A Multi-Tier Model for BER Prediction over Wireless Residual Channels

Yongju Cho[*†], Syed Ali Khayam[†], Shirish Karande[†], Hayder Radha[†], Jaegon Kim[*] and Jinwoo Hong[*]

[†]Department of Electrical & Computer Engineering
Michigan State University, East Lansing, MI 48824 USA
{choyong8, khayamsy, karandes, radha}@egr.msu.edu

[*]Electronics and Telecommunications Research Institute (ETRI)
Email: {yongjucho, jgkim, jwhong}@etri.re.kr

***Abstract* – Bit-error rate (BER) modeling and prediction over *residual* wireless channels, which represent errors not corrected by the physical layer, has emerged as an active research area. Recently, it has been shown that signal to noise ratio (SNR) is a useful side-information that could be employed for BER prediction. In this paper, we propose a novel and accurate three-tier model that leverages a received packet's SNR and checksum side-information to predict BER in future packets over a wireless residual channel. We first observe that direct inference of BER from SNR results in optimistic estimates because of the relatively large amounts of error-free data (in comparison with corrupted data) received on viable wireless networks. Consequently, we propose a model that separates packet- and bit-error prediction. At the first tier, we employ a high-order packet-level Markov model which predicts whether or not a packet is in error. The second tier model is invoked only when a corrupted packet is predicted. The second tier consists of conditional probabilities that predict future SNR values based on the current packet's SNR. Once the SNR is predicted, a third-tier provides the BER estimate for that SNR using a binary-symmetric channel model. We use 802.11b traces collected over an operational 802.11b LAN to compare the performance of the proposed predictor with state-of-the-art predictors. We show that at all three 802.11b data rates (2, 5.5 and 11 Mbps) the proposed model has higher BER prediction accuracy than the optimum Yule-Walker and finite-state Markov chain predictors.**

I. INTRODUCTION

Channel modeling and prediction are widely-researched areas of communication networks. Due to the lack of software-based control over wireless physical layers, modeling and analysis above the wireless physical layer are becoming increasingly popular [1]−[9]. These channels − referred to as residual [1] and MAC-to-MAC [2] channels in prior literature − represent the higher layers' perspective of the wireless channel. An important metric that is required by many higher layer protocols and applications is robust real-time channel prediction, in particular bit-error rate (BER) prediction, over a residual channel.

Accurate BER prediction can facilitate design, performance evaluation and parameter tuning of many wireless protocols and applications. For instance, rate-adaptive applications and data link protocols can use accurate BER predictions to adapt their source and channel coding rates in accordance with the forecasted channel conditions. Wireless congestion control protocols can use BER predictions to differentiate losses due to congestion from losses due to channel errors. Reliable routing algorithms and multidescription multimedia applications can use BER predictions to choose reliable wireless paths. These applications motivate this effort where we propose an accurate BER predictor for residual wireless channels.

Traditionally, pilot bits were used to estimate channel conditions at a wireless receiver. Such a strategy, however, results in wastage of scarce wireless bandwidth. Consequently, there has been an increasing interest in online channel estimation and prediction using channel side-information. In particular, bit-level signal to noise ratio (SNR) has been shown to be an effective side-information for BER prediction over physical layer wireless channels [10], [11]. Since residual channels are observed after physical layer processing, channel side-information such as physical-layer estimates of SNR are only available on a packet-by-packet basis to the higher layers, where the residual channel is present. Nevertheless, recent studies have shown that even this coarse side-information can be quite helpful in BER prediction [12].

In this paper, we propose a multi-tier model (MTM) to systematically leverage packet SNR information (provided in the form of signal to silence ratio (SSR) indicators) for BER prediction over residual channels[1]. The proposed model is trained and tested using a comprehensive set of wireless residual traces collected at 2, 5.5 and 11 Mbps data rates of an operational 802.11b network. Using the traces, we first observe that directly leveraging SNR information for BER prediction results in overly optimistic estimates due to the overwhelming presence of error-free data when compared to corrupted data. We, therefore, propose to employ a packet-error model at the first tier. We observe that a 3rd order Markov chain model can accurately predict packet errors. For the predicted corrupted packets, at the second tier we use probability distributions that are conditioned on the current packet's SNR to predict the next packets' SNR values. After SNR prediction, the BER estimate is obtained from a binary symmetric channel (BSC) model that is associated with each SNR value.

We compare the performance of the proposed scheme with the optimum Yule-Walker (Y-W) predictor [18], which assumes a wide-sense-stationary (WSS) process, and the finite-state Markov chain (FSMC) predictor [10], which is a representative of state-of-the-art predictors for channels with mem-

[1] Due to the similarity in their meaning, throughout this paper the terms SNR and SSR are used interchangeably.

TABLE I
STATISTICS OF TRACES USED IN THIS STUDY

Phy. data rate (Mbps)	Avg. PER	Min. PER	Max. PER	Avg. SSR (dB)	Min. SSR (dB)	Max. SSR (dB)
2	5.97%	0.75%	14.31%	14.75	0	34
5.5	9.79%	0.61%	22.74%	15.27	0	32
11	39.5%	10.99%	77.83%	16.51	0	35

TABLE II
ERROR STATISTICS FOR VARYING SSR VALUES AT 11 MBPS

SSR (dB)	Average Packet-Error Rate	BER of all (error-free & corrupted) packets	BER of corrupted packets
5	0.701	0.0253	0.0361
13	0.6248	0.0157	0.0251
20	0.2166	0.0048	0.0223
26	0.0384	0.0023	0.0591

ory. We show that for all three 802.11b data rates, the proposed MTM provides much better BER prediction than Y-W and FSMC predictors.

The rest of this paper is organized as follows. Section II describes our wireless trace collection setup and then performs some preliminary analysis on the collected data. Section III motivates and develops the MTM three-tier BER prediction model. Section V summarizes key conclusions of this work.

II. COLLECTION AND EMPIRICAL ANALYSIS OF RESIDUAL WIRELESS TRACES

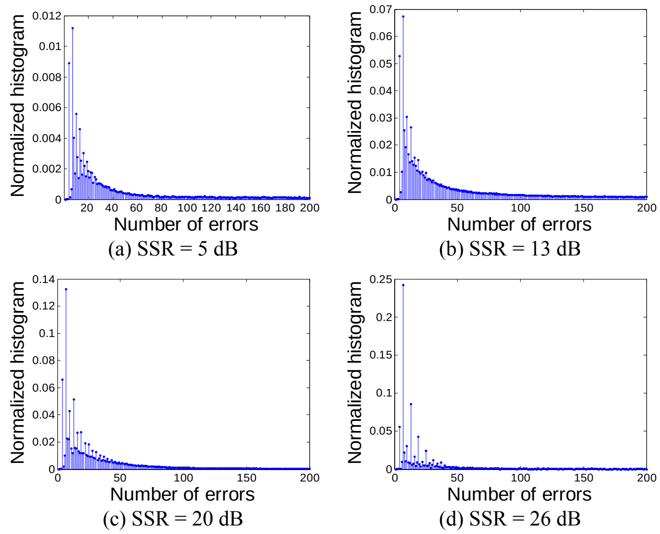
A. Data Collection

For this study, five wireless receivers were used to simultaneously collect error traces on an 802.11b LAN. The receivers were placed at different locations in a room, while the access point (AP) was placed in a room across a hallway from the receivers to simulate a realistic home/classroom/office setting. The receivers' MAC layer device drivers were modified to pass corrupted packets to higher layers. To capture packets at high transmission rates, packet dissectors were implemented inside the device drivers. These packet dissectors ensured that only packets pertinent to our wireless experiment are processed, while all other packets are dropped. Each experiment comprised of one million packets with a payload of $1,000$ bytes each, i.e., each trace has approximately 1 GB of data.

A wired sender was used to send multicast packets with a predetermined payload on the wireless LAN; multicasting disabled MAC layer retransmissions. In addition to a packet's header and payload information, we logged signal to silence ratio (SSR) for each packet. A packet's SSR is a one-byte number between 0 and 100 dB, representing an approximate measure of the SNR at which the packet was received. The sender used different transmission rates ranging from 500 Kbps to 1 Mbps for each experiment. At the physical layer, the auto rate selection feature of the AP was disabled and for each experiment the AP was forced to transmit at a fixed data rate. Each trace collection experiment was repeated multiple times at 2, 5.5 and 11 Mbps physical layer data rates and at different times of day.

B. Average Statistics of the Traces

Table I provides some statistics of the traces collected for this study. As expected, the average packet error rate increases



(a) SSR = 5 dB (b) SSR = 13 dB (c) SSR = 20 dB (d) SSR = 26 dB

Fig. 1. Normalized histograms of the number of bit-errors in a corrupted packet for varying SSR values; histograms are averaged over all 11 Mbps residual traces, and only number of errors between [1,200] are shown.

with an increase in the physical layer data rate. In particular, the average packet error rate increases from approximately 10% at 5.5 Mbps to almost 40% at 11 Mbps. Since the wireless receivers were placed at different locations, the receivers experienced different packet error rates. The minimum and maximum error rates in Table I outline that the receivers were experiencing both good and bad link conditions.

The average, minimum and maximum SSR values are also shown in Table I. Note that the minimum SSR value is zero at all three data rates. Similarly, the maximum and average SSR values do not vary much with the data rate. Thus, unlike packet error rates, the SSR values are somewhat independent of the physical layer data rate.

C. BER Behavior at Different SSR Values

Fig. 1 uses the 11 Mbps residual channel to show that the BER behavior of the channel changes considerably with a change in the received packets' SSR values. (For brevity, in this section we only show results for the 11 Mbps channels because results for 2 and 5.5 Mbps channels were similar. In the modeling sections, we show results for all three channels under consideration.) At an SSR of 5 dB, small number of errors in a corrupted packet are fairly infrequent, as shown by the low normalized frequency of errors in the [1,200] range of Fig. 1(a). This is mainly because at such low SSR values, most of the received packets are corrupted, and a large number of bits in these packets are corrupted. As the SSR increases, the skew of the histogram changes and the corrupted packets have fewer bit-errors. This trend can be observed in Fig. 1 (b), (c) and (d), which show that the frequency of small number of bit-errors increases with SSR. For instance, at an SSR of 26 dB, almost 25% of corrupted packets have less than five bit-errors. Comparison of Fig. 1 (a), (b), (c) and (d) clearly shows that an increase in SSR decreases the mean number of bit-errors in a corrupted packet.

The relationship between SSR values and the channel error rate is also shown in Table II. It is easily observed from the second column of Table II that packet error rates increase drastically with a decrease in SSR values. In particular, the packet error rate increases by approximately 18% as the SSR decrease from 26 dB to 20 dB. Similarly, there is a packet error rate increase of about 41% between SSRs 13 and 20. To avoid repetition, we defer discussion on columns 3 and 4 of Table II to a later section.

Based on the results presented so far, we deduce that SSR is a robust and effective side-information of a wireless link's condition. The following section leverages this side-information to accurately estimate and predict the BER of the channel.

III. The Multi-Tier Model For BER Prediction

In this section, we develop a multi-tier model (MTM) for BER estimation and prediction. Here it is important to explain what we mean by BER estimation and prediction. In contemporary wireless networks [13], [14], a wireless receiver's link layer performs a packet-level checksum to determine whether a packet is error-free or corrupted. Obviously, the BER is zero if a packet passes the checksum, thereby eliminating the need for BER estimation. For a packet that fails the checksum, the receiver does not know how many bits of the packet are corrupted. This knowledge is important analytically and in practice, and it has a direct implication on the effective channel capacity and the choice of certain cross-layer wireless protocols [15]–[17]. Thus for a corrupted packet, one needs a scheme that can render an accurate estimate of the number of errors in the packet. Once the BER of the current packet is estimated, the next problem is to predict the number of errors in the following packets.

The proposed MTM leverages SSR and checksum side-information to estimate the BER in the current packet and to predict the BER in future packets.

A. Tier 1: A Markov Model for Packet-Error Prediction

We first emphasize an important point highlighted by columns three and four of Table II. Note that for low SSR values (i.e., poor link conditions,) the BER computed using all (error-free and corrupted) packets is somewhat similar to the BER computed using only corrupted packets. However, when we compare the BER at higher SSR (20 and 26 dB in Table II), the BER computed using all packets is orders of magnitude different from the BER computed using corrupted packets only.

The BER difference for high SSR value is very stark because: (i) most of the received packets are error-free; and (ii) the relatively small number of corrupted packets has relatively-high BER. In general, and based on our extensive study of this issue, it became evident that the relatively-small number of corrupted packets, at relatively-high SSR/SNR values, provides good (yet conservative and slightly biased) estimates of BER. Meanwhile, including the relatively large number of error-free packets in the BER estimates (especially at high SSR/SNR values), provides highly optimistic (very biased)

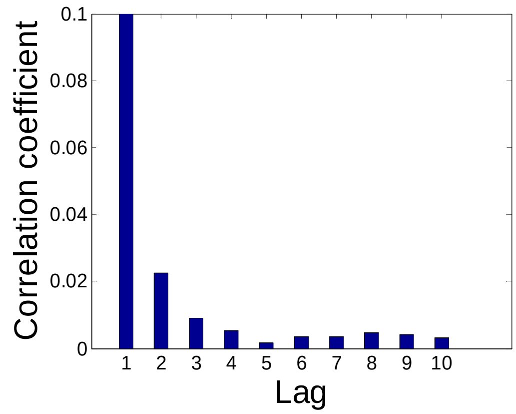


Fig. 2. Sample autocorrelation coefficient of an 11 Mbps trace.

estimates of BER in actually corrupted packets. A surprising result shown in Table II is that the BER in the corrupted packets is very high for high SSR values. We observed that while the total number of corrupted packet at high SSR values is quite small, the corrupted packets contained a large number of bit-errors. We believe that this phenomenon occurs because the corrupted packets at high SSR values are mostly due to packet collisions, and therefore these packets contain are highly corrupted.

High SSR values are quite important because over real-life wireless channels, many packets are received with high SSR values. (For instance, as shown in Table I, we observed maximum SSR values of 34, 32 and 35 dB for the 2, 5.5 and 11 Mbps channels, respectively.) Therefore, we propose that at the first tier, an accurate predictor should solely focus on packet-error prediction. In turn, BER prediction should only be done for packets which are predicted to be corrupted by the packet-error model.

A.1. Correlation of the Packet-Error Process

To determine an accurate first-tier packet-error model, we first analyze the correlation coefficient of the packet-error process. Let X_n denote a discrete binary packet-error random process. Thus for a given n, $X_n \in \{0,1\}$ is a binary random variable with $X_n = 0$ and $X_n = 1$ respectively representing that packet n is error-free and corrupted.

For each physical layer data rate, we treat the packet-error sequences obtained from the traces as realizations of the packet-error process for that data rate. Then the random process' autocorrelation function is [18]

$$R[\eta] = E\left\{X_0 X_\eta\right\}, \quad (1)$$

where $E\{.\}$ is the sample expected value computed using the process realizations. Using the autocorrelation, we compute the sample correlation coefficient of a packet-error process:

$$\rho[\eta] = \frac{E\left\{X_0 X_\eta\right\} - E\left\{X_0\right\} E\left\{X_\eta\right\}}{\sigma_{X_0} \sigma_{X_\eta}}, \quad (2)$$

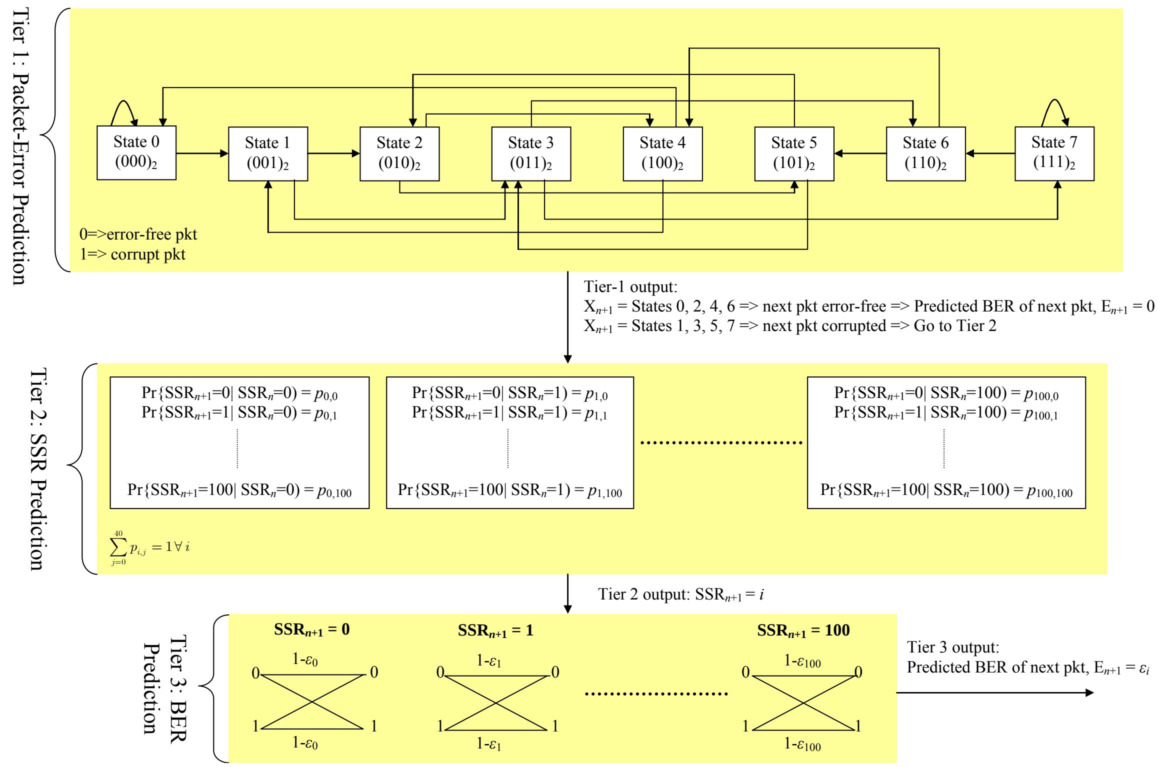


Fig. 3. The multi-tier BER prediction model.

where σ_X represents the sample standard deviation of random variable X. This correlation coefficient provides a normalized measure of the amount of correlation present in the data. Markov chains are generally used to model processes with low-correlation values, whereas highly correlated processes are typically modeled using heavy-tailed models [19].

Fig. 2 shows the correlation coefficient of a sample 11 Mbps residual trace. (Correlation decays for other traces were similar and are therefore skipped for brevity.) Clearly, the packet-error process' correlation shows an exponentially decaying trend. The correlation function drops to and stays at an insignificant value at lags of more than three. Thus we deduce that a 3rd order Markov chain can be used to model the packet-error process.

A.2. The 3rd order Packet-Error Markov Model

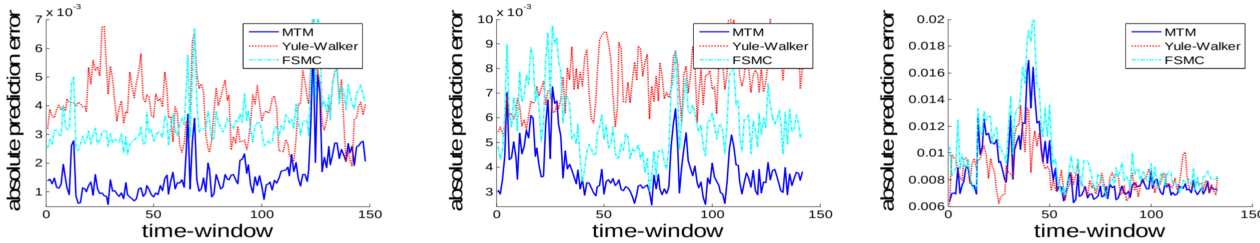
To predict packet errors, we define a discrete-time Markov chain such that each state of the chain corresponds to one of the $2^3 = 8$ possible combinations of three binary symbols; each binary symbol represents an error-free or corrupted packet. Transition probabilities of the 3rd order Markov chain are computed by sliding a 3-bit window over the wireless traces and by observing the frequency of a binary pattern $\underset{\rightarrow}{x} = [x_1 x_2 \dots x_k]$ followed by another bit-pattern $\underset{\rightarrow}{y} = [y_1 y_2 \dots y_k]$, for all patterns $\underset{\rightarrow}{x}$ and $\underset{\rightarrow}{y}$.

The 3rd order Markov chain model's transition probabilities are computed from the packet-errors observed in the traces of this study. Since the BER behavior changes drastically with respect to the physical layer data rate, for each data rate (2, 5.5 and 11 Mbps), we train a different 3rd order Markov model. After model training, given a packet's checksum side-information (pass/fail), we use the Markov chain to predict whether the next packet will be error-free or corrupted. The prediction process is conducted as follows. From any given state of the 3rd order Markov chain, the process can transit either to a state with an upcoming error-free packet or to a state with an upcoming corrupted packet. There are two transition probabilities associated with these two possible transitions, say p and $1-p$. To predict the checksum of the next packet, we treat these probabilities as a Bernoulli random variable, with probability of success p corresponding to the probability that the next packet will be error-free, and the probability of failure $1-p$ corresponding to the probability that the next packet will be corrupted. Furthermore, from the checksum of the next packet, we know whether or not our prediction was correct. If the prediction was correct then the predicted state of the Markov chain is used for the subsequent prediction. Otherwise, the Markov chain's current state is changed to the opposite of what was predicted.

As explained earlier, BER estimation is only invoked for corrupted packets. In the following section, we explain the BER estimation using SSR values.

B. Tier 2: A Packet-Level Model for SSR Prediction

Once a corrupted packet is predicted by the tier 1 model, at the second tier we use the SSR of the received packet to predict the SSR of a future packet. For each possible SSR value (which ranges between 0 and 100 dB), we maintain a discrete conditional probability distribution of the next SSR values. Thus a conditional probability value $p_{i,j}$ yields the probability



(a) Physical layer data rate = 2 Mbps (b) Physical layer data rate = 5.5 Mbps (c) Physical layer data rate = 11 Mbps

Fig. 4. Absolute error in BER prediction; time-window length $\tau = 50$ seconds, results are averaged over all the traces.

that if the SSR value of the current packet is i dB then the next packet will be received at an SSR of j dB. The conditional probability distributions are computed using corrupt packets observed in the traces.

C. Tier 3: BER Prediction using BSC Models

The second tier model predicts the SSR of the next packet using a conditional probability distribution. In accordance with prior discussions and as shown in Table II, the BER of the channel changes with respect to the channel SSR. In general, we observed a non-linear relationship between SSR and BER. Therefore, after predicting the next packet's SSR, we employ a binary symmetric channel (BSC) model to predict the BER of the next packet. While we acknowledge that the BSC model is somewhat simplistic for the present problem, we observed that this simple model can provide quite accurate BER prediction, especially at low physical layer data rates. Hence, we use the crossover probability of the BSC model corresponding to the predicted SSR as the BER estimate of the next packet.

IV. Performance Evaluation of the MTM

We now compare the performance of the proposed MTM model with two leading predictors, namely the Yule-Walker (Y-W) predictor [18] and finite-state Markov Chain (FSMC) predictor [10], [11].

For the Y-W based BER prediction, we first use SSR values of the last k packets to predict the SSR of the next packet. More specifically, let $S_{n-k+1}, S_{n-k+2}, \ldots, S_n$ be the SSR values of the last k packets. The Y-W predictor predicts the next SSR value, S_{n+1}, using a linear filter of the form:

$$S_{n+1} = \sum_{i=0}^{k-1} h_i S_{n-i} \, .$$

The coefficients of the filter are computed as:

$$\begin{bmatrix} h[0] \\ h[1] \\ \vdots \\ h[k-1] \end{bmatrix} = \begin{bmatrix} R[0] & R[1] & R[2] & \cdots & R[k-1] \\ R[1] & R[0] & R[1] & \cdots & R[k-2] \\ & & \vdots & & \\ R[k-1] & & \cdots & R[1] & R[0] \end{bmatrix}^{-1} \begin{bmatrix} R[1] \\ R[2] \\ \vdots \\ R[k] \end{bmatrix},$$

where $R[.]$ is the autocorrelation function of (1). We experimented with different values of k, and obtained the best Y-W prediction performance for $k = 5$. Once the SSR is predicted using the above equations, we use the tier 3 BSC models of Fig. 3 to predict the BER of the next packet.

TABLE III
AVERAGE ABSOLUTE ERROR OF BER PREDICTORS

Phy. data rate (Mbps)	Three-Tier Model	Yule-Walker	Finite-State Markov Chain
2	0.0015	0.0042	0.0028
5.5	0.0044	0.0075	0.0057
11	0.0094	0.0097	0.0101

The FSMC predictor [10] employs a Markov chain model of SNR values to predict future SNR values. The FSMC model of SNR values is designed specifically for a fading channel and the model assumes the availability of SNR values for each symbol. The FSMC partitions SNR values into N disjoint intervals, where each interval represents an FSMC state. Different state SNR partitioning strategies have been proposed in prior literature [10], [11]. It has also been shown that under fading conditions, an FSMC model in state i can only transit to its neighboring states $i-1$ and $i+1$. After predicting the next SNR value, BSC models are used to predict the BER of the next packet.

Since on a residual channel we only have packet-level SSR information, the previously-proposed SNR partitioning algorithms are not directly applicable here. Moreover, at times we observed large fluctuations in SSR values. These fluctuations made the constraint of transitioning only to the neighboring states impractical. Therefore, we modify the original FSMC model [10] such that the model can transit from any current SSR value to any other SSR value. For fair comparison with the MTM, we place each SSR value into a different FSMC state.

To clearly show the accuracy of a BER predictor without short-term biases, we compare the predicted and actual BERs in non-overlapping time-windows of length τ seconds. In each time-window, we compute the absolute value of the difference between the predicted and actual BERs. This difference is henceforth referred to as absolute prediction error. Clearly, smaller prediction error implies higher prediction accuracy.

Fig. 4 compares the performance of the proposed model with Y-W and FSMC predictors for $\tau = 50$ seconds; that is, each point shown in Fig. 4 is the average prediction error in a 50 second time-window. It can be observed that at 2 and 5.5 Mbps the proposed model provides consistently better performance than Y-W and FSMC predictors. At 11 Mbps, the accuracies of all the predictors are comparable. Performance of the MTM at 11 Mbps is less convincing because the bit-error characteristics of the 11 Mbps channel are quite different from 2 and 5.5 Mbps. Specifically, prior studies have shown that 11 Mbps bit-errors exhibit long-range dependence, and therefore multi-scale models are required to characterize these bit-errors [3]. We are currently incorporating such models in the multi-tier framework to improve BER prediction at 11 Mbps.

In Table III, we compare the average accuracies of the predictors under consideration. For the results of this table, the absolute prediction error was averaged over the entire trace. It can be clearly seen that average prediction accuracy of the MTM is consistently higher than both Y-W and FSMC predictors. Thus, irrespective of the physical layer data rate, on-average the MTM renders higher prediction accuracy than both Y-W and FSMC predictors.

V. Conclusion

In this paper, we proposed a multi-tier model (MTM) for BER prediction over wireless networks. The MTM relies on the premise that packet-error prediction should be performed before and in isolation from BER prediction. For predicted error-free packets, BER prediction is not required. The MTM achieved packet-error prediction using a 3rd order Markov chain model. For predicted packet-errors, the MTM used a second-tier model of SSR values to predict the next packet's SSR. These predicted SSR values were in turn used in a third tier for BER prediction. We showed that the MTM renders higher prediction accuracy than existing Yule-Walker and finite-state Markov chain predictors.

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