IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2022.Doi Number

Impacts of Transmission Power Control on Link Quality Estimation in Wireless Sensor Networks

Haoqi Hu[1]
[1]School of AI and Advanced Computing, XJTLU Entrepreneur College (Taicang), Xi'an Jiaotong-Liverpool University, Taicang, Jiangsu 215400, China
Corresponding author: Haoqi Hu (e-mail: Haoqi.Hu20@student.xjtlu.edu.cn).

ABSTRACT Transmission power control (TPC) is often utilized to achieve dynamic topology control while minimizing energy consumption in wireless sensor networks, which is usually adjusted based on the condition of links. Therefore, the accuracy of link quality estimation (LQE) is critical to the efficiency of TPC. Although there are many well-established metrics and models for LQE, most of them are developed and validated in conditions of constant transmission power. This paper systematically analyzes the influence of transmission power changes on commonly used LQE metrics and models. The results indicate that the change of transmission power has different impacts on different link quality metrics and models. As LQI is less affected by the change of transmission power, it should be the best LQE metric under TPC.

INDEX TERMS Link quality estimation, transmission power control, wireless sensor network.

I. INTRODUCTION

Wireless sensor networks (WSNs) have been widely employed in many fields, such as industrial automation, environmental monitoring, military applications, healthcare and patient monitoring, and so on [1]. Due to the limitations of battery power, WSNs typically use low-power transceivers, which results in a dynamic topology and link that vary with time. To enable WSNs to adapt to external changes, transmission power control (TPC) is often utilized to achieve dynamic topology control while minimizing energy consumption and ensuring effective network connectivity [2].

Transmission power is usually adjusted based on the condition of the link. If the link quality is good enough, transmission power can be reduced to optimize energy consumption. Conversely, if the link quality is poor, transmission power can be increased to ensure connectivity. Therefore, the accuracy of link quality estimation (LQE) is critical to the efficiency of TPC. While prior works have given many well-established metrics and models for LQE, most of them have only been developed and validated in conditions of constant transmission power. Therefore, it is necessary to assess whether the variations of transmission power have any effect on these link quality estimation metrics and models.

In this paper, the commonly used link quality estimation metrics and models are evaluated experimentally under different transmission power levels. The results indicate that the distance based LQEs do not perform well under different transmission power levels, while the SNR, RSSI and LQI based LQEs, whose estimation ability is not affected by transmission powers, are reliable under different transmission power levels. Moreover, existing LQI based LQEs are more accurate than SNR and RSSI based LQEs. The variation of transmission power has an effect on the fluctuation of RSSI and SNR, but less on the fluctuation of LQI. That means, LQI is the best link quality estimation metric under TPC.

The main contribution of this paper is the systematic experimental analysis of the impact of transmission power variations on commonly used link quality estimation metrics and models. Although a few studies have investigated the characteristics of the commonly used physical layer metrics RSSI and LQI when the transmission power varies [3~5], these studies only deal with some of the physical layer parameters and do not consider the impact of transmission power variations on the commonly used link quality estimation models. To the best knowledge of the authors, this is the first paper to systematically analyze the influence of transmission power changes on commonly used link quality estimation metrics and models.

The rest of this paper is organized as follows. In Section II, the prior works related to TPC and LQE are described. Experimental setup and link quality models are presented in Section III. Spatial characteristics and models under different transmission power levels are analyzed in Section IV. Section V evaluates the performance of physical layer metrics and models under different transmission power levels. Finally, conclusions are presented in Section VI.

II. RELATED WORKS

A. TRANSMISSION POWER CONTROL

Transmission power control has been widely adapted to optimize communication and network connectivity in wireless sensor networks. Fan *et al*. [6] introduced the transmission power control mechanism into low-duty-cycle sensor networks and propose a cross-layer approach, to minimize the energy consumption of sensor nodes while meeting the user-specified delay constraint. Yildiz *et al*. [7] investigated the impact of optimal transmission power assignment for data and ACK packets on network lifetime in WSNs. The result showed that the global optimal assignment of data and ACK packets can be replaced with link scope power level assignment strategies without any significant deterioration of network lifetime. Yildiz *et al.* [8] considered that optimizing the transmission power level (TPL) and data packet size (DPS) is of paramount importance for prolonging the WSN lifetime. Therefore, they presented a mixed-integer programming framework, which utilizes a detailed link-layer abstraction to analyze nine TPL and DPS assignment strategies for WSNs. Mu *et al.* [9] thought that using a single wireless technology therefore falls short of meeting the demands of varying workloads or changing environmental conditions. So they designed an adaptive radio and transmission power selection system, which makes available at runtime multiple wireless technologies (e.g., WiFi and ZigBee) and selects the radio(s) and transmission power(s) most suitable for the current conditions and requirements. Pal *et al.* [10] argued that reducing transmission power at low-power RF transceivers does not lead to proportional energy savings, because the baseline operations of low-power transceivers were already optimized for very low power consumption. Sabale *et al*. [11] efficiently adjusted the transmission power of the beacon node for the reliable transmission of beacon messages, which enabled unknown sensors to locate themselves with better accuracy in comparison with the existing models.

B. LINK QUALITY ESTIMATION

LQE is commonly used in the design of WSN protocols to assist the protocol in finding a reliable and accurate nexthop link. Packet reception ratio (PRR) can intuitively reflect the link performance, so some studies use PRR directly to estimate link quality [4, 12]. Existing studies typically use filters to reduce the measurement error for real-time PRR to accurately estimate current link quality [13, 14]. However, the PRR computed within small time windows is too agile and inaccurate, while the PRR computed within large time windows is too stable [12]. Extensive research has shown that by establishing the mapping models between distance, SNR, RSSI, LQI and PRR, more stable PRR estimated value can be obtained within a smaller time window, further enabling fast and accurate link quality estimation. Zhao *et al*. [15] analyzed the variation of PRR under different distances and divided the wireless link into three regions: the connected region, the disconnected region, and the transitional region. Link quality in the transitional region is particularly unstable. Sun *et al*. [16] derived the theoretical relationship model between PRR and communication distance to enhance the end-to-end data delivery reliability of industrial WSNs.

Physical layer parameters such as SNR, RSSI and LQI have been widely used for link quality estimation. For a given modulation schema, there is a certain relationship between the SNR and the PRR [12]. Therefore, some existing studies obtain the link quality estimation by developing mapping models between RSSI,SNR and PRR. Senel *et al.* [17] used Kalman filter for noise reduction of measured SNR, and then estimated the PRR by an empirical SNR-PRR curve. In contrast, Sun *et al*. [20] derived a theoretical relationship model between SNR and PRR under DSSS-OQPSK modulation. Additionally, Liu *et al*. [21] proposed a simplified relationship model between RSSI and PRR, which greatly reduces the computational overhead caused by the Q function in the theoretical mapping model. Gomes *et al*. [22] developed a normalized mapping model between RSSI and PRR to estimate the link quality of industrial wireless sensor networks. Bildea *et al*. [5] thought that the model of LQI and PRR is more accurate. Ranjan *et al*. [23] also found that LQI serves as a better candidate over RSSI in several underground WSN tests. Luo *et al*. [24] established a mapping model between LQI and PRR by using Cubic model. Carles *et al*. [25] obtained a piecewise linear model of PRR and LQI. Liu *et al*. [18] proposed 4C, which used logistic regression to establish a relationship between RSSI, SNR, LQI and PRR.

Recently, some researches have adopted fuzzy logic or machine learning algorithms for optimization or multi-parameter fusion of the link quality estimation model based on parameters such as RSSI, SNR, LQI, etc. The ELQET (Enhanced Link Quality Estimation Technique) proposed in [26] utilized four link metrics, which are the PRR obtained from LQI by using fuzzy logic, the SNR obtained by using Kalman filter, the coefficient of variation of PRR, and the mean value of LQI, to obtain accurate estimation of link quality. Huang *et al*. [27] used fuzzy logic to combine both hardware-based (LQI and SNR) and software-based (PRR) metrics to evaluate link quality. Based on weighted Euclidean distance, Liu *et al*. [28] achieved a new link quality metric by fusing LQI and PRR. Then a link quality estimator was proposed to estimate link quality quantitatively. He *et al*. [29] proposed SCForest-LQE to estimate link quality, which used deep forest to combine the mean value and the coefficient of variation of LQI, RSSI, SNR.

C. TRANSMISSION POWER CONTROL AND LINK QUALITY ESTIMATION

Recently, more and more researches combined TPC and LQE to optimize WSN protocol performance. In ATPC, proposed by Lin *et al*. [2], each node builds a model for each of its neighbors, describing the correlation between transmission power and link quality. The results from the realworld experiments demonstrate that ATPC achieves more energy savings, and it is robust even with environmental changes over time. Fernandes *et al*. [30] thought that since WBAN on-body communication channels' quality varies over time, it is not appropriate to use a static and predefined transmission power level. They proposed a novel TPC mechanism which uses the on-body communication RSSI values to approximate the fading signal during the user's gait cycle. Lee *et al*. [31] proposed grey-fuzzy-logic based TPC for mobile sensor networks using grey prediction and fuzzy inference systems, which not only reduces the energy consumption, but also maintains a proper packet delivery ratio (PDR) for mobile sensing environments. Sodhro *et al*. [32] first proposed a novel joint TPC and duty-cycle adaptation-based framework for pervasive healthcare. Then, an adaptive energy efficient transmission power control algorithm was developed by adapting the temporal variation in the on-body wireless channel amid static (i.e., standing and walking at a constant speed) and dynamic (i.e., running) body postures. Sawaguchi *et al.* [33] proposes a multi-agent actor-critic reinforcement learning for modulating both the transmitter duty-cycle and output power based on the state-of-buffer (SoB) and the state-of-charge (SoC) information as a state, which does not require any direct measurement of both harvested energy and wireless channel quality for adapting to these uncertainties. Mu *et al*. [9] given new empirical models of power consumption and packet reception ratio (the latter can also be refined online). Zoppi et al. [34] proposed an adaptive transmission power control policy in industrial WSN. Experimental result shows the measurement-based policy have more than 50% reduction in transmission power compared with model-based policy. Sabale et al. [35] proposed a new trajectory, Anchor-power, that provides transmission power control for the mobile beacon. Experimental results reveal that the proposed approach enables unknown sensors to locate themselves with better accuracy in comparison with the existing models. Yadav et al. [36] considered the power transmission problem for a fully connected cluster, with the goal of finding the minimum transmission power for each node in a given cluster without disrupting the network.

However, although existing researches have made great contributions to the study of applying TPC and LQE to WSN, few researches have evaluated the impact of transmission powers changed on LQE metrics and models caused by TPC. They may control transmission power directly by using the measured RSSI [2, 30, 31, 32] or PRR [34], or control transmission power based on the communication distance and the model between distance and RSSI (or the model between the distance and PRR) [33, 35, 36]. Therefore, the analysis of transmission powers changed influence on LQE metrics and models in this paper, which can provide a reference for the design of these TPC mechanisms.

III. EXPERIMENTAL SETUP AND LINK QUALITY MODELS

A. EXPERIMENTAL SETUP

Multiple sensor nodes were deployed in the corridor of a laboratory building, as depicted in Fig.1. Experiments were conducted using TelosB, which is equipped with a CC2420 radio chip and an integrated planar inverted F-style antenna printed directly on the circuit board. And the transmitters use TinyOS 2.1, which is an open source operating system developed by Berkeley, which is specially designed for embedded WSNs. Ten transmitters located at different points in the experimental corridor sent packets to a receiver in turn, and a laptop that was connected to the receiver recorded the received packet sequence number, RSSI, LQI, and background noise in real time. After every 500 packets sent by one transmitter, the transmission power was adjusted to simulate the change in power caused by the TPC. Four different transmission power levels, 0dBm,-5dBm,-15dBm and -25dBm, were used. After the transmitters had sent packets, they were then re-deployed in other locations to get enough experimental data. In all experiments, the 26th channel was selected, while the inter packet interval and the antenna height were set to 25ms and 1.2m, respectively. The obtained measured data were processed and analyzed using MATLAB.

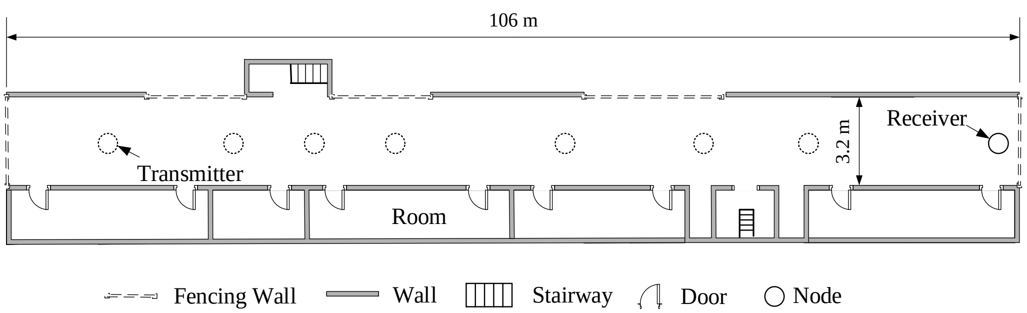


FIGURE 1. Experimental setup.

B. LQE MODELS

The LQE models used in this paper are described as follows. Unless otherwise specified, all models were fitted using test data under 0dBm. In [20], the mapping model be-tween mean value of SNR and PRR is obtained based on the theoretical model, as shown in (1).

$$PRR = \left[1 - Q\left(\sqrt{3 \times 10^{\frac{SNR}{10}}}\right)\right]^{136} \tag{1}$$

where $Q(\cdot)$ represents the Q function.

In [18], the mapping model between SNR and PRR is obtained based on logistic regression. In our experiments, measurements of SNR and PRR were collected at the receiver with the transmission power of 0dBm. Then by fitting the mapping model between SNR and PRR to the experimental data, the mapping model for the experimental environment is obtained as follows:

$$PRR = \frac{1}{1 + e^{-1.673 \times SNR + 6.7825}} \tag{2}$$

In [19], the mapping model between RSSI and PRR is obtained based on logistic regression. In our experiments, measurements of RSSI and PRR were collected at the receiver with the transmission power of 0dBm. Then by fitting the mapping model between RSSI and PRR to the experimental data, the mapping model for the experimental environment is obtained as follows:

$$PRR = \begin{cases} 1, & RSSI > -86 \\ 1 - \dfrac{1}{1 + 226.5632 \times e^{2.1416 \times RSSI + 192.5325}}, & -96 < RSSI \le -86 \\ 0, & RSSI \le -96 \end{cases} \tag{3}$$

In [22], the PRR model based on polynomial regression of normalized RSSI, referred to as the PR Model, was used. The PR Model is self-adaptive to some extent, so the model given in [22] was used directly:

$$\begin{aligned} PRR = {} & -3943.5R^6 + 6506.6R^5 - 4279R^4 + 1430.9R^3 - 256.47R^2 \\ & + 23.77R + 0.022 \end{aligned} \tag{4}$$

where P_n is the background noise.

In [24], the mapping model between LQI and PRR is obtained using the Cubic model. In our experiments, measurements of LQI and PRR were collected at the receiver with the transmission power of 0dBm. Then by fitting the mapping model between LQI and PRR to the experimental data, the mapping model for the experimental environment is obtained as shown in (5).

$$PRR = \begin{cases} 1, & LQI > 68 \\ \begin{aligned} & -0.0000032085 \times LQI^3 + 0.007848 \\ & \times LQI^2 - 0.6001 \times LQI + 14.6081 \end{aligned}, & 101 < LQI \le 68 \\ 0, & LQI \le 101 \end{cases} \tag{5}$$

In [25], the mapping model between LQI and PRR is obtained based on piecewise linear. By fitting the mapping model to the LQI and PRR experimental data under 0dBm transmission power, the mapping model for the experimental environment is obtained as follows:

$$PRR = \begin{cases} 1, & LQI > 104 \\ 0.008934 \times LQI + 0.07082, & 86 < LQI \le 104 \\ 0.05923 \times LQI - 4.2546, & 72 < LQI \le 86 \\ 0.0004545 \times LQI - 0.02272, & 50 \le LQI \le 72 \end{cases} \tag{6}$$

In [18], the mapping model between LQI and PRR is obtained based on logistic regression. By fitting the mapping model to the LQI and PRR experimental data under 0dBm transmission power, the mapping model for the experimental environment is obtained as shown in (7).

$$PRR = \frac{1}{1 + e^{-0.22 \times LQI + 18.34}} \tag{7}$$

IV. SPATIAL CHARACTERISTICS UNDER DIFFERENT TRANSMISSION POWER LEVELS

Fig. 2 demonstrates that there is no consistent mapping relationship between the communication distance and PRR under different transmission power levels in WSNs with TPC. The range of connected region, transitional region and disconnected region differs significantly for different transmission power levels. For instance, when the transmission power is -25dBm, the maximum communication distance of a node is less than 10m, while under the transmission power of -15dBm and -5dBm, the maximum communication distance extends to 20 m and 96 m respectively.

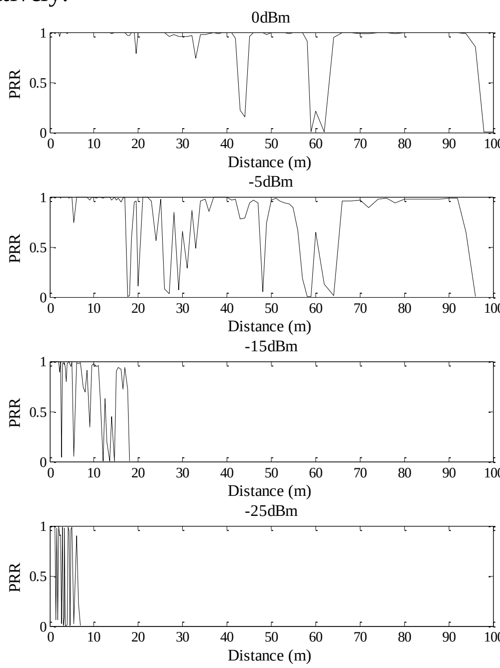


FIGURE 2. Communication distance vs. PRR under different transmission power levels.

In other words, increasing the transmission power can effectively increase the communication range of nodes, i.e., TPC can effectively improve the transmission efficiency of the network. However, as seen in Fig.2, there are some special cases. For example, at the distance of 42 m, the PRR of the node under the transmission power of 0 dBm is smaller than that of -5 dBm, which is due to the node residing in the transitional region. At the same location in the transitional region, the PRR of the link is, with high probability, very large or very small. Therefore, increasing the transmission power may not increase the PRR because some nodes in the transitional region may still be in the transitional region even after increasing the transmission power.

V. PHYSICAL LAYER METRICS AND MODELS UNDER DIFFERENT TRANSMISSION POWER LEVELS

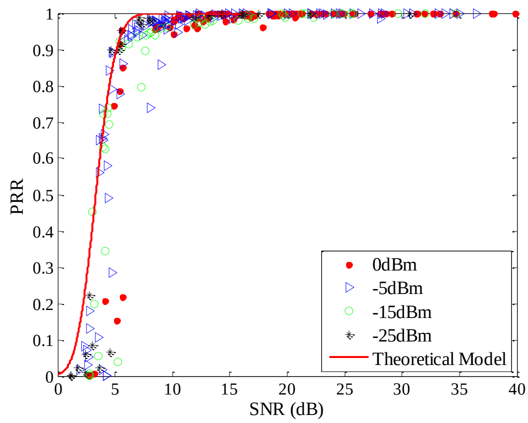
A. SNR AND SNR MODELS

Fig.3 shows the relationship between SNR and PRR under different transmission power levels in WSNs with TPC. On the whole, PRR increases as SNR increases: when SNR is below 1 dB, PRR approaches 0; when SNR is above 8 dB, PRR approaches 100%; when SNR is between 1 dB and 8 dB, PRR increases from 0 to 100%. Upon careful observation, it can be found that SNR is also above 8 dB when PRR is between 80% and 100%, such as the sample corresponding to transmission power -5 dBm. This is caused by the interference of the experimental environment, according to the subsequent analysis of the influence of channel changes. Nevertheless, as shown in Fig.3, the change trend of SNR and PRR under different transmission power levels is consistent. In summary, TPC does not have much effect on the mapping relationship between SNR and PRR.

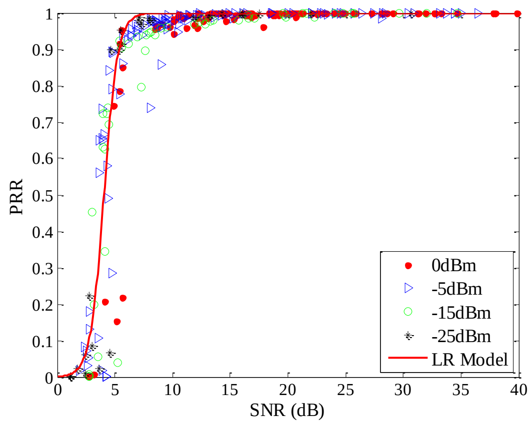
The theoretical model and the logistic regression model were employed to analyze the effect of transmit power on SNR based LQEs. The theoretical model and logistic regression model curves of PRR versus SNR under different transmission power levels can be obtained as shown in Fig. 3 (a) and Fig. 3(b), respectively. It is shown that the change trend of theoretical model and logistic regression model is consistent with measured data under different transmission power levels. To quantitatively describe the effect of trans-mission powers on these SNR based LQEs, the RMSEs of the PRR for the two models under the four different transmission powers were calculated, as shown in Table I. It can be seen that, com-pared with the theoretical model, the RMSE of the logistic regression is even lower. Although the estimation error of the theoretical model is slightly higher than that of the logistic regression model, the theoretical model does not require the collection of test data for model training, and thus has an advantage in terms of deployment cost.

In order to evaluate the effect of transmission power on the fluctuation of SNR, the fluctuation range of SNR under different transmission power levels was statistically calculated, and the cumulative probability distribution was obtained as shown in Fig.4. It can be seen that the higher the transmission power, the more drastic the fluctuation of SNR. When the transmission power is -25dBm, there is a more than 50% probability that the SNR fluctuates from 0dB to 5dB. While the transmission power is 0 dBm, there is only 5% probability that the SNR fluctuates from 0dB to 5dB. This is because the measured values of RSSI are obtained from the same node in the same environment and location. Thus, the higher the transmission power, the higher the upper limit of the measured values of RSSI, while the lower limit of the measured values of RSSI is fixed, which leads to larger fluctuations of RSSI under high transmission power. That is, the transmission power has an effect on the fluctuation of RSSI. Since the noise is constant over a short period of time in the same environment and SNR is the ratio of the RSSI to the noise, the fluctuation of SNR is also larger under high transmission power. Further analysis shows that the variation of transmission power under TPC has an effect on the fluctuation of SNR, and the drastic fluctuation of SNR may affect the accuracy of SNR based LQEs.

In order to express RMSEs more clearly, we divided test samples into 5 ranges according to measured values of PRR, including 0% ⩽ PRR ⩽ 20%, 20% < PRR ⩽ 40%, 40% < PRR ⩽ 60%, 60% < PRR ⩽ 80% and 80% < PRR ⩽ 100%, respectively draw the RMSEs of corresponding range, as shown in Fig. 5. It can be seen that RMSEs of two models are lower than 0.1 when 80% < PRR ⩽ 100%. However, RMSEs of two models are higher, even exceeding 0.6. In addition, it also can be seen from Fig. 5 that, compared with the transmit power is 0dBm, the corresponding estimation errors are greatly increased, when the transmit power is -5dBm, -15dBm or -25dBm. The main reason is that there are fewer sample points under these three transmit powers. Combining the analysis in Table I and Fig. 5, it can be seen that theoretical model and LR model between SNR and PRR constructed under a specific transmission power can be used under other transmission powers, in the case of little environmental interference.



(a) Theoretical model



(b) LR model

FIGURE 3. Effects of theoretical model and LR model under different transmission power levels.

TABLE I
RMSES OF SNR BASED LQES UNDER DIFFERENT TRANSMISSION POWER LEVELS

	0 dBm	-5 dBm	-15 dBm	-25 dBm
THM	0.1309	0.1814	0.1868	0.1946
LRM	0.1098	0.1467	0.1557	0.1536

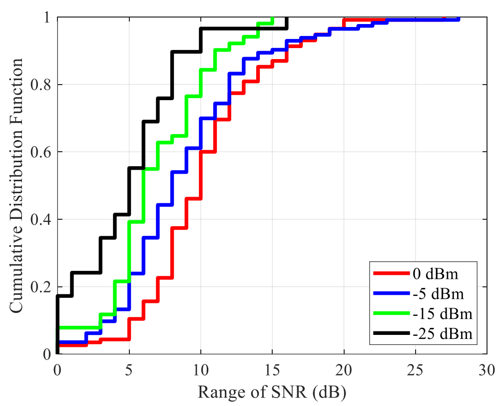
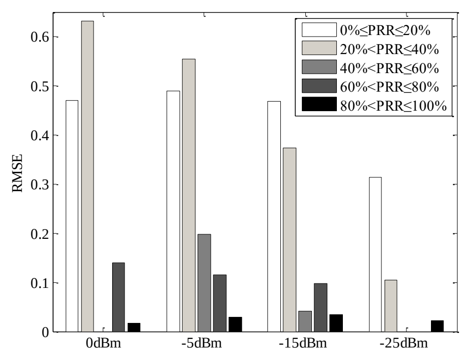
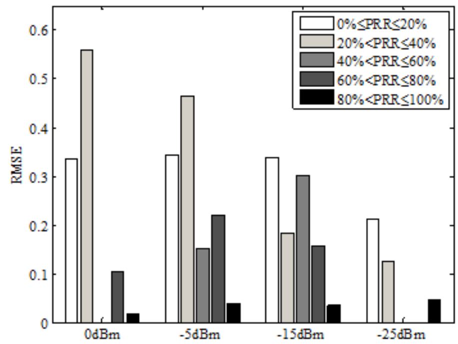


FIGURE 4. Range of SNR under different transmission power levels.



(a) Theoretical model



(b) LR model

FIGURE 5. RMSEs of theoretical model and LR model under different transmit power levels.

B. RSSI and RSSI Models

Fig. 6 shows the relationship between RSSI and PRR under different transmission power levels in WSNs with TPC. It can be seen that PRR increases as RSSI increases: when RSSI is lower than -95 dBm, PRR approaches 0; when RSSI is higher than -90 dBm, PRR approaches 100%; when RSSI is located between -95 dBm and -90 dBm, PRR rapidly in-creases from 0 to 100%. Similar to Fig. 4, the relationship between RSSI and PRR will also be affected by the interference of experimental environment. However, the change trend of RSSI and PRR is consistent under different transmission power levels, as shown in Fig. 5. In summary, TPC has little effect on the mapping relationship between RSSI and PRR.

In order to evaluate the effect of transmission power on the fluctuation of RSSI, the fluctuation range of RSSI under different transmission power levels was statistically calculated, and the cumulative probability distribution was obtained as shown in Fig. 7. It can be seen that the higher the transmission power, the more drastic the fluctuation of RSSI. When the transmission power is -25dBm, there is a more than 80% probability that the RSSI fluctuates from 0dB to 5dB. And when the transmission power is 0 dBm, there is only 10% probability that the RSSI fluctuates from 0dB to 5dB. According to the analysis in Section V(A,) the transmission power limits the upper limit of the measured values of RSSI, which affects the degree of fluctuation of RSSI. In other words, the variation of transmission power under TPC has an effect on the fluctuation of RSSI, and the fluctuation of RSSI may affect the accuracy of RSSI based LQEs.

LR model, PR model and simplified theoretical model are selected to analyze the in-fluence of transmission power on RSSI based LQEs. The logistic regression model, normalized polynomial model and theoretical model curves of PRR versus RSSI at different antenna heights can be obtained, as shown in Fig. 6 (a), (b) and (c), respectively. From Fig. 6 it can be seen that the estimated values from the theoretical and logistic regression models are basically consistent with the measured values. However, when the PRR lies in the interval [50%, 100%], some deviations between the estimated values from the normalized polynomial model and measured values were observed. This is because the test environment in the paper has low disturbance, while the PR model in the literature [22] is built in an industrial environment with high disturbance, which leads to a mismatch between the PR model and the measured data in this paper. This shows that the PR model is not superior to the theoretical and logistic regression models, and its accuracy depends entirely on the similarity between the disturbance characteristics of the test and modeling environment.

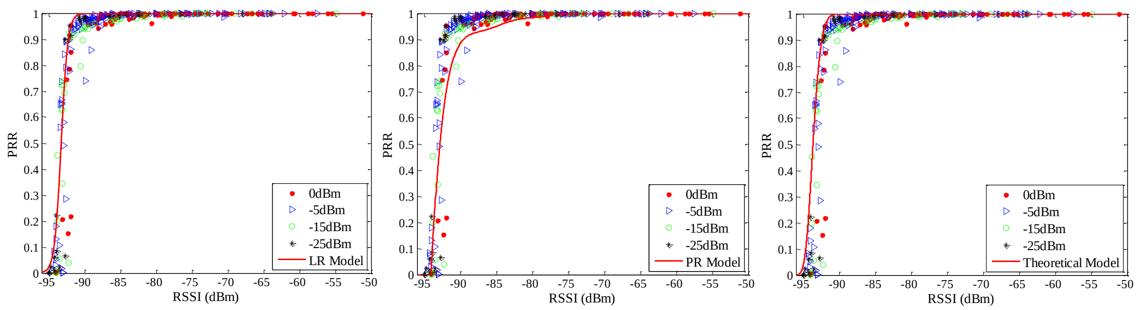
In order to describe the effect of transmission powers on these RSSI based LQEs quantitatively, the RMSEs of PRR for the three models under the four different transmission powers was calculated, as shown in Table II. It can be seen that the normalized polynomial model is not significantly different from the other two models as far as the RMSE is concerned, although there are some deviations between the measured values and values estimated by the normalized polynomial model when the PRR lies in the interval [50%, 100%].

In order to evaluate the effect of transmission power on the fluctuation of RSSI, the fluctuation range of RSSI under different transmission power levels was statistically calculated, and the cumulative probability distribution was obtained as shown in Fig. 7. The same with the fluctuation of SNR, the higher the transmission power, the higher the fluctuation of RSSI. That is to say, the variation of transmission power under TPC has an effect on the fluctuation of RSSI, and the drastic fluctuation of RSSI may affect the accuracy of RSSI based LQEs.

In order to express RMSEs more clearly, Fig. 8 shows the RMSE under different PRR ranges. It can be seen that, when 60% < PRR ⩽ 100%, RMSEs of PR model are significantly higher than simplified theoretical model and LR model. However, when 0 ⩽ PRR ⩽ 40%, RMSEs of PR model are much lower than simplified theoretical model and LR model, thus compensating for its overall estimation error. RMSE of the simplified theoretical model are almost the lowest when 60% < PRR ⩽ 100%, and its overall estimation error is mainly due to the drag when 0⩽PRR ⩽ 40%. It also shows from the side that the high mapping error of the transitional region will adversely affect the link quality estimation. Compared with the mapping model of communication distance and PRR, the RMSE of RSSI and PRR mapping model is lower, but it is basically comparable to that of SNR and PRR mapping model. Combining the analysis in Table II and Fig. 8, it can be seen that PR model, simplified theoretical model and LR model between RSSI and PRR constructed under a specific transmission power can be used under other transmission powers, in the case of little environmental interference.

TABLE II
RMSEs OF RSSI BASED LQEs UNDER DIFFERENT TRANSMISSION POWER LEVELS

	0 dBm	-5 dBm	-15 dBm	-25 dBm
LRM	0.0767	0.1643	0.1973	0.1434
PRM	0.0830	0.1476	0.1467	0.1584
THM	0.1315	0.1827	0.1867	0.1938



(a) LR model (b) PR model (c) Simplified theoretical model

FIGURE 6. Effects of LR model, PR model and theoretical model under different transmission power levels

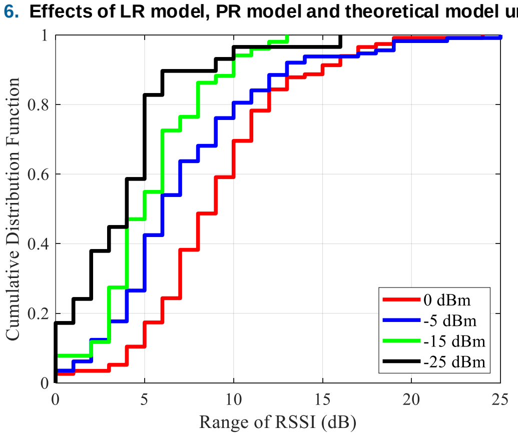
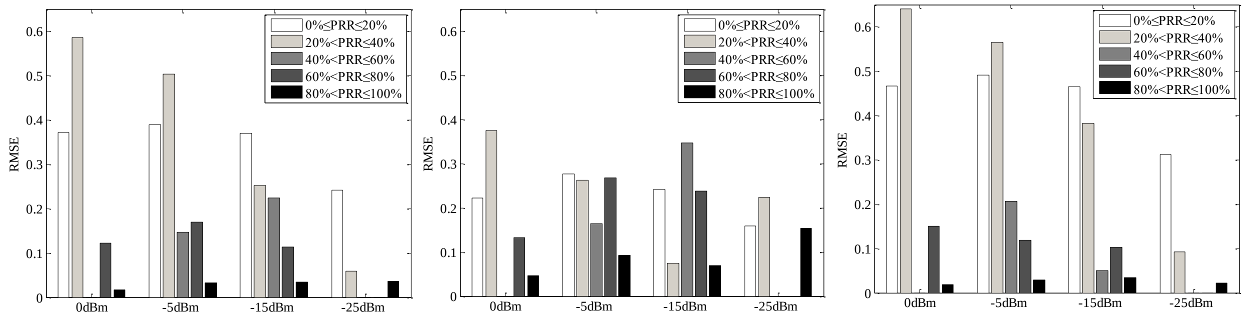


FIGURE 7. Range of RSSI under different transmission power levels.

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3368381



(a) LR model (b) PR model (c) Theoretical model

FIGURE 8. **RMSEs of LR model, PR model and theoretical model under different transmit power levels.**

C. LQI AND LQI MODELS

Fig. 9 shows the relationship between the PRR and LQI under different transmission power control in WSNs with TPC. It can be seen that PRR increases as LQI increases: when LQI is lower than 68, PRR approaches 0; when LQI is higher than 101, PRR approaches 100%; when LQI is between 68 and 101, PRR rapidly increases from 0 to 100%. Similar to the relationship between RSSI and PRR, the change trends of LQI and PRR under different transmission power levels are consistent in WSNs with TPC, as shown in Fig. 9. In summary, TPC has basically no effect on the mapping relationship between PRR and LQI.

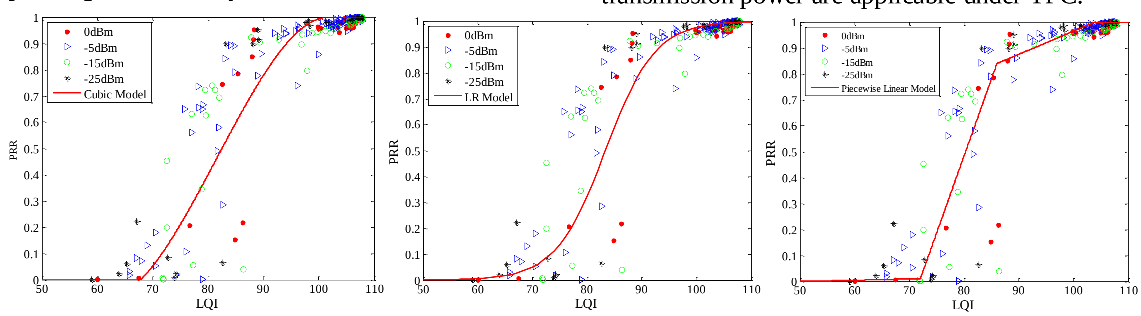
In order to observe more clearly the effect of transmission power on the fluctuation of LQI in WSNs with TPC, the cumulative probability of LQI fluctuation range under different transmission power levels is given in Fig. 10. From Figure. 10, it can be observed that there is no significant difference in the cumulative probability of the LQI fluctuation range under the four transmission power levels, with a maximum fluctuation range of about 50 and about 60% of the LQI fluctuations between 10 and 40. In other words, unlike RSSI and SNR, the variation of transmission power under TPC has little effect on LQI fluctuation.

Since the range of RSSI and SNR fluctuation changes is much wider than its transitional region in most cases, and the upper limit of RSSI and SNR is much higher than the measured value, this leads to the possibility of larger fluctuations of RSSI and SNR when the transmission power is increased. And because the LQI itself is limited to a small range, when SNR or RSSI is higher than a certain threshold, the corresponding LQI is always around 110, no matter how much SNR or RSSI increases. In other words, when the transmission power continues to rise, the LQI may always fluctuate around 110. This also leads to the fact that the change in transmission power has little effect on the fluctuation of LQI.

Cubic model, piecewise linear model and logistic regression model are selected to analyze the effect of transmission power on LQI based LQEs. The cubic model, logistic regression model and piecewise linear model curves of PRR versus RSSI under different transmission power levels can be obtained, as shown in Fig. 9(a), (b) and (c), respectively. It can be seen that the variation trends of the values estimated by the three models are basically consistent with the measured values.

In order to describe the impacts of transmission powers on these LQI based LQEs quantitatively, RMSEs of the estimated and measured PRR under the four different trans-mission powers was calculated, as shown in Table III. It can be seen that the RMSEs of all three models are lower, with a maximum value of 0.1697. In addition, the RMSEs of LQI based LQEs are significantly lower than that of communication distance, SNR, and RSSI based LQEs. That is, the mapping model of PRR to LQI under different transmission power levels is more accurate than other models.

It can be seen that although the RMSEs in the transitional region are still high, they are generally lower than those in the transitional region in Fig. 3 and Fig. 6. This is because the transitional region range of the LQI~PRR model is significantly wider than that of the SNR~PRR model and RSSI~PRR model, and thus the resolution of the LQI~PRR model is higher, which suppresses the mapping error to a certain extent. Combined with the analysis from Table III, it can be seen that the Cubic model, logistic regression model and piecewise linear model obtained by fitting at a specific transmission power are applicable under TPC.



(a) Cubic model (b) LR model (c) Piecewise linear model

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3368381

FIGURE 9. Effects of Cubic model, LR model and piecewise linear model under different transmission power levels.

From the analysis above, it can be found that the RMSE is higher under low trans-mission power. This is due to the fact that the percentage of good links is high under the large transmission power, and the accuracy of the model is high under the good link, thus the RMSE obtained is relatively low under the large transmission power. In contrast, the percentage of moderate links is high under the small transmission power, which leads to a relatively higher RMSE under the small transmission power.

In order to express RMSEs more clearly, Fig. 11 shows the RMSE under different PRR ranges. It can be seen that although the RMSEs under transitional region are still high, it is generally lower than the results corresponding to Fig. 5 and Fig. 8. The reason is that, under transitional region, the range of the models between LQI and PRR are significantly wider than that of the models between SNR and PRR and the models between RSSI and PRR, which cause the resolution of the models between LQI and PRR are higher and the mapping errors are suppressed to a certain extent. Combining the analysis in Table III and Fig. 11, it can be seen that PR model, theoretical model and LR model between LQI and PRR constructed under a specific transmission power can be used under other transmission powers, in the case of little environmental interference.

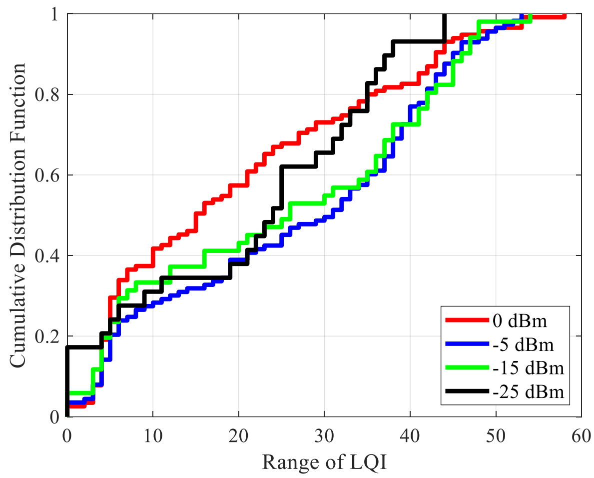


FIGURE 10. Range of LQI under different transmission power levels.

TABLE III
RMSES OF LQI BASED LQES UNDER DIFFERENT TRANSMISSION POWER LEVELS

	0 dBm	-5 dBm	-15 dBm	-25 dBm
Cubic	0.0723	0.1265	0.1547	0.1364
LRM	0.0712	0.1314	0.1697	0.1248
PLM	0.0843	0.1206	0.1557	0.1264

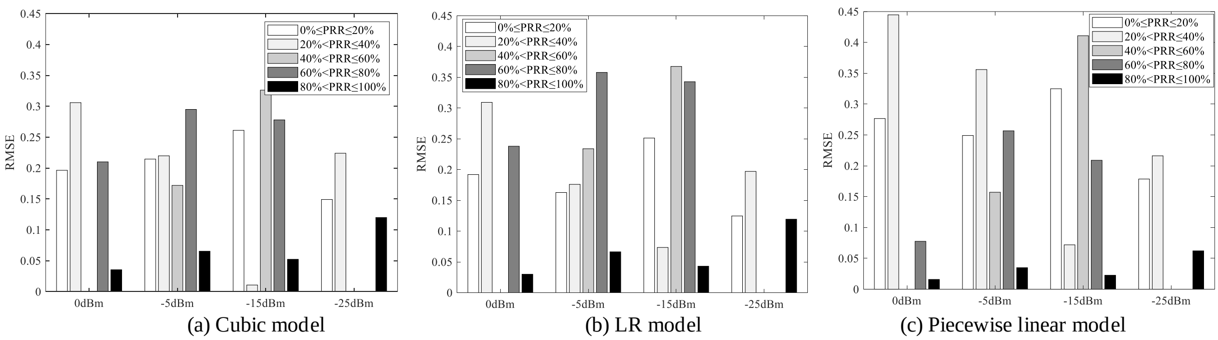


FIGURE 11. RMSEs of Cubic model, LR model and piecewise linear model under different transmit power levels.

VI. APPLICABILITY OF LINK QUALITY ESTIMATION METRICS UNDER DIFFERENT TRANSMIT POWER LEVELS

In order to analyze the configuration correlation of link quality estimation metrics under different transmit power levels, Fig. 12 shows the Spearman correlation coefficients of communication distance, SNR, RSSI, LQI and PRR under different configurations. Among them, the closer the Spearman correlation coefficient is to 1, the higher the correlation. It can be seen that there are still some differences in the correlation coefficients under different configurations.

It can be found that, under different transmission power levels, the correlation coefficient between communication distance and PRR is much lower than that of SNR, RSSI, and LQI. Among them, the correlation coefficient between communication distance and PRR are lower than 0.8 under different transmission power levels. While the correlation coefficients of SNR, RSSI, LQI and PRR are similar, and all are higher than 0.8 under different transmission power levels.

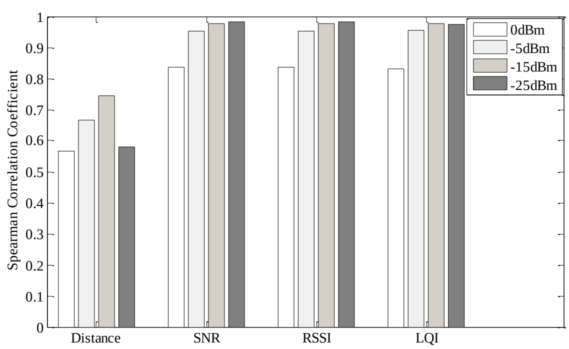


FIGURE 12. Spearman correlation coefficient between communication distance, SNR, RSSI, LQI and PRR under different transmission power levels.

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3368381

In general, communication distance is not a good link quality estimation metric in WSNs with TPC. Meanwhile, the correlation coefficient between SNR, RSSI, LQI and PRR are higher, and the RMSEs of the models between SNR, RSSI, LQI and PRR are also lower under different transmission power levels. That is to say, SNR, RSSI, LQI are good link quality estimation metrics in WSNs with TPC.

VII. APPLICABILITY OF LINK QUALITY ESTIMATION METRICS UNDER DIFFERENT EXPERIMENTAL SETUPS

Define the tests in Section III (A) as Test 1. In order to verify the applicability of the proposed conclusions under different experimental setups, three sets of tests with different configurations were carried out, which were defined as Test 2, Test 3 and Test 4. Among them, Test 2 is outdoor tests, which use the same nodes to arrange a mesh network outdoors, and arranges it in different locations to obtain data under different distances. The experimental setups of Test 3 and Test 4 are same with Test 1, except that the 500 sent packets are changed to 200 and 800 sent packets, respectively.

Fig. 13 shows the relationship between communication distance and PRR under different transmission power levels in experimental setups. It can be seen that, similar to the tests in Test 1, there is no consistent mapping relationship between the communication distance and PRR under different transmission power levels in different experimental setups.

Fig. 14 shows the relationship between SNR and PRR under different transmission power levels in different experimental setups. Fig. 15 shows the range of SNR under different transmission power levels in different experimental setups. Table IV shows the RMSEs of the PRR for two SNR based models under different transmission power levels in different experimental setups.

It can be seen from Fig. 14 that TPC does not have much effect on the mapping relationship between SNR and PRR in four experimental setups. It can be seen that, compared with the theoretical model, the RMSEs of LR model are lower. Table VI has shown that the average RMSEs of theoretical model and logistic regression model are 0.1430 and 0.1086, respectively. That is to say, the estimation error of theoretical model is higher than that of logistic regression model. It also can be seen from Fig. 14 and Table VI that, the SNR based LQEs are good approaches under different transmission power levels in four different experimental setups. Fig. 4 and Fig. 15 show that, the fluctuation range of SNR under TPC in different experimental setups are similar. They have shown that the variation of transmission power has an effect on the fluctuation of SNR, and the drastic fluctuation of SNR may affect the accuracy of SNR based LQEs.

Fig. 16 shows the relationship between RSSI and PRR under different transmission power levels in different experimental setups. Fig. 17 shows the range of RSSI under different transmission power levels in different experimental setups. Table V shows the RMSEs of the PRR for three RSSI based models under different transmission power levels in different experimental setups.

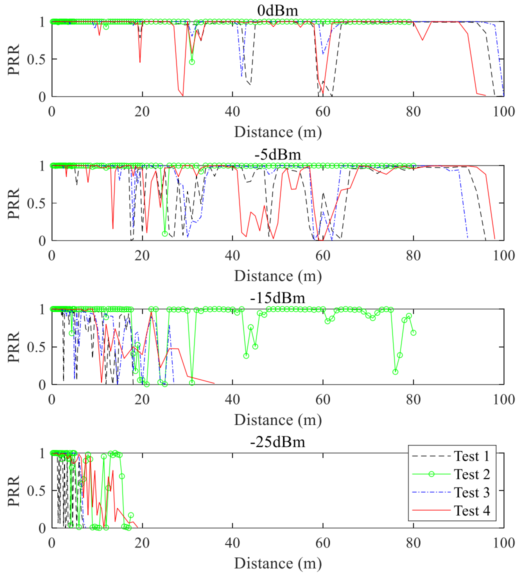
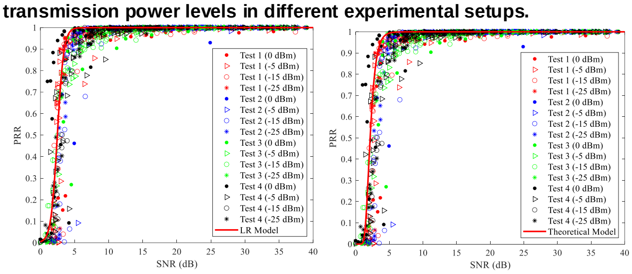


FIGURE 13. Communication distance vs. PRR under different transmission power levels in different experimental setups.



(a) LR model (b) TH model

FIGURE 14. Effects of SNR based model under different transmission power levels in different experimental setups.

TABLE IV
RMSES OF SNR BASED LQES UNDER DIFFERENT TRANSMISSION POWER LEVELS IN DIFFERENT EXPERIMENTAL SETUPS

		0 dBm	-5 dBm	-15 dBm	-25 dBm
THM	Test 1	0.1309	0.1814	0.1868	0.1946
	Test 2	0.0503	0.0847	0.1881	0.2355
	Test 3	0.0790	0.0860	0.1019	0.0652
	Test 4	0.1565	0.1404	0.2314	0.1757
LRM	Test 1	0.1098	0.1467	0.1557	0.1536
	Test 2	0.0406	0.0782	0.1118	0.0957
	Test 3	0.0773	0.0656	0.0785	0.0391
	Test 4	0.1637	0.1235	0.1791	0.1195

TABLE V
RMSES OF RSSI BASED LQES UNDER DIFFERENT TRANSMISSION POWER LEVELS IN DIFFERENT EXPERIMENTAL SETUPS

		0 dBm	-5 dBm	-15 dBm	-25 dBm
LRM	Test 1	0.0767	0.1643	0.1973	0.1434
	Test 2	0.0455	0.0818	0.1121	0.0862
	Test 3	0.0700	0.0449	0.1651	0.0800
	Test 4	0.1656	0.1442	0.0897	0.1046
PRM	Test 1	0.0830	0.1476	0.1467	0.1584
	Test 2	0.0322	0.0711	0.1326	0.1328
	Test 3	0.0820	0.0878	0.1988	0.1265
	Test 4	0.1905	0.16210	0.1707	0.2140
THM	Test 1	0.1315	0.1827	0.1867	0.1938
	Test 2	0.0438	0.0807	0.1118	0.0898
	Test 3	0.0649	0.0376	0.1189	0.0578
	Test 4	0.1815	0.1202	0.0708	0.1183

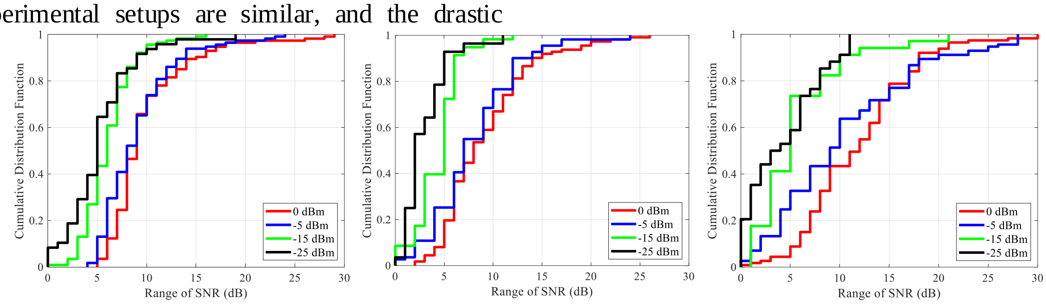
TABLE VI
RMSEs OF LQI BASED LQEs UNDER DIFFERENT TRANSMISSION POWER LEVELS IN DIFFERENT EXPERIMENTAL SETUPS

		0 dBm	-5 dBm	-15 dBm	-25 dBm
Cubic	Test 1	0.0723	0.1265	0.1547	0.1364
	Test 2	0.0356	0.0734	0.1078	0.0566
	Test 3	0.0637	0.0431	0.1517	0.1183
	Test 4	0.1108	0.1046	0.1292	0.1193
LRM	Test 1	0.0712	0.1314	0.1697	0.1248
	Test 2	0.0388	0.0766	0.1051	0.0648
	Test 3	0.0670	0.0369	0.1778	0.1243
	Test 4	0.1128	0.0968	0.1534	0.0931
PLM	Test 1	0.0843	0.1206	0.1557	0.1264
	Test 2	0.0428	0.0778	0.1067	0.0578
	Test 3	0.0608	0.0583	0.1260	0.0922
	Test 4	0.1349	0.1379	0.1326	0.1760

It can be seen from Fig. 16 that TPC does not have much effect on the mapping relationship between RSSI and PRR in four experimental setups. Table V has shown that the average RMSEs of logistic regression model, PR model and simplified theoretical model are 0.1107, 0.1336 and 0.1119, respectively. It can be seen that the PR model is not significantly different from the other two models as far as the RMSE is concerned. It also can be seen from Fig. 16 and Table V that, the RSSI based LQEs are good approaches under different transmission power levels in four different experimental setups. Fig. 7 and Fig. 17 show that, the fluctuation range of RSSI under TPC in different experimental setups are similar, and the drastic fluctuation of RSSI may affect the accuracy of RSSI based LQEs.

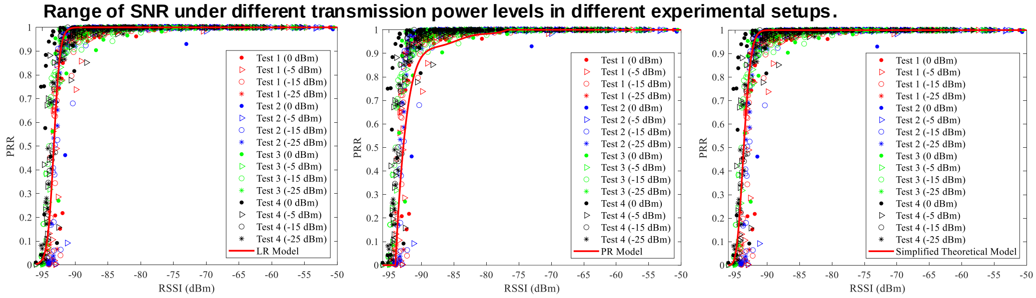
Fig. 18 shows the relationship between LQI and PRR under different transmission power levels in different experimental setups. Fig. 19 shows the range of LQI under different transmission power levels in different experimental setups. Table V shows the RMSEs of the PRR for three LQI based models under different transmission power levels in different experimental setups.

Same with the models of RSSI and SNR based LQEs, it can be seen from Fig. 18 that TPC has basically no effect on the mapping relationship between PRR and LQI in four experimental setups. Table VI has shown that the average RMSEs of Cubic model, logistic regression model and piecewise linear model are 0.1003, 0.1028 and 0.1057, respectively. It can be seen from Table VI that, the average RMSEs of three LQI based models are lower than RSSI and SNR based models. That is, the mapping models between PRR and LQI under different transmission power levels are more accurate than other models. Different from the range of RSSI and SNR fluctuation changes, Fig. 10 and Fig. 19 show that the change in transmission power has little effect on the fluctuation of LQI.



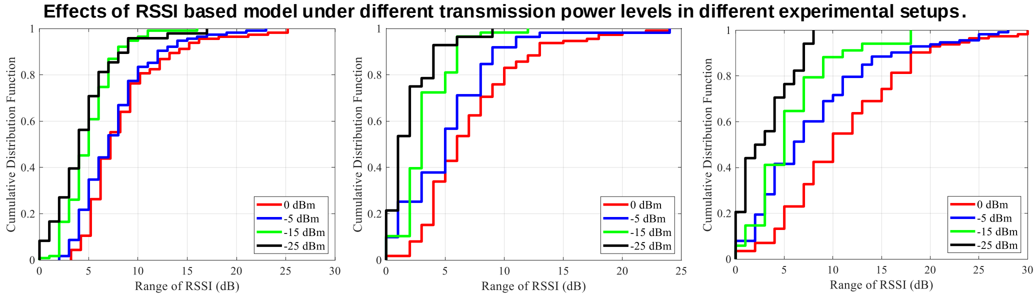
(a) Test 2 (b) Test 3 (c) Test 4

FIGURE 15. Range of SNR under different transmission power levels in different experimental setups.



(a) LR model (b) PR model (c) Simplified theoretical model

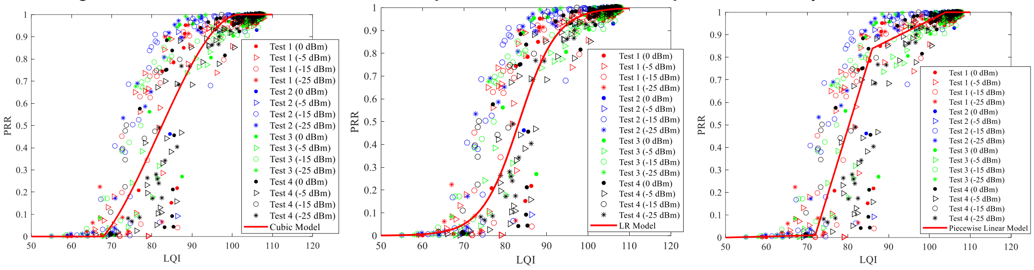
FIGURE 16. Effects of RSSI based model under different transmission power levels in different experimental setups.



(a) Test 2 (b) Test 3 (c) Test 4

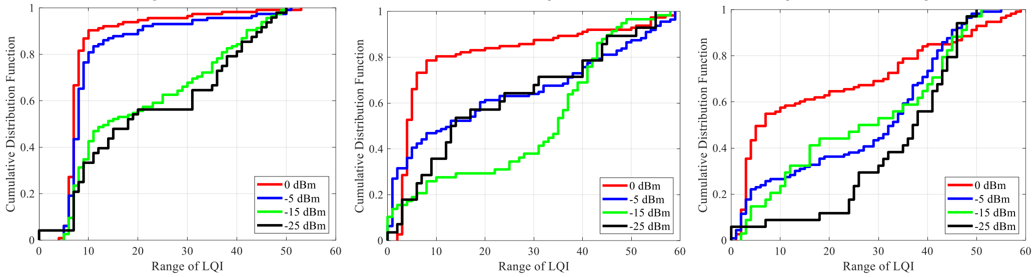
This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2024.3368381

FIGURE 17. **Range of RSSI under different transmission power levels in different experimental setups.**



(a) Cubic model (b) LR model (c) Piecewise linear model

FIGURE 18. **Effects of LQI based model under different transmission power levels in different experimental setups.**



(a) Test 2 (b) Test 3 (c) Test 4

VIII. Range of LQI under different transmission power levels in different experimental setups.

IX. CONCLUSION

TPC ensures effective network connectivity while minimizing WSN energy consumption. The network's accurate determination of link quality is critical to the efficiency of transmission power control. Although previous studies have given many proven, reliable metrics and models for link quality estimation, the vast majority of which have been developed and validated in the static transmission power case. In view of this, this paper evaluates the commonly used link quality estimators and models under different trans-mission power levels by experiments.

The results show that the distance based LQEs are not good approaches under different transmission power levels, whereas the SNR, RSSI and LQI based LQEs are good approaches under different transmission power levels, with their estimation ability remaining unaffected by the transmission power. The correlation with PRR of distance are also lower than SNR, RSSI and LQI.

For the models between SNR and PRR, compared with the theoretical model, the RMSEs of the logistic regression are lower. For the models between RSSI and PRR, the RMSEs of PR model are higher than LR model and simplified theoretical model. For the models between LQI and PRR, that the RMSEs of Cubic model, logistic regression model and piecewise linear model are lower. Compared with SNR and RSSI based LQEs, the existing LQI based LQEs are more accurate. In addition, the transmission power has an effect on the fluctuation of RSSI and SNR, but has a less effect on the fluctuation of LQI. In other words, LQI is the best link quality estimator under TPC.

REFERENCES

[1] M. A. Jamshed, K. Ali, Q. H. Abbasi, M. A. Imran and M. Ur-Rehman, “Challenges, applications, and future of wireless sensors in internet of things: A review,” *IEEE SENS J*, vol. 22, no. 6, pp. 5482-5494, 15 March15, 2022, 10.1109/JSEN.2022.3148128.

[2] S. Lin, F. Miao, J. B. Zhang, J. B. Zhou, G. Lin, He, T, J. A. Stankovic, S. Son and G. J. Pappas, “ATPC: Adaptive transmission power control for wireless sensor networks,” *ACM T Sensor Network*, vol. 12, no. 1, pp. 1-31, 2016, 10.1145/2746342.

[3] K. Srinivasan, M. A. Kazandjieva, S. Agarwal and P. A. Levis, “The β-factor: Measuring wireless link burstiness,” in *Proc. the 6th ACM conference on Embedded network sensor systems*, Raleigh, NC, USA, 19-21 November 2008, pp. 29-42.

[4] K. Srinivasan, P. Dutta, A. Tavakoli and P. Levis, “An empirical study of low-power wireless,” *ACM T Sensor Network*, vol. 6, no. 2, pp. 1-49, 2010, 10.1145/1689239.1689246.

[5] A. Bildea, O. Alphand, F. Rousseau and A. Duda, “Link quality metrics in large scale indoor wireless sensor networks,” in *Proc. the 2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications*, London, UK, 08-11 September 2013, pp.1888-1892.

[6] Z. Fan, S. Bai, S. Wang and T. He, “Delay-bounded transmission power control for low-duty-cycle sensor networks,” *IEEE Trans. Wireless Commun.*, vol. 14, no. 6, pp. 3157-3170, Jun. 2015, 10.1109/TWC.2015.2402681.

[7] H. U. Yildiz, B. Tavli and H. Yanikomeroglu, “Transmission power control for link-level handshaking in wireless sensor networks,” *IEEE SENS J*, vol. 16, no. 2, pp. 561-576, Jan. 2016, 10.1109/JSEN.2015.2486960.

[8] H. U. Yildiz, S. Kurt and B. Tavli, “Comparative analysis of transmission power level and packet size optimization strategies for WSNs,” *IEEE Syst J*, vol. 13, no. 3, pp. 2264-2274, Sept. 2019, 10.1109/JSYST.2018.2864941.

[9] D. Mu, Y. Ge, M. Sha, S. Paul and S. Chowdhury, “Robust optimal selection of radio type and transmission power for internet of things,” *ACM T Sensor Network*, vol. 15, no. 4, pp. 1-25, 2019, 10.1145/3342516.

[10] A. Pal, “Transmit power reduction ≠ proportional power savings: applicability of transmit power control in large-scale wireless sensor networks,” *IEEE IoTM*, vol. 3, no. 1, pp. 20-24, March 2020, 10.1109/IOTM.0001.1900067.

[11] K. Sabale and S. Mini, “Transmission power control for anchor-assisted localization in wireless sensor networks,” *IEEE SENS J*, vol. 21, no. 8, pp. 10102-10111, April. 2021, 10.1109/JSEN.2021.3054372.

[12] N. Baccour, A. Koubâa, L. Mottola, M. A. Zúñiga, H. Youssef, C. A. Boano and M. Alves, "Radio link quality estimation in wireless sensor networks: A survey," *ACM T Sensor Network*, vol. 8, no. 4, pp.1-33, 2012, 10.1145/2240116.2240123.

[13] A. Woo and D. E. Culler, "Evaluation of efficient link reliability estimators for low-power wireless networks," Oakland, CA, USA: Computer Science Division, University of California, 2003,1-20.

[14] W. Liu, Y. Xia and R. Luo, "FaLQE: Fluctuation adaptive link quality estimator for wireless sensor networks," *in Proc of the Wireless Sensor Networks: 13th China Conference*, Chongqing, China, 12-14 October 2019, pp. 48-60.

[15] J. Zhao and R. Govindan, "The β-factor: Understanding packet delivery performance in dense wireless sensor networks," *in Proc of the 1st ACM Conf. on Embedded Networked Sensor Systems*, Los Angeles, 05-07 November 2003, pp. 1–13.

[16] W. Sun, X. Yuan, J. Wang, Q. Li, L. Chen and D. Mu, "End-to-end data delivery reliability model for estimating and optimizing the link quality of industrial WSNs," *IEEE T AUTOM SCI ENG*, vol. 15, no. 3, pp. 1127-1137, July 2018, 10.1109/TASE.2017.2739342.

[17] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian and E. J. Coyle, "A kalman filter based link quality estimation scheme for wireless sensor networks," *in Proc of the IEEE Global Telecommunications Conference*, Washington, DC, USA, 26-30 November 2007, pp. 875-880.

[18] T. Liu and A. E. Cerpa, " Data-driven link quality prediction using link features," *ACM T Sensor Network*, vol. 10, no. 2, pp.1-35, 2014, 10.1145/2530535.

[19] R. Ye, A. Boukerche, H. Wang, X. J. Zhou and B. Yan, "RECODAN: An efficient redundancy coding-based data transmission scheme for wireless sensor networks," *Computer Networks*, vol. 110, pp.351-363, 2016, 10.1016/j.comnet.2016.10.010.

[20] W. Sun, W. Lu, Q. Li, L. Chen, D. Mu and X. Yuan, "RECODAN: WNN-LQE: wavelet-neural-network-based link quality estimation for smart grid WSNs," *IEEE Access*, vol. 5, pp. 12788-12797, 2017. 10.1109/ACCESS.2017.2723360.

[21] W. Liu, Y. Xia, J. Xie, M. Xu, R. Luo, S. R. Hu, X. Y. Dang and D. Q. Huang, "Simplified theoretical model based self-adaptive packet reception rate estimation in sensor networks," *in Proc of the IEEE Wireless Communications and Networking Conference*, Seoul, South Korea, 6-9 April 2020, pp. 1-6.

[22] R. D. Gomes, D. V. Queiroz, A. C. Lima Filho, I. E. Fonseca and M. S. Alencar, "Real-time link quality estimation for industrial wireless sensor networks using dedicated nodes," *Ad Hoc Networks*, vol. 59, pp. 116-133, 2017, 10.1016/j.adhoc.2017.02.007.

[23] A. Ranjan, H. B. Sahu, P. Misra, Y. Zhao and H. Sun, H, "RSSI or LQI: Insights from real-time deployments for underground sensing and applications," *in Proc of the IEEE INFOCOM 2020 - IEEE Conference on Computer Communications Workshops*, Toronto, ON, Canada, 06-09 July 2020, pp. 1231-1236.

[24] J. Luo, L. Yu, D. F. Zhang, Z. Xia and W. Chen, "A new link Quality estimation mechanism based on LQI in WSN," *Information Technology Journal*, vol. 12, no. 8, pp. 1626-1631, 2013, 10.3923/itj.2013.1626.1631.

[25] G. Carles, B. Antoni and P. Josep, "Impact of LQI-Based routing metrics on the performance of a one-to-one routing protocol for IEEE 802.15.4 multihop networks," *EURASIP Journal on Wireless Communications and Networking 2010*, vol. 6, pp. 1-20, https://doi.org/10.1155/2010/205407

[26] T. Jayasri and M. Hemalatha, "Link quality estimation for adaptive data streaming in WSN," *Wireless Personal Communications*, vol. 94, pp. 1543-1562, 2016, 10.1007/s11277-016-3697-7.

[27] Z. Huang, L. Y. Por, T. F. Ang, M. H. Anisi and M. S. Adam, "Improving the accuracy rate of link quality estimation using fuzzy logic in mobile wireless sensor network," *Advances in Fuzzy Systems*, vol. 1, pp. 1-13, 2019, 10.1155/2019/3478027.

[28] W. Liu, Y. Xia, R. Luo and S. Hu, "Lightweight, fluctuation insensitive multi-parameter fusion link quality estimation for wireless sensor networks," *IEEE Access*, vol. 8, pp. 28496-28511, 2020, 10.1109/ACCESS.2020.2972326.

[29] M. He and J. Shu, "A link quality estimation method for wireless sensor networks based on deep forest," *IEEE Access*, vol. 9, pp. 2564-2575, 2021, 10.1109/ACCESS.2020.3047648.

[30] D. Fernandes, A. G. Ferreira, R. Abrishambaf, J. Mendes and J. Cabral, "A low traffic overhead transmission power control for wireless body area networks," *IEEE SENS J*, vol. 18, no. 3, pp. 1301-1313, 1 Feb.1, 2018, 10.1109/JSEN.2017.2778802.

[31] J. -S. Lee and Y. -C. Lee, "An application of grey prediction to transmission power control in mobile sensor networks," *IEEE Internet Things J*, vol. 5, no. 3, pp. 2154-2162, Jun. 2018, 10.1109/JIOT.2018.2826008.

[32] A. H. Sodhro, S. Pirbhulal, G. H. Sodhro, A. Gurtov, M. Muzammal and Z. Luo, "A joint transmission power control and duty-cycle approach for smart healthcare system," *IEEE SENS J*, vol. 19, no. 19, pp. 8479-8486, 1 Oct. 2019, 10.1109/JSEN.2018.2881611.

[33] S. Sawaguchi, J. F. Christmann, A. Molnos, C. Bernier and S. Lesecq, "Multi-agent actor-critic method for joint duty-cycle and transmission power control," *in Proc of the 2020 Design, Automation & Test in Europe Conference & Exhibition*, Grenoble, France, 09-13 March 2020, pp. 1015-1018.

[34] S. Zoppi, I. Smolin and W. Kellerer, "Experimental transmission power control policy for remote state estimation in industrial WSN," *in Proc of IEEE ICC 2021*, Montreal, QC, Canada, 2021, pp. 1-6.

[35] K. Sabale and S. Mini, "Transmission power control for anchor-assisted localization in wireless sensor networks," *IEEE Sensors Journal*, vol. 21, no. 8, pp. 10102-10111, 15 April15, 2021.

[36] A. K. Yadav, A. Sharma, A. Yadav, A. Vijayvargiya, A. Saxena and R. Kumar, "Optimization scheme for power transmission in wireless sensor network," *in Proc of* PIECON 2023, Aligarh, India, 2023, pp. 1-6.

Haoqi Hu was born in Chongqing, China. She is currently pursuing a BEng degree in Data Science and Big Data Technology with Contemporary Entrepreneurialism at the School of AI and Advanced Computing, XJTLU Entrepreneur College (Taicang), Xi'an Jiaotong-Liverpool University, Taicang, Jiangsu, China. Her major field of study is artificial intelligence and advanced computing.