Improving WSN Simulation and Analysis Accuracy Using Two-Tier Channel Models

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Abstract— Accurate simulation and analysis of wireless protocols and systems is inherently dependent on an accurate model of the underlying channel. In this paper, we propose and evaluate two different classes of WSN channel models for residual MAC layer bit-errors. In the first class of channel models, referred to as 1-Tier models, residual bit-errors are modeled as a standalone error process. Two variants of 1-Tier models are investigated: (i) a Memoryless Binary Symmetric Channel (BSC); and (ii) a 3rd Order Markov Model. In the second class of channel models, called 2-Tier models, a high-level (tier 1) frame-level model excites a lower-level (tier 2) bit-error model. Similar to the 1-Tier models, two variants of 2-Tier models are proposed and validated. First, we evaluate a 2-Tier model that employs a BSC model at the frame-level and excites another BSC model for residual bit-errors when a frame is in error. Second, we propose a 2-Tier model that takes memory into consideration and uses a Gilbert model for frame errors at tier 1 and a 3rd order Markov model for bit-errors at tier 2.

These models are trained and tested using a comprehensive set of WSN residual traces. From the traces, we first obtain three important metrics: (i) recovery ratio for an abstract Forward Error Correction (FEC) scheme, (ii) frame goodput of an unreliable protocol over a multihop network, and (iii) number of retransmissions per packet for a reliable protocol.

I. INTRODUCTION

Accurate system simulation and analysis are necessary to validate emerging wireless sensor network (WSN) protocols and applications before their deployment on actual sensor devices. In this context, an accurate channel model is a fundamentally important requirement for reliable theoretical or simulation-based study of wireless protocols and systems. The wireless channel modeling problem has been extensively studied for 802.11 networks [3]-[7] and some recent studies have also proposed WSN channel models [8],[9]. Nevertheless, most WSN studies assume memoryless binary symmetric or 1st order Markov channel models for bit- and frame-level errors [1],[2]. An accurate WSN channel model based on real residual channel error traces and the impact of such a model on simulation and analysis for WSN protocols is largely unexplored.

In this paper, we propose and evaluate two different classes of WSN channel models for residual MAC layer bit-errors. In the first class of channel models, referred to as 1-Tier models, residual bit-errors are modeled as a standalone error process. Two variants of 1-Tier models are investigated: (i) a Memoryless Binary Symmetric Channel (BSC); and (ii) a 3rd Order Markov Model. In the second class of channel models, called 2-Tier models, a high-level (tier 1) frame-level model excites a lower-level (tier 2) bit-error model. Similar to the 1-Tier models, two variants of 2-Tier models are proposed and validated. First, we evaluate a 2-Tier model that employs a BSC model at the frame-level and excites another BSC model for residual bit-errors when a frame is in error. Second, we propose a 2-Tier model that takes memory into consideration and uses a Gilbert model for frame errors at tier 1 and a 3rd order Markov model for bit-errors at tier 2.

These models are trained and tested using a comprehensive set of WSN residual traces. From the traces, we first obtain three important metrics: (i) recovery ratio for an abstract Forward Error Correction (FEC) scheme, (ii) frame goodput of an unreliable protocol over a multihop network, and (iii) number of retransmissions per packet for a reliable protocol.

II. DATA COLLECTION AND ANALYSIS

A. Data Collection

We used Crossbow’s Micaz motes and TinyOS to collect residual bit-error traces. Traces were collected in four different setups. In each experiment, one sender transmitted data to the other and vice versa.
base station and the other senders were inactive. Distance between a sender and the base station varied from 5 to 12 meters. The senders transmitted fixed-sized 20-byte frames at a rate of 10 frames per second.

In each setup, six or more traces were collected. The average number of frames per trace is approximately 31,000. Throughout this paper, we use a total of 6 traces per setup for our experimental evaluation.

B. Trace Analysis

In this section, we describe the preliminary bit-error statistics. Discussion of error rates is followed by autocorrelation based analysis of the data to characterize the burstiness and correlation of the bit-errors.

1) Preliminary Bit-Error Statistics

Table I shows some preliminary statistics of the collected bit-error traces. Columns 2 and 3 of Table I provide the average (over 6 traces/setup) bit- and frame-error rates for the traces collected in each setup. It can be seen that the highest frame error rate of 20% and bit error rate of 0.9% are both observed in the setup of Room 3. Under this setup, the sender and receiver were at the farthest distance from each other. Frame-error rates of 13% and 15% are also observed for traces collected on the stairs or on the upper floor.

We also analyze the burstiness of the bit-errors in each setup. We compute frequency histograms of bit-error burst-lengths for all traces. We observed that while isolated errors (burst-length=1) are most common in the traces, a significant fraction of observed error bursts have lengths of 2, 3 or 4 bits and 99% of the error bursts have lengths smaller than 4 bits.

In Columns 4 and 5 of Table I, we tabulate the averaged expected values and variances of the bit-error burst distributions. It can be observed that the expected value is consistently greater than one bit, and the average variance is approximately 0.8. That is, bursts of 1, 2 and 3 bits occur quite frequently. Based on these results, we conclude that the bit-errors on a residual WSN channel occur in short bursts.

2) Bit-Error Correlation

We compute autocorrelation to quantify the memory of the 802.15.4 bit-error random process. Let the output of the binary bit-error random process at a discrete time instance \( i \) be represented as \( X[i] \in \{0,1\} \), where 0 \( \Rightarrow \) an error free bit. Each bit-error trace collected for this paper represents a realization of this random process. To quantify the memory of the bit-error process \( X \), we use the autocorrelation measure as described in [10]:

\[
\rho[k] = \frac{E\{X[0]X[k]\} - E\{X[0]\}E\{X[k]\}}{\sqrt{\text{var}\{X[0]\}} \sqrt{\text{var}\{X[k]\}}},
\]

where \( E\{\cdot\} \) and \( \text{var}\{\cdot\} \) represent the expected value and variance of the random process. From the ensemble of the bit-error process realizations that are provided by the traces, we compute sample expectations and sample variances which are then used to calculate the sample autocorrelation of each trace.

Figure 2 shows the bit-error sample autocorrelation of one trace per setup. The results for the remaining traces are very similar to the ones reported in Figure 2. It can be seen that the autocorrelation decays significantly with an increase in the time lag between bits. The autocorrelation shows a linear decrease between lags 1 and 3. After a lag of 3 bits, correlation of the bit-error process drops to and stays at a very low value. Thus every bit observed on the channel is dependent on the last 3 bits.

We also evaluated memory properties of the bit-error process using conditional entropy [13]. These results are in agreement with autocorrelation-based findings. Using results of this section, we have ascertained that residual bit-errors on a WSN channel have 3-rd order memory and should be modeled using a 3-rd order Markov chain.

III. Modeling

In this section, we develop and evaluate models to accurately capture the statistical properties of the residual bit-errors. We investigate both memoryless as well as Markov models for the
present channel in order to quantify the level and scale of inaccuracies that incur by ignoring channel memory. These models are explained in the next four subsections.

A. 1-Tier Memoryless Model

This model is commonly known as the Binary Symmetric Channel (BSC) model. In this model, behavior of every bit is independent of any previous bit; Probability that a bit is in error does not change with any information about the previously-received bits. Henceforth, we refer to this model as the 1-Tier Memoryless model.

B. 1-Tier Markov Model

To realistically model the bit-error process, we consider that the behavior of the next bit is influenced by the previous K bits. $K=1$ is a special case where next bit is dependent on only one previous bit; this model is commonly known as the Gilbert Model [12]. Generalizing the Markov notion to higher values of K leads to higher-order Markov chains described below. (Higher-order Markov models are commonly-used in wireless measurement and modeling studies [6], [7], [10], [11].)

The states of a K-th order (memory-length=K) Markov chain comprise $2^K$ possible combinations of K consecutive bits; that is, each Markov state corresponds to the decimal equivalent of a unique K bit sequence. Transition probabilities between states are computed by sliding a K bit memory-window over the training data and counting the number of times a bit-pattern $[x_1, x_2, ..., x_k]$ is followed by another bit pattern $[y_1, y_2, ..., y_k]$. We used 3-rd order Markov model on the basis of traces’ autocorrelation and conditional entropy. To train our model using 1-Tier Markov model with memory length 3, we need 16 parameters to represent state transition probabilities at frame level, extracted from source trace; throughout this paper, the term source trace is used to refer to a real-world trace collected over the 802.15.4 network. A 1-Tier Markov model with the trained parameters is used to generate a synthetic trace.

C. 2-Tier Memoryless Model

A 2-Tier model is a combination of a frame-error model and a bit-error model. The frame-error model at tier 1 is used to excite the bit-error model at tier 2. That is, if the tier 1 frame-error model predicts an error-free frame then there is no need to invoke the bit-error model because we know that all the bits in the frame are error-free. On the other hand, if the tier 1 frame-error model predicts a corrupted frame then the bit-level model at tier 2 is used to generate bit-errors in the corrupted frame.

It has been shown in prior studies that bit-error memory does not persist beyond packet boundaries and a memoryless or a 1st order Markov model is sufficient to characterize frame-/packet-level errors [4], [6], [11]. We observed similar frame level behavior in our traces and therefore apply low-order models at the frame level.

For the 2-Tier memoryless model, we apply BSC models at both tiers. Thus both frame- and bit-level models are memoryless BSC models. BER and FER parameters for these models are extracted from source traces.

D. 2-Tier Markov Model

This model employs Markov models of different orders at the two tiers. At tier 1, we apply a Gilbert model for frame-errors and at tier 2 we apply a 3-rd order Markov model for bit-errors. Thus this model incorporates memory at both frame and bit levels.

To train the model, we need two sets of parameters. At tier 1, 4 parameters are required. These parameters represent state transition probabilities at frame level, extracted from source frame-error traces. At tier 2 we use the 3rd order Markov model described earlier.

E. Model Accuracy Evaluation

1) Bit- and Frame-Error Rates

We have evaluated each model against source bit-error traces using different measures. We start our analysis with statistics of bit-error rates (BER) and frame-error rates (FER). For the BER, we find that all models do reasonably well except the 1-Tier Markov model which provides overly pessimistic results.

In case of FER, we observe that both 1-Tier models are highly and consistently inaccurate; For the Upper Floor setup, 1-Tier memoryless and Markov models incur an average error of 33.55% and 44.59%, respectively. elaborates FER for each setup (averaged over 6 traces per setup). These results suggest that it is very important to properly leverage the knowledge about memory in the process. In particular, the results for the 1-Tier Markov model challenge a commonly-held belief in the channel modeling community [3]-[7] by showing that it is possible to come up with an inaccurate model despite correct knowledge of memory in the channel error process.

2) Information Divergence of Burst-Lengths

Bit and frame error rates are averaged measures that do not capture the burstiness or memory properties of the underlying error process. To evaluate the accuracy of the proposed models in capturing error burstiness, we compare source and synthetic traces using a Kullback-Leibler-based information divergence
The Kullback-Leibler (K-L) divergence $D$ is computed as:

$$D(p \parallel q) = \sum_x p(x) \log \frac{p(x)}{q(x)},$$

where, in the present context, $p, q$ respectively represent the burst-length probability mass functions derived from source and synthetic traces. The burst-length divergence comparison is performed for both good and bad bursts. Higher divergence values represent that a model is not accurately capturing the burstiness of the source.

The K-L divergence is not symmetric and it requires the two distributions $p$ and $q$ to be continuous with respect to each other. Therefore, instead of K-L, we use the resistor-average $R$ divergence measure defined as [15].

$$\frac{1}{R(p \parallel q)} \equiv \frac{1}{D(p \parallel q)} + \frac{1}{D(q \parallel p)}.$$  

As with the K-L measure, smaller values of $R$ represent more similarity between $p$ and $q$.

Figure 3 presents a comparison of $R$ divergence values computed between a source bit-error trace and synthetic bit-error traces. (Other results are skipped for brevity.) From this figure, we can see that for good bursts, 2-Tier Markov model results in the smallest divergence among all the models under consideration. Furthermore, in case of bad bursts, value of $R$ is relatively so small (0.0009) that it is not even visible on this graph. These results validate our assumptions regarding the 2-Tier Markov model and suggest that this model captures good and bad bursts with very high accuracy.

The inaccuracy of the 1-Tier models is consistent with the results in the last section. Moreover, Figure 3 shows that the 2-Tier BSC model, that ignores the underlying channel’s memory, incurs significant inaccuracies when capturing channel burstiness; recall that this model had quite accurate FER and BER accuracy. Thus for accurate characterization of a WSN channel, a 2-Tier model that incorporates memory at both tiers is required.

IV. IMPACT OF INACCURATE MODELS ON WSN SIMULATIONS

Choice of a bad model in simulators can result in inaccurate deductions about the protocols being analyzed. In this section, we elaborate this point by focusing on three different simulations that are first performed using the collected source traces and then repeated using synthetic traces that are generated by models trained using the source traces.

A. Frame Recovery using Forward Error Correction

In this simulation, we consider a one-hop network of two nodes where unreliable transmissions between the sender and the receiver are protected using a maximum distance separable (MDS) FEC code. The sender sends a predefined number of FEC-coded frames with fixed amount of FEC redundancy (32 bits). Based on number of frames recovered successfully after FEC decoding, we calculate error recovery ratio $E$, which is the ratio of the total number of decodable FEC codewords at the receiver and the total number transmitted codewords. We repeated this experiment with different FEC symbol sizes of 1, 2, 4, 8 and 16 bits. We first use the source traces to simulate the channel between the sender and the receiver. Then the experiments are repeated using synthetic traces generated by the four models under consideration.

Figure 4 presents the percent error in the recovery ratios averaged over each setup and all symbol sizes. Thus this figure shows the normalized difference between the recovery ratio of the source trace-based simulations and the recovery ratio of the simulations performed using synthesized trace. Traces generated using the 2-Tier Markov model report the lowest recovery ratio error. Highest error values are reported for Room 3 setup. In this setup minimum percent error is 3.7% (2-Tier Markov) and maximum error is 40.3% (1-Tier Markov). Similar trend can be observed for all other setups. Note that the 1-Tier Markov model incurs gross errors of up to 40% and is therefore extremely inaccurate. However, this model when used in a 2-Tier framework can provide highly accurate performance.

B. Frame Goodput of an Abstract Unreliable Protocol

Frame goodput is a simple, yet very important, measure in networks studies. We evaluate the accuracy of the models in capturing frame goodput by simulating an abstract unreliable
In this paper, we evaluated the accuracy of different bit-error WSN channel models. Two important findings of the paper are: i) Memory in the frame- and bit-error processes should not be ignored, and ii) highest accuracy is provided by a 2-Tier channel model in which a frame-level model excites a bit-level model. We showed that 2-Tier Markov model performs significantly better than all other models regardless of the nature of application/protocol being simulated.

V. CONCLUSION

Figure 5 shows that the 2-Tier Markov model based results are almost identical to the results obtained from source traces. Average goodput error for the 2-Tier Markov model over all setups is about 3.8%. Second best performance is provided by the 2-Tier memoryless model with average goodput error of 10.8%. Both 1-Tier models provide grossly inaccurate results for this metric. Thus from these results we deduce that the 2-Tier Markov model is consistently and considerably better than all other models.

C. Average Retransmission Length

Number of retransmissions determines the delay and bandwidth cost of a reliable protocol. To evaluate this performance metric, we define the expected retransmission length as the average number of retransmissions for a packet to be received correctly. We simulate an abstract reliable protocol over one-hop channel using source and synthetic traces. These results are again averaged over 6 traces per setup. The total packet length is 20 bytes and a total of approximately 50,000 packets are transmitted in each experiment.

Table III shows that there are very minor differences between expected retransmission lengths of source traces and synthetic traces generated by the 2-Tier Markov model. Highest value of expected retransmission length is reported for Room 2 (2.53 packets for source traces), 2-Tier Markov model is the closest (2.36 packets) to real traces. A similar pattern is seen for other setups. An interesting observation is that all traces generated using the 2-Tier memoryless model report an optimistic value of retransmission length which is always less than source traces.

<table>
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<tr>
<th>Setup</th>
<th>Source</th>
<th>1-Tier Memoryless</th>
<th>1-Tier Markov</th>
<th>2-Tier Memoryless</th>
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REFERENCES