Environmental Impacts on Hardware-Based Link Quality Estimators in Wireless Sensor Networks

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Abstract: Hardware-based link quality estimators (LQEs) in wireless sensor networks generally use physical layer parameters to estimate packet reception ratio, which has advantages of high agility and low overhead. However, many existing studies didn’t consider the impacts of environmental changes on the applicability of these estimators. This paper compares the performance of typical hardware-based LQEs in different environments. Meanwhile, aiming at the problematic Signal-to-Noise Ratio (SNR) calculation used in existing studies, a more reasonable calculation method is proposed. The results show that it is not accurate to estimate the packet reception rate using the communication distance, and it may be useless when the environment changes. Meanwhile, the fluctuation range of the Received Signal Strength Indicator (RSSI) and SNR will be affected and that of Link Quality Indicator (LQI) is almost unchanged. The performance of RSSI based LQEs may degrade when the environment changes. Fortunately, this degradation is mainly caused by the change of background noise, which could be compensated conveniently. The best environmental adaptability is gained by LQI and SNR based LQEs, as they are almost unaffected when the environment changes. Moreover, LQI based LQEs are more accurate than SNR based ones in the transitional region. Nevertheless, compared with SNR, the fluctuation range of LQI is much larger, which needs a larger smoothing window to converge. In addition, the calculation of LQI is typically vendor-specific. Therefore, the tradeoff between accuracy, agility, and convenience should be considered in practice.

Keywords: link quality estimation; wireless sensor networks; environmental impact; physical layer parameters; received signal strength indicator; signal-to-noise ratio; link quality indicator; communication distance

1. Introduction

In the past few decades, wireless sensors networks (WSNs) have drawn much attention from academia and industry. WSNs are multi-hop self-organizing networks composed of hundreds and thousands of sensor nodes, which can monitor and collect various information from the deployed area in real-time. They have been successfully used in many fields, such as military surveillance, environmental monitoring, industrial control, and medical care [1]. Link quality estimation is crucial for WSNs due to their self-organizing characteristics as an effective estimation of link quality is the basis of high network performance. The packet reception rate (PRR) is the most direct metric for link quality. Although the PRR could reflect link quality directly, it always takes a long time to obtain an accurate estimation. Therefore, it is not sensitive to link changes and cannot adapt to the dynamic characteristics of the wireless channel in WSNs [2].
In view of this, finding more agile link quality metrics has become a hot topic in the past years. Several studies have confirmed that certain mapping relationships exist between some link metrics and PRR, such as the Received Signal Strength Indicator (RSSI), Signal-to-Noise Ratio (SNR), and Link Quality Indicator (LQI). These metrics are easier to get than PRR itself. Therefore, link quality could be estimated indirectly by constructing mapping models between these metrics and PRR, which improves the estimating agility greatly. Such approaches are often called hardware-based Link Quality Estimators (LQEs).

However, the experimental environment in which the mapping model was obtained in most existing studies is relatively single, and the possible impacts of environmental changes are ignored. There are two important questions to be considered: 1. How does the change of environment affect the link metrics? 2. Can the mapping model be obtained in a specific environment be directly used in other environments? To answer these questions, this paper compares the performance of typical hardware-based LQEs in different environments. Then, the impacts of environmental changes on the applicability of these estimators are analyzed quantitatively. The results show that some link metrics will be affected when the environment changes. Depending on the metrics used, the hardware-based LQEs constructed in a specific environment may not be directly applicable to other environments. Consequently, it is necessary to fully consider the impacts of environmental changes in practice.

The contributions of this study are as follows: (1) A comprehensive survey on the experimental environments and modeling methods in existing studies is presented. (2) Impacts of environmental changes on RSSI, SNR, and LQI are discussed. The results show that the fluctuation range of RSSI and SNR is more sensitive to environmental changes, while that of LQI is almost unaffected when the environment changes. (3) Aiming at the problematic SNR calculation used in existing studies, a more reasonable calculation method is proposed. It is shown that with the proposed method, more accurate PRR estimation could be made, especially when SNR is low. (4) Impacts of environmental changes on typical hardware-based LQEs are analyzed. The results show that the environmental adaptability of hardware-based LQEs is completely different. LQI based LQEs is the least susceptible to changing environments.

The rest of this paper is organized as follows. In Section 2, related works are given. This is followed by an experimental setup in Section 3. Section 4 summarizes typical hardware-based LQEs which are classified according to the link metrics they used, such as the RSSI, SNR, and LQI. The impacts of environmental changes on these LQEs are fully analyzed in Section 5. Finally, conclusions are presented and suggestions are made for future works.

2. Related Works

Knowing the PRR of neighbors could help sensor nodes to select the next-hop more effectively, which will improve network efficiency. To reduce the fluctuation of PRR, some studies use an exponentially weighted moving average (EWMA) to smooth PRR. Woo et al. [3] proposed WMEWMA, which combines window averaging with EWMA for low pass filtering of PRR. Baccour et al. [4] proposed F-LQE (Fuzzy-LQE), which uses fuzzy logic to fuse four link parameters, namely smoothed PRR filtered by WMEWMA, link stability factor, link asymmetry level, and averaged SNR. As F-LQE is too stable, Rekik et al. [5] and Jayasri et al. [6] adjusted the link parameters involved in fuzzy logic respectively to achieve more agile and accurate estimations. Opt-FLQE (Optimized version of F-LQE) replaces the link stability factor in F-LQE with the smoothed required number of packet retransmissions [5]. ELQET (Enhanced LQE Technique) also uses four link parameters, namely PRR obtained by LQI mapping, SNR obtained by Kalman filtering, coefficient of variation of PRR, and averaged LQI, to characterize link quality [6]. Liu et al. [7] proposed FaLQE, which realizes link adaptation by dynamically adjusting the smoothing factor according to the fluctuation of the link. Although these works have effectively improved the accuracy and stability, the inherent problem of PRR is still not resolved: It always needs to take a long time to obtain an accurate PRR estimation [8].
The mapping models between the communication distance and PRR can be obtained by counting the PRRs at different distances. Then, the communication distance could be used as an indirect link quality metric. Zhao et al. [9] classified the wireless link into three regions according to PRR values at different distances, which are connected region, transitional region, and disconnected region. Although the range of transitional region is the largest, links within this region are extremely unstable. Srinivasan et al. [10] found that the percentage of links in transitional region ranges from 5% to 60%, and typical characteristic of these links is bursty. Liu et al. [11] established a mapping model between the communication distance and packet loss rate (PLR) by data fitting. Sun et al. [12] proposed a mapping model between the communication distance and PRR by combining the theoretical PRR model and the log-normal path loss model.

As RSSI and LQI can be obtained from the physical layer directly and are related to PRR closely, they have been widely used in LQEs. Popular radio transceivers used in WSNs, such as CC2420 [13] and AT86RF230 [14] all provide RSSI and LQI measurements. By analyzing the correlations between RSSI, LQI, and PRR, Bildea et al. pointed out that RSSI is not a good discriminator of link categories, while LQI could effectively distinguish good, moderate, and bad links [15]. Jayasri et al. also pointed out that the correlation coefficient of LQI and PRR is higher than that of RSSI [6]. By studying the relationship between LQI and PLR in outdoor environments, Shu et al. [16] pointed out that there is a definite relationship between LQI and PLR. Luo et al. [17] fitted a mapping model between LQI and PRR using the Cubic model. Carles et al. [18] constructed a piecewise linear model of PRR as a function of averaged LQI. Gomes et al. [19] pointed out that only using LQI may overestimate the link quality under bad links. Meanwhile, there are also differences in the definition and implementation of LQI in different radio transceivers. Ye et al. [20] constructed a mapping model between RSSI and PRR based on logistic regression.

In the IEEE 802.15.4 standard, DSSS-OQPSK (Direct Sequence Spread Spectrum Offset-Quadrature Phase Shift Keying) modulation scheme is used in the 2.4 GHz physical layer. Therefore, PRR could be computed using the theoretical bit error rate model and SNR, which can be calculated by subtracting background noise from RSSI. For instance, Sun et al. [21] and Chang et al. [22] respectively use the theoretical model of DSSS-OQPSK for PRR estimation. When there are no co-channel interferences, the background noise usually remains stable for a few seconds or even minutes. As a result, changes in SNR with time are mainly caused by changes in RSSI [23]. On the other hand, some studies obtained the mapping relationships between SNR and PRR through data fitting. For instance, Senel et al. [8] use a locally available SNR-PRR curve to estimate the PRR. Some studies also use the combination of SNR and LQI to estimate the link quality. Qin et al. [24] estimated the link quality by Effective-SNR, which is produced by combining SNR and LQI with minimal additional overhead. Liu et al. [25] proposed a lightweight multi-parameter fusion estimator, in which weighted Euclidean distance is used to fuse SNR and LQI effectively.

Recently, machine learning algorithms began to be employed to optimize the mapping models, to improve the agility and accuracy of LQEs. Liu et al. [26] proposed a machine learning-based scheme 4C, which uses a naive Bayes classifier, artificial neural network, and logistic regression to train historical data of RSSI, SNR, LQI and PRR offline and predicts PRR effectively. Liu et al. [27] proposed a real-time link quality prediction model TALENT, which uses stochastic gradient descent online learning algorithm to train logistic regression classifiers using LQI and PRR values. Marinca et al. [28] took LQI as input and utilized a prediction game to construct an expert system model for link quality estimation. Fu et al. [29] proposed RADIUS, a thresholding method based on Bayes theory, which uses mean value and variance of RSSI to identify the degradation of links, namely, from good links to bad links. Shu et al. [30] proposed a link quality classification model, which fuses two physical layer parameters LQI and RSSI and trains the mean values of them by support vector machine. Sun et al. [22] proposed WNN-LQE, which employs a wavelet neural network to predict SNR and its variance, and then estimates link quality quantitatively using the theoretical model between SNR and PRR.
Table 1 summarizes the main features of existing studies. It can be seen that most studies are conducted in a single environment. Although some studies [5,7,9,10,12,20,21,23,25,26,28] considered two or three different environments, they did not explore the impacts of environmental changes on the applicability of hardware-based LQEs. In fact, WSN applications may face a variety of deployment environments. Although existing studies have conducted an in-depth analysis of the relationships between communication distance, RSSI, LQI, and PRR, their results still cannot answer the two questions about environmental impacts presented in Section 1.

Table 1. Main features of existing studies.

| Ref. | RF Chip (Node Type) | Experimental Environment | Parameters | Modeling Method |
|------|---------------------|--------------------------|------------|-----------------|
| [3]  | N/A (Berkeley Mote)| indoor                   | PRR        | N/A             |
| [4]  | CC2420 (TelosB)     | outdoor (garden), indoor (underground transformer vault and main power control room) | SNR, PRR, RNP | N/A             |
| [5]  | CC2420 (TelosB)     | indoor (industrial environment), outdoor (roof top and playground) | SNR, LQI, PRR | N/A             |
| [6]  | CC2420 (N/A)        | indoor (office)          | SNR, PRR   | Pre-calibrated SNR-PRR relationship |
| [7]  | CC2420 (TelosB)     | indoor (office), outdoor (dry lake) | RSSI, PRR  | N/A             |
| [8]  | CC2420 (N/A)        | outdoor (road)           | Distance, PRR | N/A             |
| [9]  | CC2420 (MicaZ, TelosB) | indoor (office), outdoor (square and grove) | Distance, PRR, LQI, PRR | Theoretical model |
| [10] | CC2420 (Imote2)     | indoor (office), indoor (square and grove) | SNR, RSSI, LQI, PRR, PRR | N/A             |
| [11] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [12] | CC2530 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [13] | CC1101 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [14] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [15] | CC2420 (MicaZ, TelosB) | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [16] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [17] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [18] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [19] | CC2420 (Imote2)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [20] | CC2420 (MicaZ, TelosB) | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [21] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [22] | CC2420 (MicaZ, TelosB) | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [23] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [24] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [25] | CC2420 (MicaZ, TelosB) | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [26] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [27] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [28] | CC2420 (N/A)        | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [29] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |
| [30] | CC2420 (TelosB)     | indoor (office), outdoor (parking lot) | Distance, PRR, LQI, PRR | N/A             |

3. Experimental Setup

3.1. Experimental Environments

Experiments were conducted using TelosB, which is equipped with an IEEE 802.15.4 compliant radio chip CC2420 and an integrated planar inverted F-style antenna printed directly on the circuit board [31]. TelosB has been widely used in WSNs due to its advantages of small size, low power,
were conducted on channel 26 and with 0 dBm transmit power. Antenna height was set to 1.2 m. The communication distance between transmitter and receiver was increased from 0 to 100 m, and the receiver was connected to a laptop through a serial port, as shown in Figure 2. All experiments were conducted using TelosB, which is equipped with an IEEE 802.15.4 compliant open-source operating system developed by Berkeley, which is specially designed for embedded WSNs. TelosB uses TinyOS 2.1 and is programmed with NesC language. TinyOS is an open-source operating system developed by Berkeley, which is specially designed for embedded WSNs.

Several experimental environments were chosen, as shown in Figure 1. Among which, there were not only typical outdoor environments which have simple propagation channels and low external interferences but also a semi-enclosed environment which has complex propagation channel and high external interferences. The corridor was located in the first experimental building of the Chongqing University of Technology. Its length, width, and height were 106, 3.2, and 2.8 m, respectively. It was relatively clean and has almost no obstacles in the corridor. The runway and artificial lawn were located in the playground of the Chongqing University of Technology, which both have no obstacles in the line of sight (LOS). During the experiments, changes in wind speed, temperature, and humidity could be neglected, and there were no other interferences such as walking people.

There were two reasons for choosing the above three environments. First, the propagation characteristics of wireless signals were significantly different in these environments. The surface of the runway was relatively flat. Therefore, the received signal was mainly composed of the LOS component and the reflection component. In addition to the LOS propagation component, there were also scattering components in the artificial lawn, so the composition of the received signal was more complicated. There were many reflective surfaces on the signal propagation path in the corridor, such as the ceiling, ground, and single-sided wall. Therefore, the received signal was a combination of the LOS component and multiple reflection components. These diversities will lead to significant differences in the received signal strength and fluctuation range. Second, the background noise of these three environments were also different. Runway and artificial lawn are typical outdoor environments, in which background noise is typically lower than that in the corridor.

3.2. Data Acquiring and Processing

Experiments were conducted using two nodes, one as transmitter and the other as receiver. The receiver was connected to a laptop through a serial port, as shown in Figure 2. All experiments were conducted on channel 26 and with 0 dBm transmit power. Antenna height was set to 1.2 m. The communication distance between transmitter and receiver was increased from 0 to 100 m, and the antenna directions of both nodes remained unchanged during this process. Considering that RSSI and LQI change greatly when the distance is small, the measurement points were chosen as follows: the step is 0.2 m in the first 5 m, 0.5 m from 5 to 20 m, 1 m from 20 to 60 m, and 2 m from 60 to 100 m respectively. In brief, there is a total of 115 measurement points.
Typical mapping models between indirect metrics and packet reception rate (PRR).

Figure 2. The experiment conducted using two nodes.

500 packets were sent at each distance, and the inter-packet interval was set to 25 ms. Each packet carried a sequentially increased serial number, so PRR could be calculated using the number of successfully received packets. RSSI, LQI, background noise power, and serial number of successfully received packets were transmitted to the laptop for analysis, in which PRR and the mean values of RSSI, SNR, and LQI were calculated using MATLAB.

CC2420 provides RSSI and LQI measurements, which can be obtained by accessing corresponding internal registers [13]. The received power can be calculated using the RSSI value according to the following equation:

\[
P = \text{RSSI}_{\text{VAL}} + \text{RSSI}_{\text{OFFSET}}
\]

where \( \text{RSSI}_{\text{VAL}} \) is the RSSI value provided by CC2420. \( \text{RSSI}_{\text{OFFSET}} \) is an empirical correction value, which is \(-45\) dBm according to the CC2420 datasheet. LQI presents the quality of received packets, and its values usually range from 50 to 110. The larger the LQI, the higher the quality of the received packet.

4. Typical Hardware-Based LQEs: A Survey

According to the analysis in Section 2, typical mapping models for hardware-based LQEs used in existing studies are summarized, as shown in Figure 3. These mapping models are classified according to the link metrics they used, including the RSSI, SNR, and LQI. For each kind of link metric, the frequently used methods for constructing the mapping model with PRR are also given. For example, the theoretical model, polynomial regression, and logistic regression are usually used to construct mapping models between RSSI and PRR in typical RSSI based LQEs. For each kind of modeling method, only one instance was chosen and analyzed in the following chapters.

It should be noted that communication distance is usually used for analyzing and modeling radio links [9,10], and not for online link quality estimation. However, there is already research that utilizes distance to assess the link quality in the design and deployment phase [11,12]. For example, Sun et al. presented a reliability model based on the mapping models between distance and PRR, which was used to improve the link estimation and optimize the deployment parameters [12]. Meanwhile, the distance...
between nodes may be acquired as deployment parameters or measured using appropriate ranging techniques. Therefore, it is meaningful to analyze the influence of environmental changes on these mapping models. With these considerations in mind, these mapping models are also classified and summarized here, although they are exactly not hardware-based LQEs.

4.1. Mapping Models between Communication Distance and PRR

According to Figure 3, the theoretical model and fitting model are usually used as mapping models between communication distance and PRR. In [12], a theoretical model between communication distance and PRR is proposed as follows:

$$PRR = \left(1 - Q\left(\sqrt{2 \cdot 10^{(P_t + L_c - PL(d_0) - 10n \log_{10}(\frac{d_0}{d}) + X_\sigma - P_n)/10}} \cdot \frac{B_N}{R}\right)\right)^{136}$$  \(\text{(2)}\)

where \(Q(\cdot)\) represents the Q function, \(P_t\) is the transmit power (dBm), \(L_c\) is the signal strength gain (or loss, if its value is negative) in the hardware circuit (dB), \(n\) is the path loss exponent characterizing the attenuation of wireless signals in the environment, \(d\) is the distance between the transceiver and receiver (m), \(d_0\) is the reference distance and its value is usually 1 m, \(PL(d_0)\) is the free-space path loss (dBm) at the reference distance, \(X_\sigma\) is a normally distributed random variable with a mean of zero and a standard deviation of \(\sigma\) (dB), \(P_n\) is the background noise power (dBm), \(B_N\) is the noise bandwidth of the transceiver (kHz), \(R\) is the communication data rate (kb/s), and \(l\) is the length of the data packet (bytes). Among which, the value of \(PL(d_0)\) can be calculated as follows [12]:

$$PL(d_0) = 32.44 + 20 \log_{10}(d_0 \cdot f)$$  \(\text{(3)}\)

where \(f\) is the carrier frequency (MHz).

As CC2420 was used in [12], the values of \(B_N\) and \(R\) are 384 kHz and 250 kb/s, respectively. Further, the transmit power \(P_t\), carrier frequency \(f\), and packet length \(l\) were set to 0 dBm, 2480 MHz (corresponding to channel 26), and 17 bytes, respectively. Therefore, substituting Equation (3) into Equation (2), we have

$$PRR = \left(1 - Q\left(\sqrt{3 \cdot 10^{(31.6899 - 20 \log_{10}(2400) - 15.871 \times \log_{10}(d_0) + X_\sigma - P_n)/10}}\right)\right)^{136}$$  \(\text{(4)}\)

With the measured data in the runway, relevant parameters of Equation (4) were determined, as shown in Table 2. Standard deviation \(\sigma\) of the random variable \(X_\sigma\) was calculated from the variances of RSSI at different distances, the measured background noise power was used as \(P_n\), and \(L_c\) and \(n\) are obtained by the least squares fitting method.

**Table 2. Relevant parameters of Equation (4).**

| Parameter | Value |
|-----------|-------|
| \(L_c\)  | 31.6899 dB |
| \(n\)    | 1.5871 |
| \(\sigma\) | 1.0081 dB |
| \(P_n\)  | -98.37 dBm |

Therefore, the mapping model between the communication distance \(d\) and \(PRR\) in the runway could be obtained by substituting the above parameters into Equation (4), as expressed as

$$PRR = \left(1 - Q\left(\sqrt{3 \cdot 10^{(97.6199 - 20 \log_{10}(2400) - 15.871 \times \log_{10}(d_0) + X_\sigma)/10}}\right)\right)^{136}$$  \(\text{(5)}\)
In [11], the mapping model between communication distance and \( PLR \) was constructed by data fitting, expressed as follows:

\[
\text{PLR} = \begin{cases} 
0, & 0 \leq d < d_1 \\
a_1 \tan(a_2 d + a_3) + a_4, & d_1 \leq d < d_2 \\
1, & d \geq d_2
\end{cases}
\]  

(6)

where \( a_1, a_2, a_3, a_4 \) are fitting parameters. With the measured data in the runway, the fitting model between communication distance \( d \) and \( PRR \) was obtained, as shown in Equation (7).

\[
\text{PRR} = \begin{cases} 
1, & 0 \leq d < 18 \\
0.5094 - 0.3401 \times \tan(0.3316 \times d - 13.72), & 18 \leq d < 82 \\
0, & d \geq 82
\end{cases}
\]  

(7)

4.2. SNR Based LQEs and Their Mapping Models

According to Figure 3, the theoretical model and logistic regression model (for short, LR model) are usually used as mapping models between SNR and \( PRR \) for SNR based LQEs. In [21], the theoretical model was used as the mapping model between averaged SNR (defined as \( \mu_{\text{snr}} \)) and \( PRR \), as shown in Equation (8).

\[
\text{PRR} = \frac{1}{1 - Q\left(\sqrt{2 \times \frac{B_N}{R} \times 10^{\mu_{\text{snr}}/10}}\right)^l}
\]  

(8)

where \( Q(\cdot) \) represents the Q function, \( l \) is the number of bits in a packet, \( R \) is the data rate in kb/s, and \( B_N \) is the noise bandwidth of the transceiver in kHz. The values of \( R \) and \( B_N \) are also 250 kb/s and 384 kHz, respectively.

In [26], the mapping model between \( \mu_{\text{snr}} \) and \( PRR \) is obtained based on logistic regression. Using the measured data in the runway, a mapping model was obtained, as shown in Equation (9).

\[
\text{PRR} = \frac{1}{1 + e^{3.4435 - 1.1047 \times \mu_{\text{snr}}}}
\]  

(9)

4.3. RSSI Based LQEs and Their Mapping Models

According to Figure 3, the LR model and polynomial regression model (for short, PR model) are usually used as mapping models between RSSI and \( PRR \) for RSSI based LQEs. In [20], the mapping model between averaged RSSI (defined as \( \mu_{\text{rssi}} \)) and \( PRR \) was obtained based on logistic regression. Using the measured data in the runway, a mapping model was obtained, as shown in Equation (10).

\[
\text{PRR} = \begin{cases} 
1, & \mu_{\text{rssi}} > -86 \\
1 \times 2.1771 \times e^{2.1771 \times \mu_{\text{rssi}}} + 198.4593, & -96 < \mu_{\text{rssi}} \leq -86 \\
0, & \mu_{\text{rssi}} \leq -96
\end{cases}
\]  

(10)

In [19], the mapping model between normalized RSSI and \( PRR \) was obtained based on polynomial regression. As normalized RSSI is used, the PR Model is self-adaptive essentially. Therefore, the model given in [19] was used directly:

\[
\text{PRR} = -3943.5 R_{\text{avg}}^6 + 6506.6 R_{\text{avg}}^5 - 4279 R_{\text{avg}}^4 + 1430.9 R_{\text{avg}}^3 - 256.47 R_{\text{avg}}^2 + 23.77 R_{\text{avg}} + 0.022
\]  

(11)

where \( R_{\text{avg}} \) is the mean value of normalized RSSI obtained by the median filter, and its value ranges from 0 to 0.5.
4.4. LQI Based LQEs and Their Mapping Models

According to Figure 3, the Cubic model, LR model, and piecewise linear model are usually used as mapping models between LQI and PRR for LQI based LQEs. In [17], the mapping model between averaged LQI (defined as $\mu_{lqi}$) and PRR is obtained using the Cubic model. Using the measured data in the runway, a mapping model was obtained, as shown in Equation (12).

$$PRR = \begin{cases} 1, & \mu_{lqi} > 98 \\ -0.0000066147 \times \mu_{lqi}^3 + 0.0010661 \times \mu_{lqi}^2 - 0.0063 \times \mu_{lqi} - 2.3975, & 68 < \mu_{lqi} \leq 98 \\ 0, & \mu_{lqi} \leq 68 \end{cases}$$

(12)

In [18], the mapping model between $\mu_{lqi}$ and PRR is obtained based on the piecewise linear model. Using the measured data in the runway, a mapping model was obtained, as shown in Equation (13).

$$PRR = \begin{cases} 1, & \mu_{lqi} > 96 \\ 0.02492 \times \mu_{lqi} - 1.392, & 80 < \mu_{lqi} \leq 96 \\ 0.04986 \times \mu_{lqi} - 3.389, & 68 < \mu_{lqi} \leq 80 \\ 0.00008222 \times \mu_{lqi} - 0.004111, & 50 \leq \mu_{lqi} \leq 68 \end{cases}$$

(13)

In [26], the mapping model between $\mu_{lqi}$ and PRR is obtained based on logistic regression. Using the measured data in the runway, a mapping model was obtained, as shown in Equation (14).

$$PRR = \frac{1}{1 + e^{16.9491 - 0.2125 \times \mu_{lqi}}}$$

(14)

5. Environmental Impacts on Hardware-Based LQEs

The fluctuation range of SNR, RSSI, and LQI in different environments was analyzed. Meanwhile, the models between communication distance, SNR, RSSI, LQI, and PRR summarized in Section 4 were also explored in different environments. Root mean squared error (RMSE) of the estimated PRR and real PRR was chosen as the evaluation index of accuracy, as shown in Equation (15).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (PRR(i) - PRR_m(i))^2}{n}}$$

(15)

where $n$ is the number of samples, $PRR(i)$ is the practical value of the $i$-th sample, and $PRR_m(i)$ is the corresponding estimated value using mapping models.

5.1. Environmental Impacts on Mapping Models between Distance and PRR

5.1.1. Communication Distance and PRR in Different Environments

The relationships between communication distance and PRR in different environments are shown in Figure 4. It can be seen that there is no consistent mapping relationship between the communication distance and PRR in different environments. The starting and ending distance of the connected region, the transitional region, and the disconnected region are totally different in the three environments. For example, the communication range from 70 m to 90 m belongs to the disconnected region of the runway, while this range belongs to the connected region of the corridor and transitional region of the artificial lawn, respectively. Even the range of the transitional region is also different in the three environments. Moreover, the difference between PRR at the same distance is even up to 90%. That is to say, the relationship between communication distance and PRR will be greatly affected in changing environments.
5.1.2. Environmental Impacts on Mapping Models between Distance and PRR

Using Equation (5), the theoretical model between communication distance and PRR in three environments was plotted, as shown in Figure 5. As the background noise is easy to be got, the measured noise power of the corresponding environment was used as $P_n$ in the corresponding model. It can be seen from Figure 5 that the theoretical model is basically in agreement with the measured data in the runway. However, it is quite different from the measured data in the other two environments. Even in the artificial lawn which channel condition is closer to the runway, the relationship between communication distance and PRR is inconsistent with the theoretical model. Taking a closer look at Figure 5, it can be found that there are some differences between the theoretical curves in three environments. This is caused by the random variable $X_r$ in Equation (5). Although the theoretical curve obtained for each run will be a little different, the pattern of the theoretical curves is not changed and it does not affect the above conclusions. Using Equation (7), the fitting model between communication distance and PRR in three environments was plotted, as shown in Figure 6. From Figure 6, it is obvious that this model is also basically in agreement with the measured data in the runway. It is also quite different from the measured data in the other two environments.

To describe the environmental impacts on these mapping models quantitatively, RMSE of the estimated PRR and real PRR in the three environments was calculated, as shown in Table 3. It can be seen that even the smallest RMSE is as high as 0.2862. This indicates that it is not accurate to estimate PRR using communication distance. On the other hand, RMSEs in the artificial lawn and corridor are much higher than those in the runway when using the mapping model constructed in the runway, no matter whether the model is a theoretical model or a fitting one. Compared with the runway, RMSEs of the theoretical model in the artificial lawn and corridor increase by 57.48% and 85.32%, respectively. Meanwhile, RMSEs of the fitting model in the artificial lawn and corridor increase by 37.95% and 40.31%, respectively. That is to say, the mapping model between communication distance and PRR constructed in a specific environment cannot be directly used in other environments.

Figure 4. Communication distance vs. PRR in different environments.
respectively. Meanwhile, RMSEs of the fitting model in the artificial lawn and corridor increase by 37.95% and 40.31%, respectively. That is to say, the mapping model between communication distance and PRR constructed in a specific environment cannot be directly used in other environments.

### Table 3.

| Environment | Theoretical Model | Fitting Model |
|-------------|-------------------|---------------|
| Runway      | 0.2862            | 0.3191        |
| Lawn        | 0.4507            | 0.4402        |
| Corridor    | 0.5304            | 0.4474        |

Figure 5. Effects of the theoretical model in different environments.

Figure 6. Effects of the fitting model in different environments.

5.2. Environmental Impacts on RSSI Based LQEs

5.2.1. RSSI and PRR in Different Environments

Figure 7 shows the relationship between RSSI and PRR in different environments, including the minimum, maximum, and mean value of RSSI. It can be seen that the trend of change between RSSI and PRR is basically the same for the three different environments. In terms of $\mu_{\text{rssi}}$, PRR increases as $\mu_{\text{rssi}}$ increase: when $\mu_{\text{rssi}}$ is lower than $-95$ dBm, PRR approaches 0; when $\mu_{\text{rssi}}$ is higher than $-90$ dBm, PRR approaches 100%; when $\mu_{\text{rssi}}$ is located between $-95$ dBm and $-90$ dBm, PRR rapidly increases from 0 to 100%.

In terms of the fluctuations of RSSI, it is significantly greater in the corridor than that in the runway and artificial lawn.

To observe the environmental impact on the relationship between RSSI and PRR more clearly, the relationship between $\mu_{\text{rssi}}$ and PRR is shown in Figure 8. There already exist some studies which utilize the relationship between RSSI and PRR to estimate link quality [12,19,20,26,27]. Although the pattern between $\mu_{\text{rssi}}$ and PRR is basically the same in different environments, it is not difficult to find out that there are still some differences among the relationships between $\mu_{\text{rssi}}$ and PRR in different environments. For example, compared with the relationship between $\mu_{\text{rssi}}$ and PRR in the runway, the relationship in the corridor translates to the right by about 2 dB. This means that the received signal power in the corridor should be 2 dB higher than that in the runway to get the same PRR. The 2 dB difference may cause misjudgment of the link quality.

For example, when $\mu_{\text{rssi}}$ is $-93$ dBm, PRR in the corridor is less than 10% which means a bad link, while PRR in the runway is greater than 90% which means a good link.
5.2. Environmental Impacts on RSSI Based LQEs

5.2.1. RSSI and PRR in Different Environments

Figure 7 shows the relationship between RSSI and PRR in different environments, including the minimum, maximum, and mean value of RSSI. It can be seen that the trend of change between RSSI and PRR is basically the same for the three different environments. In terms of \( \mu_{\text{rssi}} \), PRR increases as \( \mu_{\text{rssi}} \) increase: when \( \mu_{\text{rssi}} \) is lower than \(-95\) dBm, PRR approaches 0; when \( \mu_{\text{rssi}} \) is higher than \(-90\) dBm, PRR approaches 100%; when \( \mu_{\text{rssi}} \) is located between \(-95\) dBm and \(-90\) dBm, PRR rapidly increases from 0 to 100%. In terms of the fluctuations of RSSI, it is significantly greater in the corridor than that in the runway and artificial lawn.

![Figure 7. Received Signal Strength Indicator (RSSI) vs. PRR in different environments.](image)

To observe the environmental impact on the relationship between RSSI and PRR more clearly, the relationship between \( \mu_{\text{rssi}} \) and PRR is shown in Figure 8. There already exist some studies which utilize the relationship between RSSI and PRR to estimate link quality [12,19,20,26,27]. Although the pattern between \( \mu_{\text{rssi}} \) and PRR is basically the same in different environments, it is not difficult to find out that there are still some differences among the relationships between \( \mu_{\text{rssi}} \) and PRR in different environments. For example, compared with the relationship between \( \mu_{\text{rssi}} \) and PRR in the runway, the relationship in the corridor translates to the right by about 2 dB. This means that the received signal power in the corridor should be 2 dB higher than that in the runway to get the same PRR. The 2 dB difference may cause misjudgment of the link quality. For example, when \( \mu_{\text{rssi}} \) is \(-93\) dBm, PRR in the corridor is less than 10% which means a bad link, while PRR in the runway is greater than 90% which means a good link.

Table 3. The root mean square errors (RMSEs) of the mapping models in different environments.

|                | Runway | Lawn  | Corridor |
|----------------|--------|-------|----------|
| Theoretical model | 0.2862 | 0.4507| 0.5304   |
| Fitting model   | 0.3191 | 0.4402| 0.4474   |

Theoretically, the translation of the relationships between \( \mu_{\text{rssi}} \) and PRR should be caused by the difference in background noise. To confirm this conjecture, background noise in these different environments was measured. The noise power in the corridor, artificial lawn, and runway are \(-96.20\) dBm, \(-99.61\) dBm, and \(-98.37\) dBm, respectively. The difference between the corridor and the runway happens to be 2.17 dB. This indicates that translation of the relationships between \( \mu_{\text{rssi}} \) and PRR in different environments is indeed caused by the difference in background noise.
5.2.2. Environmental Impacts on RSSI Based LQEs

To describe the impact of environmental changes on the fluctuation of RSSI more intuitively, the fluctuation ranges of RSSI in different environments were statistically obtained, and their cumulative distribution functions (CDFs) are shown in Figure 9. The fluctuation range of RSSI is calculated by subtracting the minimum RSSI from the maximum one. It can be seen that the fluctuation range of RSSI in the corridor is the largest, with about 30% of the fluctuation range higher than 10 dBm, and about 9.73% of the fluctuation range higher than 15 dBm. In contrast, the fluctuation range of RSSI in the artificial lawn is much smaller, with only about 10.91% of the fluctuation range higher than 5 dBm, and 100% of the fluctuation range lower than 10 dBm. The fluctuation range of RSSI in the runway is between that in the corridor and artificial lawn. The fluctuation range of RSSI is mainly determined by the number of propagation paths. The more the factors that cause signal reflection, diffraction, and scattering, the greater the fluctuation range of RSSI.

5.2.2. Environmental Impacts on RSSI Based LQEs

Using Equation (10), the LR model between $\mu_{\text{rssi}}$ and PRR in three environments was plotted, as shown in Figure 10. It is clear that only the measured data in the runway are nearly coincident with the LR model. There are obvious translations from the model curve to the measured data in the artificial lawn and corridor. Using Equation (11), the PR model between $\mu_{\text{rssi}}$ and PRR in three
environments was plotted, as shown in Figure 11. Unlike the LR model, there is no obvious translation from the PR model to the measured data in the artificial lawn and corridor.

![Figure 10. Effects of the logistic regression (LR) model in different environments.](image)

**Figure 10.** Effects of the logistic regression (LR) model in different environments.

To describe the environmental impact on RSSI based LQEs quantitatively, RMSE of the estimated PRR and real PRR in three environments were calculated, as shown in Table 4. It can be seen that RMSEs of the LR model in the artificial lawn and corridor are much higher than that in the runway. Compared with the runway, RMSEs of the LR model in the artificial lawn and corridor increase by 40.74% and 131.96%, respectively. It can be concluded that the LR model is not suitable for both the artificial lawn and corridor. That is to say, the LR model between $\mu_{\text{real}}$ and PRR constructed in a specific environment cannot be directly used in other environments.

**Table 4.** RMSEs of RSSI based link quality estimators (LQEs) in different environments.

|          | Runway | Artificial Lawn | Corridor |
|----------|--------|-----------------|----------|
| LR model | 0.1161 | 0.1634          | 0.2693   |
| PR model | 0.1284 | 0.1455          | 0.1129   |

On the other hand, the RMSEs of the PR model in the three environments are quite close. Compared with the runway, RMSE of the PR model in the artificial lawn increases by 13.32%, but RMSE in the corridor reduces by 12.07%. Thanks to the normalization of RSSI, the PR model is adaptive to the
environment to a certain extent. However, it is obvious from Figure 11 that the PR model is not in good agreement with the measured data when PRR changes from 0.8 to 1.0. The environment in which the PR model was constructed is a typical industrial environment [26], where high interference may exist. This is also explained from the side why the RMSE in the corridor is the smallest, as the corridor is the closest to the industrial environment.

5.3. Environmental Impacts on SNR Based LQEs

5.3.1. SNR and PRR in Different Environments

Figure 12 shows the relationship between SNR and PRR in different environments, including the minimum, maximum, and mean value of SNR. Generally, SNR is calculated as follows [12,21,22]:

\[
SNR = RSSI - N
\]  

(16)

where RSSI and N are the received signal power and background noise power in dBm. It can be seen that the trend of change between SNR and PRR is basically the same for the three different environments. In terms of \( \mu_{SNR} \) PRR increases as \( \mu_{SNR} \) increases. When \( \mu_{SNR} \) is lower than 4.5 dB, PRR approaches 0; when \( \mu_{SNR} \) is higher than 8 dB, PRR approaches 100%; when \( \mu_{SNR} \) is located between 4.5 dB and 8 dB, PRR rapidly increases from 0 to 100%. In terms of the fluctuations of SNR, it is significantly greater in the corridor than that in the runway and artificial lawn.

![Figure 12. SNR vs. PRR in different environments.](image)

To describe the impact of environmental changes on the fluctuations of SNR more intuitively, the fluctuation ranges of SNR in different environments were statistically obtained, and their CDFs are shown in Figure 13. The fluctuation range of SNR is calculated by subtracting the minimum SNR from the maximum one. It can be seen that the fluctuation range of SNR in the corridor is the largest, with more than 80% of the fluctuation range higher than 10 dB, and about 30% higher than 15 dB. In contrast, the fluctuation range in the artificial lawn is much smaller. There is less than 2% of the fluctuation range higher than 10 dB, while none is higher than 15 dB. The fluctuation range in the runway is between the corridor and artificial lawn, with about 20% of the fluctuation range higher than 10 dB and about 3% higher than 15 dB.

Furthermore, the background noise in these different environments was also measured, and their CDFs in different environments are shown in Figure 14. It is clear that the fluctuation range of background noise in the corridor is the largest, and that in the lawn is the smallest. From Equation (16), it is obvious that SNR is related to both RSSI and background noise. Combined with Figures 9 and 13, it is reasonable to say that background noise is also contributed to the fluctuation range of SNR in different environments.
To observe the environmental impact on the relationship between SNR and PRR more clearly, the relationship between $\mu_{\text{snr}}$ and PRR is shown in Figure 15. There already exist some studies which utilize the relationship between SNR and PRR to estimate link quality [8,21–24,26,27]. It can be seen that there is no obvious difference between the relationships between $\mu_{\text{snr}}$ and PRR in different environments. This means that the relationship between $\mu_{\text{snr}}$ and PRR is almost unaffected when the environment changes.

![CDFs of the fluctuation range of SNR in different environments.](image)

**Figure 13.** Cumulative distribution functions (CDFs) of the fluctuation range of SNR in different environments.

![CDFs of the background noise in different environments.](image)

**Figure 14.** CDFs of the background noise in different environments.

![$\mu_{\text{snr}}$ vs. PRR in different environments.](image)

**Figure 15.** $\mu_{\text{snr}}$ vs. PRR in different environments.
5.3.2. Environmental Impacts on SNR Based LQEs

Using Equation (8), the theoretical model between $\mu_{\text{SNR}}$ and $\text{PRR}$ was plotted, as shown in Figure 16. The measured data in all three environments are not coincident with the theoretical model. There is an obvious deviation from the model to the measured data. To describe the environmental impact on the theoretical model between $\text{SNR}$ and $\text{PRR}$ quantitatively, RMSE of the estimated $\text{PRR}$ and real $\text{PRR}$ in the three environments were calculated, as shown in the first row of Table 5. It can be seen that RMSEs in all three environments are quite large.

![Figure 16. Effects of the theoretical model in different environments.](image)

**Table 5.** RMSEs of SNR based LQEs in different environments.

|                | Runway | Artificial Lawn | Corridor |
|----------------|--------|-----------------|----------|
| Theoretical model before calibration | 0.3009 | 0.1909 | 0.1749 |
| Theoretical model after calibration  | 0.1253 | 0.0609 | 0.1442 |
| LR model after calibration            | 0.1154 | 0.0659 | 0.1284 |

It looks like that the theoretical model between $\text{SNR}$ and $\text{PRR}$ is invalid. However, when getting down to the details, we can find that the calculation of $\text{SNR}$ in Equation (16) is problematic. $\text{SNR}$ is calculated by subtracting the measured noise power ($N$ in dBm) directly from the measured signal power ($\text{RSSI}$ in dBm). However, the transceiver only measures the power at the antenna without attempting to distinguish whether it is due to signal or noise. That is to say, the noise power also contributes to the $\text{RSSI}$ value. Therefore, the actual ratio of the signal power to noise power should be:

$$\gamma = \frac{P_{\text{RSSI}} - P_{N}}{P_{N}} = \frac{P_{\text{RSSI}}}{P_{N}} - 1 = 10^{\frac{\text{RSSI-N}}{10}} - 1$$

(17)

where $P_{\text{RSSI}}$ and $P_{N}$ are corresponding values in mW for $\text{RSSI}$ and $N$, respectively. Consequently, the $\text{SNR}$ in dB should be expressed as follows

$$\text{SNR} = 10 \log_{10} \left(10^{\frac{\text{RSSI-N}}{10}} - 1\right)$$

(18)

Figure 17 shows the theoretical model after correction. It is obvious that after correction, the theoretical model coincides well with the measured data. The relationship between $\text{SNR}$ and $\text{RSSI-N}$ is also shown in Figure 17. It can be seen that the actual $\text{SNR}$ is nonlinear with $\text{RSSI-N}$, especially when $\text{RSSI-N}$ is small. That explains why the original theoretical model deviates from the measured data, especially when $\text{SNR}$ is small, as shown in Figure 16.
Using Equation (9), the LR model between SNR and PRR was plotted, as shown in Figure 18. From Figure 18, it is obvious that estimated values gained by the LR model basically coincide with the measured data.

RMSEs of the estimated PRR and real PRR in three environments were also calculated for the theoretical model after correction and the LR model, as shown in Table 4. After correction, RMSEs of the theoretical model in all three environments are reduced effectively, which means that the proposed calculation method of SNR is reasonable. Compared with the runway, RMSE of the theoretical model in the artificial lawn reduces by 51.40%, but RMSE in the corridor increases by 15.08%. Compared with the runway, RMSE of the LR model in the artificial lawn reduces by 42.89%, but RMSE in the corridor increases by 11.27%. That is to say, the SNR based LQE\s are almost unaffected by environmental changes.

5.4. Environmental Impacts on LQI Based LQEs

5.4.1. LQI and PRR in Different Environments

Figure 19 shows the relationship between LQI and PRR in different environments, including the minimum, maximum, and mean value of LQI. It can be seen that the trend of change between LQI and PRR is basically the same for the three different environments. In terms of $\mu_{lqi}$, PRR increases as $\mu_{lqi}$ increases. To describe the impact of environmental changes on the fluctuation of LQI, the fluctuation ranges of LQI in different environments were statistically obtained, and their CDFs are shown in

[Figure 17: Effects of the theoretical model after correction.]

[Figure 18: Effects of the LR model in different environments.]

[Figure 19: Relationship between LQI and PRR in different environments.]
The fluctuation range of LQI is calculated by subtracting the minimum LQI from the maximum one. It can be seen that the maximum fluctuation ranges of LQI in the runway and corridor are close to 60, while the maximum fluctuation range of LQI in the artificial lawn is less than 50. The fluctuation of LQI in the corridor is the most violent, while the fluctuation in the artificial lawn is the gentlest. The fluctuation of LQI in the runway is between them. These relationships are consistent with the fluctuation of RSSI in the three environments. Considering the linear relationship between LQI and SNR [32], this consistency is not difficult to understand.

To observe the environmental impact on the relationship between LQI and PRR more clearly, the relationship between $\mu_{lqi}$ and PRR is shown in Figure 21. There already exist some studies which utilize the relationship between LQI and PRR to estimate link quality [6,15–18,26–28,30]. It can be seen that there is no obvious difference among the relationships between $\mu_{lqi}$ and PRR in different environments. This means that the relationship between $\mu_{lqi}$ and PRR is almost unaffected when the environment changes.
5.4.2. Environmental Impacts on LQI Based LQEs

Using Equation (12), the Cubic model between $\mu_{lqi}$ and PRR in three environments was plotted, as shown in Figure 22. It is clear that all the measured data from the three environments are basically coincident with the Cubic model. Using Equations (13) and (14), the piecewise linear model and LR model in the three environments were also plotted respectively, are shown in Figures 23 and 24. It is clear that all the measured data from the three environments are also basically coincident with two models.

To describe the environmental impact on LQI based LQEs quantitatively, RMSE of the estimated PRR and real PRR in the three environments were calculated, as shown in Table 6. It can be seen that RMSEs of the three environments are almost the same, no matter whether the model is. Compared with that in the runway, RMSE of the Cubic model in the artificial lawn reduces by 19.63%, but increases by 20.94% in the corridor. RMSE of the piecewise linear model in the artificial lawn reduces by 28.30%, but increases by 30.12% in the corridor. RMSE of the LR model in the artificial lawn reduces by 22.14%, but increases by 23.00% in the corridor. That is to say, the mapping model between $\mu_{lqi}$ and PRR constructed in a specific environment can be directly used in other environments.
5.5. Main Conclusions and Deep Analysis

According to the analysis in Sections 5.1–5.4, environmental impacts on hardware-based LQEs in WSNs are summarized as follows:

- **Conclusion 1.** It is not accurate to estimate PRR using communication distance, and they may be useless when changing environments.
- **Conclusion 2.** When the environment changes, the fluctuation range of RSSI and SNR will be affected and that of LQI is almost unchanged.

|                | Runway | Lawn | Corridor |
|----------------|--------|------|----------|
| Cubic model    | 0.1146 | 0.0921 | 0.1386 |
| Piecewise linear model | 0.1152 | 0.0826 | 0.1499 |
| LR model       | 0.1152 | 0.0897 | 0.1417 |

Figure 23. Effects of the piecewise linear model in different environments.

Figure 24. Effects of the LR model in different environments.
• **Conclusion 3.** RSSI based LQEs may degrade when the environment changes. Fortunately, this degradation is mainly caused by the change of background noise, which could be compensated conveniently.

• **Conclusion 4.** The best environmental adaptability is gained by LQI and SNR based LQEs, as they are almost unaffected when the environment changes.

Combined with Figures 7, 12 and 19, it can be seen that the fluctuation range of SNR and RSSI is significantly smaller than that of LQI with the same PRR. This indicates that a larger window is needed to smooth LQI, which will inevitably affect the agility of LQI based LQEs. As can be seen from Figures 8, 15 and 21, when PRR changes from 20% to 80%, \( \mu_{\text{lqi}} \) corresponds to a range from about 70 to 100, while \( \mu_{\text{snr}} \) and \( \mu_{\text{rssi}} \) correspond to a range from about 1.8 dB to 4.5 dB and from about \(-95\) dBm to \(-91\) dBm, respectively. This indicates that using \( \mu_{\text{lqi}} \) to estimate PRR in the transitional region has a better resolution than \( \mu_{\text{snr}} \) and \( \mu_{\text{rssi}} \), which means higher accuracy in the transitional region. To verify this conclusion, RMSEs in the connected region, transitional region, and disconnected region for SNR and LQI based LQEs were plotted, as shown in Figures 25 and 26, respectively. It is shown that LQI based LQEs are really more accurate in the transitional region than SNR based LQEs, especially for the environments with higher fluctuation ranges of LQI and SNR. Therefore, we have one more conclusion:

![Figure 25. RMSEs of SNR based LQEs in different regions.](image)

![Figure 26. RMSEs of LQI based LQEs in different regions.](image)

• **Conclusion 5.** LQI based LQEs are more accurate than SNR based ones in the transitional region. Nevertheless, compared with SNR, the fluctuation range of LQI is much larger, which needs a larger smoothing window to converge. In addition, the calculation of LQI is typically vendor-specific [2]. Therefore, the tradeoff between accuracy, agility, and convenience should be considered in practice.

The superiority of LQI over the remaining indicators can be explained as follows: For the radio chip we used, LQI and RSSI are both calculated over the first eight symbols of the incoming packet, following the start of the frame delimiter [13]. RSSI represents the average radio signal power received during these eight symbols, and it includes both the useful signal and eventual interference. The key drawback of RSSI is that it is a measure of raw electromagnetic energy on the channel, which does not distinguish the useful signal from interference and does not consider the signal correctness. That’s
why SNR based LQEs are more accurate than RSSI based ones because SNR considers the influence of noise and interference to some extent. On the other hand, each of the eight symbols is correlated with all 16 possible chip sequences, and the closest match is chosen for decoding. Then, LQI is calculated by the chip error rate with respect to the closest match [33]. In other words, LQI reflects the signal quality, not just the signal strength. Therefore, it has a better and more stable correlation with PRR. Therefore, LQI based LQEs are more susceptible to changing environments than RSSI and SNR based ones.

6. Conclusions and Future Works

To satisfy the performance requirements of WSNs, agile, and accurate link quality estimation is necessary. To achieve this goal, hardware-based LQEs are usually employed which depend on mapping models between PRR and some indirect metrics such as the SNR, RSSI, and LQI. However, existing studies did not consider the impacts of environmental changes on the applicability of these estimators. To solve this problem, three different environments are chosen in this paper, and environmental impacts on typical hardware-based LQEs are analyzed quantitatively.

The experimental results expose that the traditional calculation method of SNR used in existing studies is problematic. The transceiver only measures the power at the antenna without attempting to distinguish whether it is due to signal or noise. Therefore, the noise power also contributes to the RSSI value, which makes the actual SNR nonlinear with RSSI and noise power, especially when SNR is small. For this problem, a more reasonable calculation method is proposed. It is shown that after correction, the SNR based theoretical model is more accurate, which makes the LQEs based on this model much more valuable.

It is not accurate to estimate PRR using communication distance and may be useless when the environment changes. The performance of RSSI based LQEs may degrade when the environment changes. Fortunately, it could be compensated conveniently by measuring the background noise or carrying out normalization to RSSI. The best environmental adaptability is gained by LQI and SNR based LQEs, as they are almost unaffected when the environment changes. Moreover, LQI based LQEs are more accurate than SNR based ones in the transitional region. On the other hand, when the environment changes, the fluctuation range of RSSI and SNR will be affected and that of LQI is almost unchanged. However, compared with SNR and RSSI, the fluctuation range of LQI is much larger, which needs a larger smoothing window to converge. In addition, the calculation of LQI is typically vendor-specific. Therefore, the tradeoff between accuracy, agility, and convenience should be considered in practice.

In the future, the impacts of node configurations (in other words, heterogeneous nodes) on LQEs will be explored to gain a deeper understanding, including the antenna height, frequency channel, transmit power, antenna angle, and others.

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