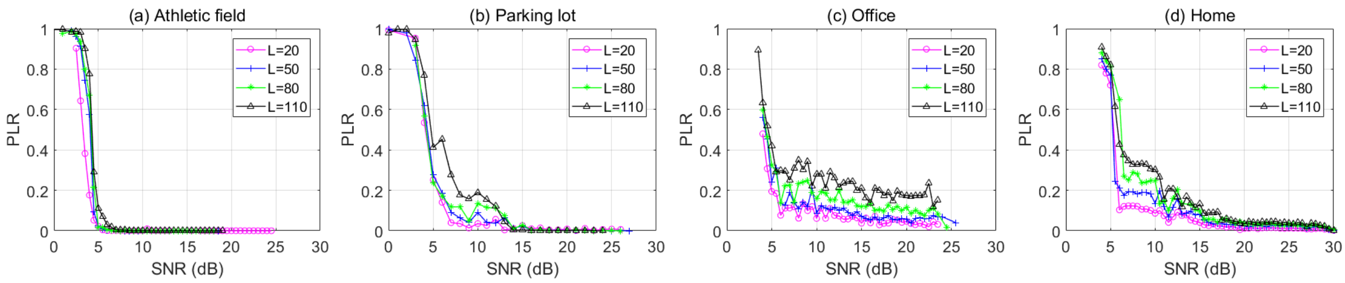

Fig. 1: The dependency between PLR, SNR and packet payload size L (in bytes) in different environments.

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 SNR (at a step of 0.5 dB).

Observation 1. The correlation of PLR with SNR and packet length can be significantly different in different environments. Specifically, the extent of the transitional region in terms of SNR varies significantly with packet length and environment.

Figure 1 shows that although the PLR-SNR curves look similar in the region of bad links (PLR higher than 90%), the curves turn to be significantly different in the transitional region (PLR between 10% and 90%). In the athletic field, PLR decreases drastically with SNR after 3 dB, similar to the sharp PLR-RSSI curves reported in [2]. However, in other environments (e.g., office), PLR decreases much more slowly with SNR. In other words, the width of the transitional region in terms of SNR strongly depends on the environment. For example, such width is found to be approximately 2 dB (for 80 bytes payload) in the athletic field (Figure 1(a)) and 12 dB in the office building (Figure 1(c)). We further find that the width of the transitional region of links in indoor environments is in general larger than those in outdoor environments.

Another factor that impacts on the PLR-SNR relationship is the packet length. In Figure 1, we observe that the extent of the transitional region increases with a larger packet size. However, such impact also depends on the environment. For example, the PLR-SNR curves of various packet payload sizes almost overlap in the athletic field while there is a clear separation between those curves in other environments.

As a result, the SNR threshold of good links (PLR less than 10%) varies significantly with the environment and packet length. The maximum SNR threshold of good links observed in our experiments is 28 dB for a link in the office building while the minimum is 4 dB for a link in the athletic field. Such variation of the threshold of good links (24 dB) is found to be much larger than the variation of RSSI threshold (2 dB) reported in [7], even after considering the difference of noise power measured in all experimented environments. One possible reason is that we additionally considered the impact of packet length and other environmental factors (e.g., human presence and WiFi interference) in the experiments.

Observation 2. In all experimented environments, the dependency between PLR, SNR and packet length can be modeled as an exponential function in the following form:

$$PLR = \alpha \cdot L \cdot \exp(-\beta \cdot \mathrm{SNR}), \qquad (1)$$

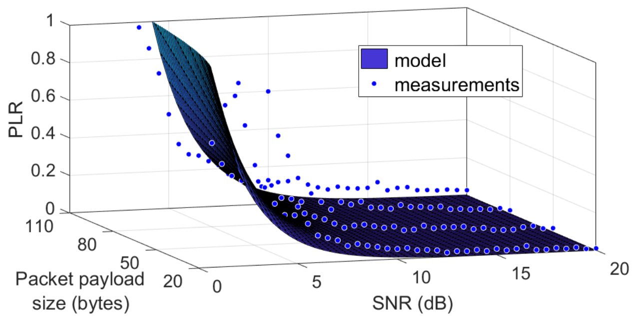

Fig. 2: Modeling the PLR of an exemplary link as an exponential function of SNR and payload size ($\alpha = 0.065$, $\beta = 0.473$).

where L is the packet payload size in bytes, α and β are the model parameters. While the mathematical expression for the correlation of PLR with SNR and packet length remains in the same form of Equation 1 in different environments, the values of the model parameters may be different.

Figure 2 shows an example of modeling PLR for a link in the Home scenario. We used Matlab to find the best distribution fit for our data set. Different theoretical distributions are compared according to chi-square test and the exponential function is the best fit and is accepted for all experiments. The values of model parameters are found with 95% confidence level.

We remark that the exponential function relation between PLR and SNR interestingly matches with a recent analytical result found in [13], where it is proved that for typical wireless channels, their instantaneous capacity and cumulative capacity are both light-tailed, i.e. their complementary cumulative distribution function is exponentially bounded.

B. Spatial Correlation in One Environment

In this section, we first examine whether the PLR model differs from link to link in the same environment. We select 3 different links from each experimented environment and plot the PLR-SNR curves in Figure 3. The curves in each graph are plotted based on the same data traces.

Observation 3. The PLR-SNR relation of different links in the same environment may differ significantly from each other. Such spatial variation is largely due to e.g., obstruction in line of sight and shadowing effects of objects (human, car, etc.).

In the athletic field (Figure 3(a)), the extent of the transitional region of link 2 is clearly larger than that of link 1 and link 3. A possible reason is that link 1 and link 3 maintained line-of-sight (LOS) between the transmitter and receiver while link 2 has non-line-of-sight (NLOS) radio communication.

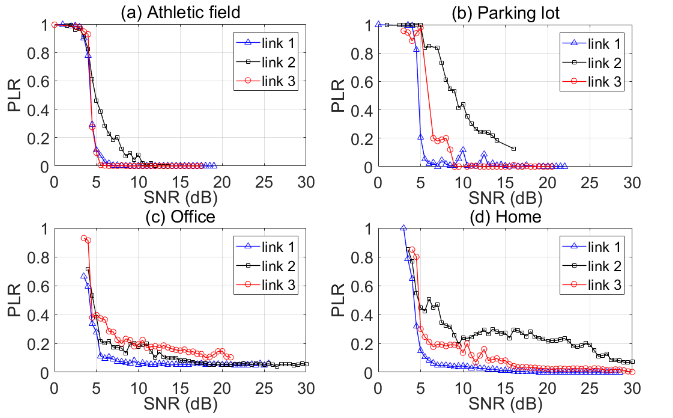

Fig. 3: The PLR-SNR relationship (for 110 bytes payload) of three different links in each experimented environment.

Such difference in the PLR-SNR relation between LOS and NLOS links is also observed in other scenarios, indicating that blocking line of sight may impact the PLR-SNR relation of a link, possibly extending the transitional region.

The three selected links in the parking lot (Figure 3(b)) are all NLOS links while the PLR-SNR curves yet look different from each other. We believe that such difference is caused by the different shadowing effects of objects (in this case, cars) on each link. Similarly, the difference of PLR-SNR relation between different links in the office (Figure 3(c)) and home scenarios (Figure 3(d)) is largely due to the different shadowing effects of human, furniture, etc.

We further investigate whether there exists a spatial dependency between the PLR-SNR relation of nearby links. The answer to this question can help to reduce the overhead of building PLR models for every link in a network. We analyzed the data traces collected from the indoor testbed, in which 32 TelosB nodes are deployed over a floor (around 500 m^2) in an university building. The analysis of the spatial dependency is done in three steps. First, we find the PLR model of each link in the testbed. Then we compute the correlation coefficient between any two links, i.e., between any two receivers, as all links in the experiment have the same sender node.

We formally define the PLR model correlation coefficient between two receivers x and y as:

$$R_{x,y} = \frac{\sum_{i=n}^{m}(\mathrm{P}^{x}_{snr=i} - \overline{\mathrm{P}^{x}})(\mathrm{P}^{y}_{snr=i} - \overline{\mathrm{P}^{y}})}{(m-n+1)\sigma_{\mathrm{P}^{x}}\sigma_{\mathrm{P}^{y}}} \quad (2)$$

where $\overline{\mathrm{P}^{x}}$ and $\overline{\mathrm{P}^{y}}$ are means of the PLR values from $\mathrm{SNR} = n$ dB to $\mathrm{SNR} = m$ dB for receiver x and y, respectively, and $\sigma_{\mathrm{P}^{x}}$ and $\sigma_{\mathrm{P}^{y}}$ are the standard deviations of the PLR values.

The last step of the spatial dependency analysis uses a data clustering algorithm to calculate a clustering of nodes based on the computed correlation coefficient. We employed an agglomerative approach, which starts with each node being its own cluster. In each step of the clustering process, the two most correlated clusters are combined to form a new cluster. This is repeated until the correlation between clusters is below a threshold. We show in Figure 4 the results of clustering after applying such approach to the 32 testbed nodes.

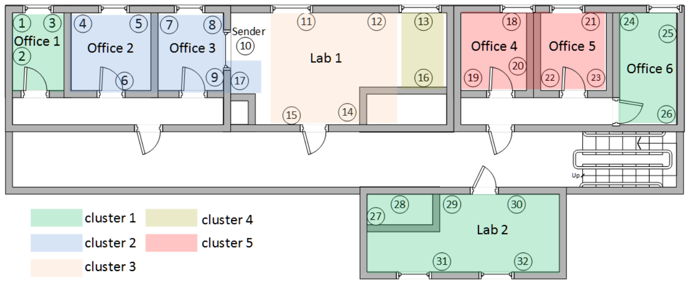

Fig. 4: Clusters of testbed links based on the spatial correlation of PLR models. All links have the same transmitter (node 10).

Observation 4. Links that are geographically close to each other may have spatially correlated PLR-SNR models.

Figure 4 shows that most nodes located in the same office are grouped into one cluster. Such resemblance of the PLR models may spread in nearby offices if the offices share similar environmental factors. For example, both cluster 2 and 5 cover two offices, where there were heavy human-related activities. We believe the same reason caused the nodes in Lab 1 to split into different clusters as there was people presence only around node 13 and 16. Interestingly, although not all the nodes in cluster 1 are geographically close to each other, their PLR models have high correlation because of similar environmental characteristics: almost no human activity in those rooms. We notice that the clusters may change during night when there was almost no human activity on the entire floor. In such case, most of the nodes are grouped into one big cluster. Details of such temporal effects will be presented in Section IV.

IV. Temporal Characteristics

This section explores the temporal variation of the dependency between PLR, SNR and packet length due to changes in outdoor and indoor environmental characteristics, respectively.

A. Temporal Variation Outdoors

Impact of climate change from day to night. We first turn our attention to the temporal variation in outdoor environments induced by the interleaving of night and day, which affects environmental factors such as temperature and humidity.

Figure 5 provides two examples showing the dependency between PLR, SNR and packet length during both day and night. The top graphs show the results of a link in the athletic field and the bottom ones show the results of a link in the parking lot. Note that the data trace from the parking lot was collected during a weekend, when no cars were parked during both day and night and hence the effect of cars is minimized.

Observation 5. The climate change from day to night induces almost no variation of the PLR-SNR relationship.

We notice that when changing from day to night, the link quality under the same transmission power increases, i.e., PLR decreases and SNR increases, which matches previous results [6] [14]. However, the dependency between PLR, SNR and packet length remains surprisingly almost unchanged in both scenarios, showing no clear temporal variation due to the transition between day and night. This indicates that the change in climate conditions (temperature, humidity) may impact on

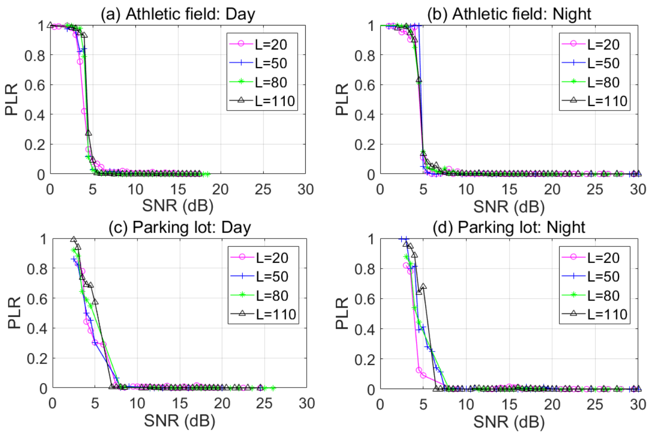

Fig. 5: Impact of the climate change from day to night.

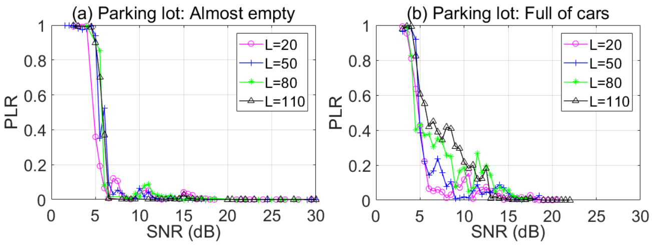

Fig. 6: Impact of cars in the parking lot.

PLR or SNR individually, however, it has little impact on the mapping between PLR and SNR.

Impact of the shadowing effect of objects. We consider the impact of the shadowing effect of objects, such as the cars in the parking lot, on the correlation of PLR with SNR. Figure 6 shows the PLR-SNR curves during the day when the parking lot was full of cars, and during the night when the parking lot was almost empty. As the figure depicts, the width of transitional region of the link during the day is larger than that during the night. As we showed that the climate change from day to night induces almost no variation, the major variation here is due to the presence of cars. This suggests that the shadowing effect of objects may strongly impact on the dependency between PLR, SNR and packet length.

B. Temporal Variation Indoors

Impact of human-related activities. For indoor environments, we evaluate the impact of two human-related factors: (1) human presence and movement, and (2) WLAN interference. The former imposes shadowing effects on the links; the latter is known to have a strong impact on link quality [5]. Some existing work (e.g., [15]) predicts PLR based on SINR (signal to interference plus noise ratio) under the existence of WiFi sources. In this work, we still use SNR to estimate PLR because the measurement of SINR itself may require accurate time synchronization and is difficult to obtain in reality.

To evaluate the impact of these two factors, we use the indoor testbed to perform a set of experiments in a weekend, to minimize the interference from other possible sources. We first let a student walk around the transmitter, and then, close to a link, we place a laptop that downloads a file from an access pointer (AP) using WiFi. During the experiment, we select

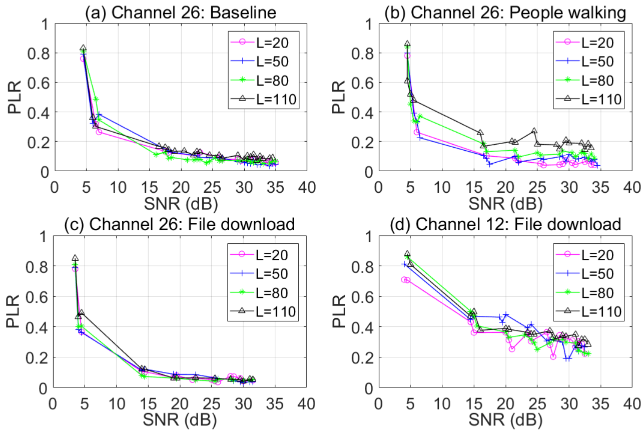

Fig. 7: Impact of people walking and WLAN interference.

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 [10].

Some results are plotted in Figure 7. We first observe that human presence and walking extend the width of the transitional region (Figure 7(b)), compared to the baseline (Figure 7(a)), similar to the impact of cars in the parking lot scenario. Furthermore, the figure shows that the WLAN interference has a strong impact on the PLR-SNR relationship on channel 12 (Figure 7(d)) while it has almost no impact on channel 26 (Figure 7(c)). We further examined with different WLAN traffic (video streaming) and obtained similar results.

Bringing the previous observations together, we can summarize the causes of temporal variation as following.

Observation 6. The PLR-SNR relation may vary over time due to interference and shadowing effects of human, obstacles, etc. Despite of the temporal variation, we validate that the correlation of PLR with SNR and packet payload size can still be modeled using the same exponential function (Equation 1) with the values of model parameters varying over time.

Weekly variation of PLR model indoors. To understand the real temporal variation of PLR models in the office environment, we performed a 7-day experiment on the testbed (see Figure 4) in the office building. The weekly variation of PLR model parameters for a link from node 10 to node 8 is plotted in Figure 8, where model parameters α and β are updated approximately every four hours.

The figure shows that the PLR model parameters change dramatically 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. Figure 9 provides the model variation in 24 hours on Saturday and Monday, respectively. The curves in the graphs are plotted for 110 bytes payload.

V. Implications

The observed spatio-temporal characteristics of the dependency between link PLR, SNR and packet length are essential for the design of higher-layer protocols, where accurate PLR prediction is desirable. Recall that this work is motivated by our previous study [12] for link performance optimization. We take this as an example to show the benefits of this work.

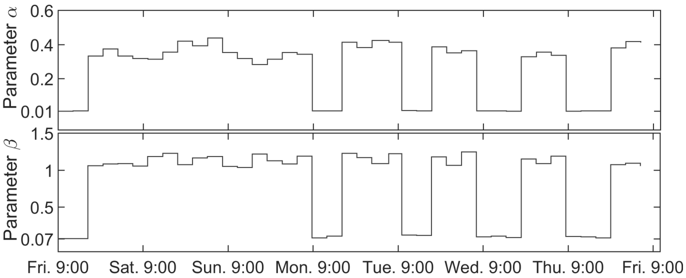

Fig. 8: The weekly variation of PLR model parameters α and β in the office environment.

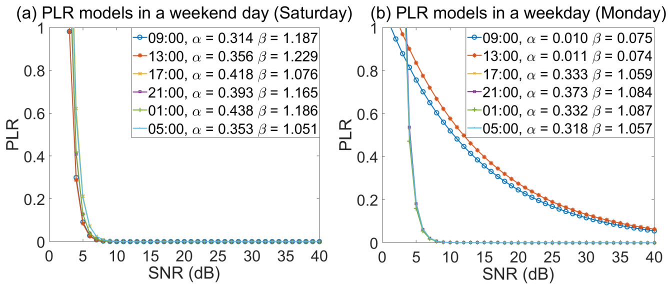

Fig. 9: The daily variation of PLR models in the office environment.

Our observations, for instance, imply that when the link is in the transitional region, tuning packet length is much more effective to improve link reliability in offices than in the open field. In addition, the SNR value required for good links varies significantly from 4 dB to 28 dB, depending on the environment and packet length. Such spatial variation implies that every link in a network should have its own PLR model to find the best settings of stack parameters (e.g., packet length, transmission power) for optimal performance. Nevertheless, thanks to the spatial correlation of PLR models between nearby links, it might be enough to construct PLR models only for representative links of the network (e.g., one link for each cluster) to reduce the overall modeling overhead.

Table II lists the typical parameter values of the PLR models found with 95% confidence level in all experimented scenarios, together with model precision in terms of two standard error measures: R^2 and RMSE (Root Mean Square Error). R^2 is a value between 0 and 1, with a value closer to 1 indicating a greater proportion of variance is accounted for by the model.

Based on the finding that the link PLR can be modeled with the same exponential function in all experimented scenarios, we developed an online PLR modeling scheme running on sensor nodes. In this scheme, we first linearize the exponential function (Equation 1) by taking the logarithm of both sides and then 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 3 minutes measurement of probing packets (at an interval of 20 ms), we achieved good tradeoffs between modeling overhead and model accuracy in all experimented environments.

The acquired empirical PLR models after the probing phase need to adapt to environmental changes due to the observed temporal characteristics. In indoor environments, the modeling process can be triggered again, e.g., by a motion detection system detecting people entering or leaving the rooms. In

TABLE II: Typical values of model parameters in different scenarios

Scenarios	Param. α	Param. β	R^2	RMSE
Open field - LOS	0.644	1.043	0.984	0.023
Open field - NLOS	0.084	0.356	0.952	0.091
Parking lot - cars	0.018	0.203	0.958	0.079
Parking lot - no cars	0.543	0.872	0.974	0.038
Office - people walking	0.011	0.067	0.961	0.094
Office - interference	0.009	0.039	0.962	0.052
Office - weekend	0.356	1.229	0.981	0.037
Home	0.065	0.473	0.987	0.062

outdoor environments where surrounding objects rarely change or move, the PLR models only need to be updated when detecting a drastic change in PLR for the same SNR value. However, in environments where frequent movement of objects are not predictable, the models need to be updated at regular intervals.

VI. Conclusion

This paper has presented the results of indoor and outdoor experimental campaigns to understand how environment impacts the dependency between link PLR, SNR and packet length. The results and observations enable us to have a comprehensive understanding of the spatio-temporal characteristics of such dependency. Various environmental factors were examined to validate that the proposed link PLR model is applicable in all experimented scenarios. Implications are provided for applications to construct PLR models and maintain model accuracy over time in different environments. As a future work, the dependency of PLR on another hardware indicator LQI (link quality indicator) will be investigated to understand which of SNR and LQI is a better predictor of PLR.

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