EasiPLED: Discriminating the Causes of Packet Losses and Errors in Indoor WSNs

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***Abstract*—It is well known that there are two kinds of causes, namely channel-errors and collisions, which lead to high probability of packet losses and errors in wireless networks. The ability of discriminating the above two causes provides many opportunities for implementing high efficient networking protocols in wireless sensor networks (WSNs). This paper presents EasiPLED, a discriminator that can accurately and timely predict these two causes. EasiPLED has three salient features. First, it investigates F-BER patterns and statistic characteristics of RSSI in different indoor environments through extensive experimental studies. F-BER is the Frame-level Bit Error Rate measured at the receiver side by a coarse-grained method without incurring any overhead. An adaptive RSSI estimator based on error-based filter is proposed to mitigate effects of noise on RSSI readings for successfully received packets. Second, EasiPLED designs an off-line dominant-factor classifier using machine learning method. The classifier takes a combination of F-BER and RSSI features as input and outputs the probability of dominant causes of failed transmissions. Finally, it presents a lightweight on-line discriminator which diagnoses the root cause of a packet loss or error when it occurs at the receiver side. Experimental results show that EasiPLED achieves an accuracy by up to 95.4%. We evaluate the effectiveness of EasiPLED by applying it to link-layer retransmission scheme, which yields a reduction of single-hop transmission delay by up to 47%, and provides high packet delivery ratios as compared to the existing retransmission methods.**

I. INTRODUCTION

It is widely aware that packet transmission failures, namely losses and errors, occur with high probability during transmissions in wireless networks [1, 2]. The causes that induce such failures can be classified into two main categories: channel-errors and collisions. The former stems from channel fading or multi-path fading at physical layer. The latter is mainly due to multiple concurrent packet transmissions within the same network, or high power cross-technology interferences from other networks, such as 802.11 networks. For protocol design in wireless sensor networks (WSNs), it is crucial to know the exact causes of packet losses and errors to improve its performance. For example, MAC-layer protocols could adapt operation decisions (e.g., channel allocation, power control or retransmission) according to current packet transmission outcomes [3]. Routing protocols could select links with lower channel-errors but temporarily heavier interference to route packets more reliably and rapidly [4]. It is worth noting that in this paper we differentiate packet loss from packet error. In particular, the former occurs when receiver does not sense any bits of a packet, while the latter occurs when receiver receives a packet with one or more error bits.

Despite its potential for improving protocol performance, such as robustness and efficiency, diagnosing causes of packet transmission failures has received little attention in WSNs. A few research work [2, 5] have been presented for 802.11 networks, but they are not applicable to WSNs due to their moderate to significant measurement overheads. To the best of our knowledge, only two recent research work [6, 7] have been proposed for WSNs. [6] is implemented on USRP and is hard to implement on current commercial sensor motes. [7] needs continuous RSSI sampling which incurs significant measurement overhead.

Fig. 1. EZ240 sensor mote

To cope with above problems, we design a novel discriminator, named EasiPLED, to predict the root causes of packet transmission failures for indoor WSNs. Essentially, EasiPLED is designed by exploiting our observed fact that error packet tends to have more error bits and its RSSI fluctuates more sharply in collision-dominated environments. In particular, EasiPLED models and trains a dominant-factor classifier using machine learning method. EasiPLED is motivated by the increasing mission-critical indoor WSN applications, such as industrial monitoring and health care, in which the reliable and timely communications are crucial. Channel-errors and collisions pose great challenges to such applications, as they lead to transmission failures, high delay and reduce communication reliability due to incorrect operations. EasiPLED explicitly feeds back discrimination results from the receiver to the transmitter. Therefore, EasiPLED provides transmitter accurate and timely information necessary for implementing robust and reliable networking protocols, thereby improving the performance of communications in WSNs.

We implement and evaluate EasiPLED on our EZ240 sensor mote [8] as shown in Fig. 1 using TinyOS-2.x operation system. EZ240 is equipped with a 802.15.4-compliant CC2420 radio [9]. Experimental results show that EasiPLED distinguishes the causes of transmission failures with an accuracy range between 86.3% and 95.4%. We also evaluate the effectiveness of EasiPLED by introducing it to link-layer retransmission scheme, which reduces the single-hop transmission delay by 13% to 47%, while keeping relatively high single-hop packet delivery ratios.

This paper makes the following three main contributions.

First, we study frame-level bit error rate (F-BER) patterns and statistic characteristics of received signal strength indicator (RSSI) and link quality indicator (LQI) through extensive experimental measurements in different indoor scenarios with diverse settings.

Second, we design a coarse-grained F-BER computation method at the receiver side without requiring explicit knowledge of data content sent by the transmitter. Also, we propose an adaptive RSSI estimator based on error-based filter. Then, we adopt a cross-layer design scheme which combines F-BER and RSSI together as input features to model and train an off-line dominant-factor classifier using machine learning method. The classifier outputs the probability of causes that induce packet transmission failures, either channel-errors or collisions.

Finally, we present a lightweight and timely on-line discriminator, which predicts the root cause of every failed transmission. Based on the discrimination results of EasiPLED, we optimize link-layer retransmission scheme to improve the performance of WSNs in terms of single-hop transmission delay without sacrificing communication reliability.

The remainder of the paper is organized as follows. Section II discusses some related work on diagnosis of packet transmission outcomes. In Section III, we perform extensive experimental study to investigate the features of packet transmission failures. Section IV describes the design details of EasiPLED. An adaptive link-layer retransmission scheme based on EasiPLED is presented and evaluated in Section V. Section VI concludes the paper.

II. Related Work

Related work falls into the following two categories.

PHY-based: PHY-based methods exploit physical-layer information to classify packet transmission outcomes. COLLIE [2] examines error patterns within a physical-layer symbol to separate collision from weak signal for 802.11 networks. However, COLLIE requires the receiver to feed back error packets to the sender. So COLLIE is not applicable to WSNs because of the following reasons. First, the error packet may be corrupted again when it is sent back to the transmitter. Second, it incurs significant measurement overheads and reduces energy efficiency and bandwidth utilization. SoftRate [10] identifies collision by detecting sudden changes in the BER estimated from SoftPHY hints. SoftRate is designed for 802.11 networks and needs access to physical layer which is difficult to implement on the current commercial sensor motes. [7] studies chip error patterns in physical layer based on IEEE 802.15.4 standard. Thus, it also needs access to physical layer and is hard to implement on the sensor motes. [6] presents a joint RSSI-LQI based classifier for WSNs, which classifies packet transmission outcomes into four types: lost, successfully received, error due to collisions and error due to weak signal. However, it does not discriminate the causes of packet losses. Moreover, it needs continuous RSSI sampling which incurs heavy overhead, thus leading to high energy consumption.

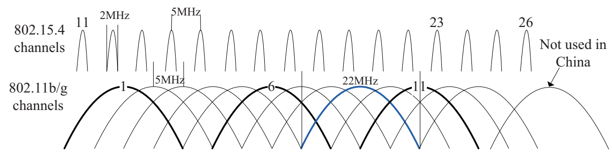


Fig. 2. 802.11b/g and 802.15.4 channels in 2.4 GHz ISM band

Frame-based: Frame-based methods [11, 12] use RTS/CTS frames to distinguish between collisions and channel-errors under the assumption that the packet lost is duo to collisions if RTS-CTS exchange has completed. Because RTS-CTS exchange has reserved channel, packet transmission will only encounter failure by channel-errors. [5] uses RTS/CTS frames and packet fragmentation mechanisms to isolate channel-error induced packet losses. However, RTS/CTS is often disabled in WSNs because it will introduce additional control overhead.

III. Observations from Experiments

In this section, we conduct extensive experiments in different indoor environments to investigate F-BER patterns and statistic characteristics of RSSI and LQI of received packets.

A. Background and Experimental Methodology

Background: CC2420 radio operates on a total of 16 channels in 2.4 GHz unlicensed ISM band, numbered 11 through 26. Each of these channels is 2 MHz wide with a center frequency separation of 5 MHz for adjacent channels. CC2420 radio provides a built-in RSSI and LQI sampling mechanisms. RSSI is the estimate of signal power and is always averaged over 8 symbol periods. LQI is an average correlation value based on 8 first symbols of each incoming packet.

Experimental setup and methodology: We conduct all our experiments in three different indoor environments: dormitory building of Chinese Academy of Sciences (Dor), top floor (Roof) and laboratory (Lab) in ICT's (Institute of Computing Technology) office building. The objective of these experiments is to explore F-BER patterns and statistic characteristics of RSSI and LQI of received packets in channel-error-dominated and collision-dominated environments.

1) Dor and Roof scenarios. We first conduct experiments in environments without or with mild cross-technology interference: Dor and Roof. In the Dor scenario, the sensor nodes are sparsely deployed out of line of sight, and separated by doors or thick walls. However, in the Roof scenario, the environment is more open and the distances between nodes are in line of sight. As shown in Fig. 2, two 802.15.4 channels, numbered 11 and 26, are free from potential 802.11 interference. Therefore, in these two scenarios, we set nodes operate on channel 26 to avoid interference from 802.11 networks. These experiments mainly focus on capturing the features of packet losses and errors caused by channel-errors or collisions from 802.15.4 transmissions.

2) Lab scenario. We also conduct experiments in our laboratory. The nodes in this scenario operate on channel 23, which mainly overlaps with two 802.11 channels, namely channel 11 and channel 12. We find that, in our laboratory, there are almost 25 active APs (Access Point) occupying all channels except 14 during the office hours. So in the

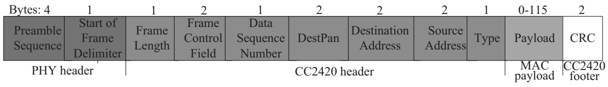
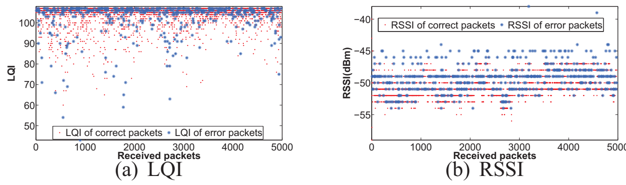
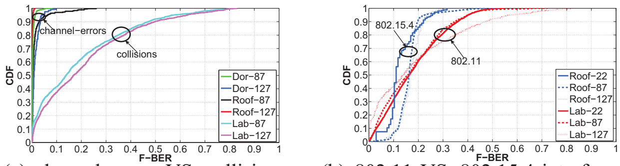


Fig. 3. Format of packet implemented in TinyOS-2.x



(a) LQI (b) RSSI

Fig. 4. Instant RSSI and LQI of received packets in Lab scenario with 127-byte packet



(a) channel-errors VS. collisions (b) 802.11 VS. 802.15.4 interference

Fig. 5. Distribution of F-BERs in different scenarios

Lab scenario, packet transmissions on 802.15.4 channels will suffer severe 802.11 interferences. These experiments are to exploit the characters of transmission failures due to collisions from 802.11 or 802.15.4 or both.

In all environments, we run experiments under various settings by using different size of packets (22/87/127 bytes), different number of transmitters, and different transmission power levels. The experiments are conducted in daytime and night to compare effects of light and heavy interferences on nodes' communication. In all experiments, we disable clear channel assessment (CCA) to increase the probability of collisions. The function of cyclic redundancy check (CRC) and address recognition are also canceled to intercept error packets. Moreover, data content sent by transmitters are random numbers other than all zeros or all ones.

In single-transmitter scenarios, one transmitter sends 5000 packets every 300 millisecond to another receiver. The receiver records every received packet including those with errors and their RSSI and LQI. In multiple-transmitter settings, there are multiple transmitters, one receiver and one synchro node. The synchro node broadcasts a synchro packet every one second to make all transmitters send packets in synchronization. We adjust transmission power level to ensure the receiver can receive almost all packets successfully when there is no interference. Every experiment is conducted repeatedly for 10 or more times.

B. Empirical Observations

In this section, we analyze the F-BER patterns and the statistic characteristics of RSSI and LQI of received packets. F-BER is the frame-level bit error rate of packet. Fig. 3 shows the format of packet implemented in TinyOS-2.x. Due to space limitations, we only plot a part of results observed in our experiments, since the others are similar. Our key observations from the above empirical studies are summarized as follows.

- As shown in Table I, error packets make up moderate to significant fractions of whole received packets (E/R: 45.3% in Dor, 22.9% in Roof and 57.8% in Lab), and the whole failures (E/F: 53.8% in Dor, 87.6% in Roof and 44.8% in Lab). We can make full use of information obtained from these error packets to distinguish the causes of packet losses and errors.
- Fig. 4 plots the instant RSSI and LQI of all received packets. We find that the instant RSSI and LQI fluctuate quickly. Moreover, through deeper analysis of the results, we find that averaged RSSI of error packets over a short-term increases in the collision-dominated scenarios (e.g., Lab) but decreases in channel-error-dominated scenarios (e.g., Dor and Roof). However, averaged LQI of error packets decreases in all scenarios. Meanwhile, as shown in Table I, the extent of RSSI fluctuations in different scenarios is different. In collision-dominated scenarios, RSSI varies more greatly than that in channel-error-dominated scenarios. For example, the variance of RSSI of error packets is 0.29 in Roof, while it is 16.4 in Lab. However, the extent of LQI fluctuations has no such differences between theses two scenarios. Based on these observations, we use the variance of RSSI fluctuations between error packets and correct ones (denoted as $var(RSSI)$) as one input feature of our machine learning model.
- Fig. 5 plots the empirical CDF of F-BERs. We find that packets received with errors result from collisions have much wider distribution of F-BERs. For example, 90% of error packets due to channel-errors have F-BERs of 3% or less, while only about 25% of error packets due to collisions have F-BERs of 3% or less. Meanwhile, F-BERs under 802.11 and 802.15.4 interferences have similar distribution patterns as shown in Fig. 5(b). Therefore, we use F-BER as another input feature of our machine learning model.

IV. Design of EasiPLED

In this section, we present the design of EasiPLED in detail.

A. An Overview of EasiPLED

EasiPLED is data-driven and receiver-initiated which consists of three main steps: information collection and analysis (ICA), off-line modeling and training (OLMT) and on-line diagnosis (OLD).

ICA: ICA step extracts features which characterize the causes of packet losses and errors. Specifically, ICA passively captures all the arrived packets and records their RSSI values. Meanwhile, ICA computes F-BER for every packet with error bits, and then extracts features and builds training and testing data sets for the next step OLMT.

OLMT: OLMT step achieves an off-line classifier using machine learning method to predict the dominant factor of packet failures. Our model takes a combination of F-BER and $var(RSSI)$ as input features, and outputs the probability of dominant-factor that causes packet losses and errors, either channel-errors or collisions.

OLD: OLD step implements a lightweight on-line discriminator, which runs at the receiver side and timely diagnoses the root causes of a packet transmission failure when it occurs.

TABLE I
STATISTIC RESULTS WITH 127-BYTE PACKETS (VAR: VARIANCE, E: ERROR, F: FAILED (ERROR AND LOST), R: RECEIVED (ERROR AND CORRECT))

Scenario	Mean(RSSI,C)	Mean(RSSI,E)	Var(RSSI,C)	Var(RSSI,E)	E/F	E/R	Mean(F-BER)	Max(F-BER)
Dor	-91.35	-92.46	0.35	0.51	53.8%	45.3%	0.9%	7.8%
Roof	-91.49	-91.5	0.28	0.29	87.6%	22.9%	0.2%	1.3%
Lab	-70.38	-66.95	3.8	16.4	44.8%	57.8%	17.3%	72.1%

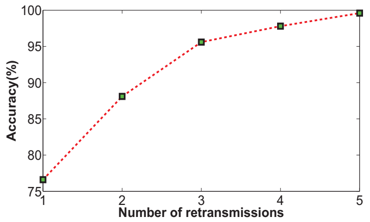


Fig. 6. Accuracy of F-BER computation method under different retransmission times

B. Information Collection and Analysis

For the ICA step, the novelty is mainly embodied in its method to compute F-BER and estimate RSSI. Here, we describe them in detail.

F-BER computation: The idea behind F-BER is inspired by the error detection scheme employed in Ethernet. An Ethernet station detects errors by comparing the transmitted signal with the simultaneously received signal at the transmitter side. However, in wireless networks, radio often operates in a half-duplex mode and cannot send and listen simultaneously to detect errors. Even if nodes have multiple radios, they can not detect errors at transmitter side because any channel status around the transmitter can not explain errors at receiver due to signal attenuation.

In this paper, we present a coarse-grained F-BER computation method at the receiver side. Unlike COLLIE [2], it does not need to know the content of packet sent by transmitter. Because current protocols in link layer always employ retransmission schemes to ensure reliable communications in WSNs. ICA keeps the error packet and computes F-BER when the final correct one is arrived. If the packet is received by multiple times of (re)transmissions with different bits in error, we will compute F-BER for each time of (re)transmission. The final F-BER is an average over its multiple (re)transmission times. The accuracy of F-BER is affected by the retransmission times. Fig. 6 shows the accuracy of F-BER computation method under different retransmission times. We find that more than 95% of packets which are in error at first arrival can be received successfully after three times of retransmissions. In Section V, we will evaluate and discuss how EasiPLED can be integrated to adapt link-layer retransmission scheme in return.

RSSI estimation: Because RSSI reading is influenced by hardware and communication environments greatly [13, 14], we use error-based filter (EF) [15] to mitigate the effects of noises on RSSI estimation of successfully received packets. RSSI estimator is formulated as follows.

$$RSSI_t = \alpha RSSI_{t-1} + (1-\alpha) RSSI_{new}, \tag{1}$$

where $RSSI_t$ is the current estimate of RSSI, $RSSI_{t-1}$ is the prior estimate of RSSI, and $RSSI_{new}$ is the current observation of RSSI. α is the smoothing factor, which is not constant and calculated by the following formula.

$$\alpha = 1 - \frac{\delta_t}{\delta_{max}}, \tag{2}$$

where δ_t is the predictive power of the EF estimator, which can be adapted to control the error deviation of the EF estimator. So δ_t is also named as estimator error. When the EF estimator produces estimates that match well with reality, it increases the weight of the prior estimates through increasing the smoothing factor α. Otherwise, it reduces the weight of the prior estimates by decreasing the smoothing factor. The estimate error δ_t is the absolute difference between the prior estimate and the current observation. Rather than uses the raw error directly, the EF estimator uses a secondary EWMA (Exponentially Weighted Moving Average) filter to smooth the estimation error δ_t.

$$\delta_t = \beta\delta_{t-1} + (1-\beta)|RSSI_{t-1} - RSSI_{new}|. \tag{3}$$

δ_{max} is the largest estimation error of the latest measurements.

C. Off-Line Modeling and Training

Problem modeling: Based on the features and data sets provided by the ICA step, we propose to use machine learning method to build a binary classifier model. Our model adopts a cross-layer design scheme which takes the RSSI from physical layer and F-BER from link layer as input, and outputs the probability of the dominant-factor which causes packet transmission failures. We use x to denote the input vector of our model and is written as

$$x = [var(RSSI), F\text{-}BER], \tag{4}$$

and y to denote the output which is the probability of the dominant-factor, either channel-errors or collisions.

$$y = p(dominant\text{-}factor \mid x). \tag{5}$$

We define the extent of RSSI fluctuation between error packet and correct packet as follows.

$$d(RSSI) = (RSSI_t(C) - RSSI_{new}(E))^2, \tag{6}$$

where $RSSI_t(C)$ is the estimated value of RSSI of correctly received packet, and $RSSI_{new}(E)$ is the current observation of error packet. $var(RSSI)$ is the standard deviation of the last W $d(RSSI)$s. When the packet is lost, we set F-BER to be the average of the last W error packets'. For the RSSI value of the lost packet, it is set to be lower than the receiver sensitivity threshold which is -95 dBm for the CC420 radio.

Model training and testing: The modeling method should take following practical requirements into consideration.

1) Sampling complexity. The model should not need significant deployment efforts for collecting training and testing data sets in a long period. Otherwise, the overhead of collecting data sets will outweigh the benefits gained by using the model. **2) Computation and space complexity**. While training the model offline can be computationally and spatially costly, the implementation of on-line diagnosis using the trained model should have low computation complexity and small memory requirements.

Based on the above requirements, we address the binary classification problem using logistic regression model. Logistic regression model is widely used in machine learning field and can be easily to implement on the sensor motes. Therefore, our problem can be modeled as follows.

$$p(y|x;\theta) = (h_\theta(x))^y(1 - h_\theta(x))^{1-y}, \tag{7}$$

where

$$h_\theta(x) = \frac{1}{1+e^{-z}}, \tag{8}$$

$$z = \theta^T x = \theta_0 + \theta_1 var(RSSI) + \theta_2 F\text{-}BER. \tag{9}$$

We use $y = 0$ to denote channel-errors and $y = 1$ to denote collisions.

All the data sets used in our model are obtained in three scenarios introduced in Section III. We randomly choose 60% of data sets to train our model, and the remaining 40% to test our model. In the training process, we consider three parameters: size of packet (L), size of feature estimation window (W) and size of training set (M). For each setting, we repeat the training and testing procedures for 10 times.

Results analysis: Here, we present evaluation results of our model. We plot the mean square error (MSE) as a function of L, W and M, respectively. Ideally, we would like to have the MSE as low as possible when W and M are small and irrelevant to packet size of L. As shown in Fig. 7, we find that: 1) Intuitively, the shorter the packet, the lower probability of packet failures. However, once bit error occurs, the F-BER pattern and statistic characteristics of RSSI have no great difference in the settings with different packet size. 2) The larger W, the smaller prediction error of the model. However, this trend is negligible when W is greater than 3. Therefore, our model should work reasonably well with a small size of feature estimation windows, particularly it is 3 observed from the figure. 3) When the size of training set M is larger than 500, the prediction errors are all most the same. This shows that we only need about 500 packets to train our model, which enables our model easily be implemented in real WSNs deployment.

D. On-Line Diagnosing

In this section, we describe the design of on-line discriminator EasiPLED, which diagnoses the root causes for each packet loss or error at the receiver side. The pseudo code of EasiPLED is shown in Algorithm 1. Whenever node receives a packet, it estimates the value of RSSI using the method introduced in Section IV-B and records it in its neighbor table. If the packet does not pass address recognition or CRC check, receiver computes its F-BER and $var(RSSI)$ using the method introduced in Section IV-B and records them in neighbor table. Receiver uses F-BER and $var(RSSI)$ as input of logistic regression model and outputs the probability of dominant-factor p. In order to reduce the probability of misclassification, we exploit the F-BER pattern of packet's header which further confirms the outputs of the logistic regression model. Specifically, we measure the probability of error occurred in CC2420 header of all error packets by the metric $R_{F\text{-}BER}$, which is defined as follows.

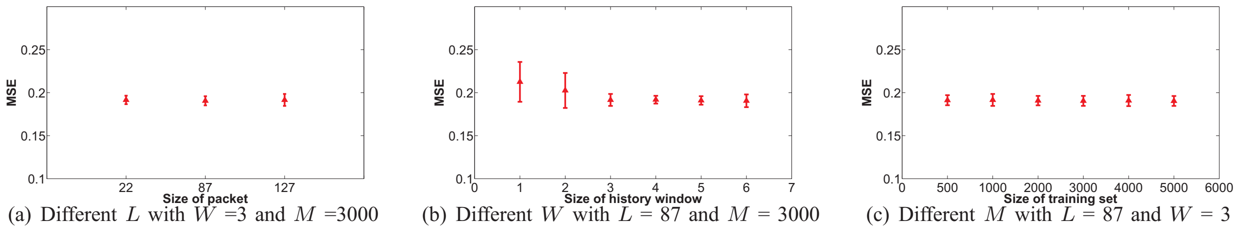
$$R_{F\text{-}BER} = \frac{\#\_F\text{-}BER(header) \neq 0}{\#\_F\text{-}BER(packet)}. \tag{10}$$

When p falls into the critical region [0.5 - ϵ, 0.5 + ϵ], EasiPLED initiates critical region detection process using the metric $R_{F\text{-}BER}$ as shown from line 10 to 15 in Algorithm 1. This is motivated by the observations that the probability of header is corrupted in collision-dominant scenarios is much lower than that in channel-error-dominant scenarios. We set ϵ to 0.1 and $F\text{-}BER_h$ to 0.06 in our experiments.

Algorithm 1 EasiPLED algorithm

Input:
ϵ, $F\text{-}BER_h$, θ_0, θ_1, θ_2;
Output:
Root causes: channel-errors or collisions;
1: Compute $F\text{-}BER$;
2: Compute $var(RSSI)$;
3: Compute p using logistic regression model with input $F\text{-}BER$ and $var(RSSI)$;
4: **if** ($p \in$ [0.5+ϵ, 1]) **then**
5:   **return** collisions;
6: **else**
7:   **if** ($p \in$ [0, 0.5-ϵ]) **then**
8:     **return** channel-errors;
9:   **else**
10:     Compute $R_{F\text{-}BER}$;
11:     **if** ($R_{F\text{-}BER} \leq F\text{-}BER_h$) **then**
12:       **return** collisions;
13:     **else**
14:       **return** channel-errors;
15:     **end if**
16:   **end if**
17: **end if**

We evaluate the performance of EasiPLED in Dor, Roof and Lab environments. The prediction accuracy is computed as the ratio of the number of correct diagnosis to the total number of lost or error packets. The evaluation experiments are conducted as presented in Section III with the exception that here we enable CCA before transmissions. Fig. 8 shows the evaluation results. As environment becomes more complex and the number of contenders increases, it is more difficult to identify the exact causes of packet losses or errors. Especially in the environment where collisions or interference are severe but signal is not very strong, the accuracy of diagnosis decreases. However, the maximal rate of misdiagnosis is 13.7% which works well as evaluated in Section V. We also evaluate the method used by [6] on our EZ240 sensor motes. Evaluation results show that the joint RSSI-LQI method has high prediction errors in our experiments, which can be up to 28%. This is because that the relationship between RSSI and LQI can not be accurately captured by a simple linear model.



(a) Different L with W =3 and M =3000 (b) Different W with L = 87 and M = 3000 (c) Different M with L = 87 and W = 3

Fig. 7. Prediction errors under different training settings

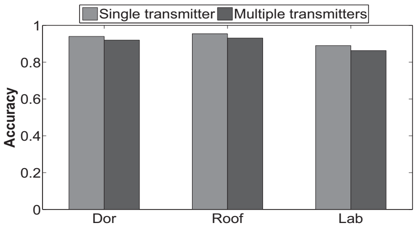


Fig. 8. Prediction accuracy of EasiPLED in different scenarios

TABLE II
RETRANSMISSION PARAMETERS USED BY DIFFERENT SCHEMES. CO: COLLISIONS, CE: CHANNEL-ERRORS

Schemes	Retransmission delay	Retransmission times
A-ARQ	CO: [0,25], CE: 0	CO: 2, CE: 4
F-ARQ	12/25	3
E-ARQ	[0,25]	3

V. APPLICATION OF EASIPLED TO LINK-LAYER RETRANSMISSION SCHEME

In this section, we introduce EasiPLED to link-layer retransmission scheme and demonstrate how EasiPLED can help make more intelligent retransmission decisions, therefore, achieving a good tradeoff between delay and reliability.

A. Adaptive Retransmission Scheme based on EasiPLED

Per-hop retransmission (or Automatic Repeat Request, ARQ) is a widely used technique in link layer to improve the reliability of communication in WSNs [16]. ARQ has two important operation parameters: retransmission times and delay between consecutive retransmissions. Traditional ARQ can be classified into two categories: fixed ARQ (F-ARQ) and exponential ARQ (E-ARQ). F-ARQ adopts fixed retransmission times and delays, no matter what is the causes of packet transmission failures. E-ARQ takes for granted that packet transmission failure is due to collisions and increases retransmission delay exponentially when failure occurs. However, if the packet transmission failure results from channel-errors, blindly increasing retransmission delay will increase the single-hop transmission delay. On the contrary, if the transmission fails due to collisions, a short retransmission delay will increase the probability of repeated collisions and finally leads to low reliability of communications. Therefore, F-ARQ and E-ARQ can not adapt to different communication scenarios. More retransmission times will improve the reliability of communication, but increase transmission delay as well. Therefore, ARQ has great impact on the performance of link-layer protocols in terms of delay and reliability. Here, the goal of our adaptive ARQ (A-ARQ) is to achieve a good tradeoff between delay and reliability by utilizing the diagnosis results of EasiPLED to adapt the above two parameters of retransmission scheme.

The key idea behind A-ARQ is intuitive. When the packet transmission failure is diagnosed to be caused by collisions, A-ARQ increases retransmission delay and reduces retransmission times. Otherwise, A-ARQ retransmits packet immediately without any delay and increases retransmission times. Because EasiPLED is implemented at the receiver side, so we need feed back the diagnosis result of EasiPLED to the transmitter. Therefore, we define another MAC control frame, named non-acknowledgement packet (NACK). When packet transmission failure is detected, receiver initiates EasiPLED diagnosis process and then sends back a NACK frame to explicitly inform the transmitter of the diagnosis result of EasiPLED. The format of NACK is defined as the same with that of acknowledgement (ACK).

B. Experimental Evaluation

Experimental setup: In this section, we evaluate the performance of A-ARQ through experiments conducted in the Roof and Lab scenarios. We integrate A-ARQ into CC2420 radio stack in TinyOS 2.x and implement it on the EZ240 sensor mote. In order to study the performance of A-ARQ in environments with heavy contentions, three transmitters are assigned to send 5000 back-to-back packets to a same receiver. The transmitters are synchronized to start transmitting packets at different time points. In each scenario, we consider different distance from transmitter to receiver as shown in Fig. 9. We adjust the distance between transmitter and receiver in order to create collision-dominated (Lab) and channel-error-dominated scenarios (Roof). We compare the performance of A-ARQ with that of F-ARQ and E-ARQ in terms of single-hop transmission delay and packet delivery ratio. The single-hop transmission delay is the averaged transmission time of the total transmitted packets. The experimental parameters used in our study are shown in Table II. For F-ARQ, we consider two settings: F-ARQ(12) with 12 ms retransmission delay and F-ARQ(25) with 25 ms retransmission delay. The results presented below are averages of 5 times of repeated experiments.

Experimental results: Fig. 10 and 11 plot the single-hop transmission delay and packet delivery ratio in the Lab and Roof scenarios respectively.

- In comparison with F-ARQ and E-ARQ, A-ARQ reduces single-hop transmission delay (by 13% to 47%) in all scenar-

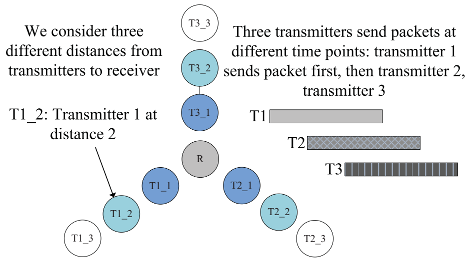
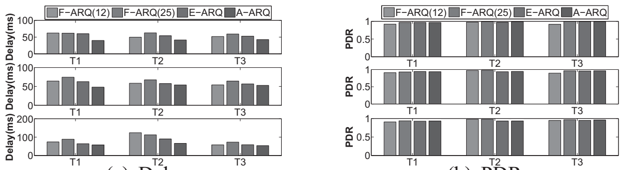


Fig. 9. Experimental topology



(a) Delay (b) PDR

Fig. 10. Single-hop transmission delay and packet delivery ratio in Lab scenarios. Up: Distance 1, Middle: Distance 2, Down: Distance 3

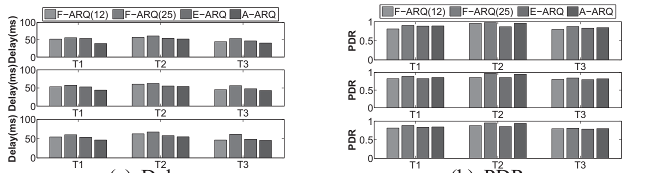
ios without reducing the communication reliability. This is due to its use of diagnosis results of EasiPLED to help make more intelligent retransmission decisions. This observation can also be validated by Fig. 12, which plots the instant delay of A-ARQ and E-ARQ. We find that more packets in E-ARQ suffer larger delays.

- In channel-error-dominated scenarios (Roof), the performance improvement achieved by A-ARQ becomes not so obvious and the PDR declines when compared to that in collision-dominated scenarios. This is because we reduce transmission power level in order to create channel-error-dominated scenarios, which makes communication links more unstable.
- F-ARQ(25) achieves relative high reliability at the cost of high delay. In contrast, F-ARQ(12) has the worst reliability in all scenarios because of its fixed retransmission decisions.
- Transmitter 2 has highest delay in both scenarios. This is because it (re)transmits about one third of packets when there are three transmitters send packets simultaneously. One the contrary, transmitter 3 has the lowest delay.

VI. Conclusions and Future Work

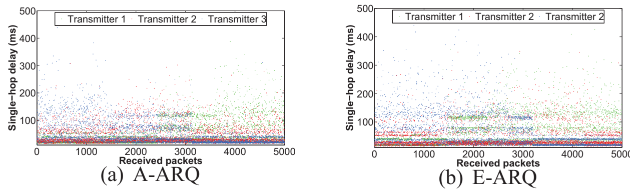
This paper presents EasiPLED, a lightweight and timely online discriminator, which can accurately and timely predict the root causes of packet losses and errors at the receiver side. Extensive experimental evaluations show that EasiPLED can provide an accuracy by up to 95.4% without incurring any measurement overhead. The effectiveness of EasiPLED is also evaluated by the proposed A-ARQ, an adaptive link-layer retransmission scheme. Experimental results show that A-ARQ yields significant reduction in single-hop transmission delay by up to 47%, as well as high packet delivery ratios as compared to F-ARQ and E-ARQ.

We believe that our solution will benefit the development of reliable and time-critical protocols for WSNs. In terms of future work, we will evaluate our method in practical applications.



(a) Delay (b) PDR

Fig. 11. Single-hop transmission delay and packet delivery ratio in Roof scenarios. Up: Distance 1, Middle: Distance 2, Down: Distance 3



(a) A-ARQ (b) E-ARQ

Fig. 12. Instant delay using A-ARQ and E-ARQ schemes in Lab scenarios

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