# On Modeling of 802.11b Residue Errors

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***Abstract*— Errors that are observed at the MAC layer of a wireless protocol are known as *residue errors* due to the failure of the physical layer to correct them. In this paper, based on experimentation with actual 802.11b Wireless LANs (WLANs), it is shown that the 802.11b residue error process is a highly non-stationary process; and hence error models derived on the basis of observations at one time/environment may not be applicable at/in another. Thus MAC-layer modeling/prediction techniques need to adapt on the basis of some Channel State Information (CSI). Consequently, in this work, we characterize the variation in the behavior of the residue error process in accordance to the radio-link Signal to Silence Ratio (SSR) Indications (SSRI). The residue error process is treated as a piecewise stationary process, where each piece corresponds to a PHY/MAC packet. In particular, we construct a unified Markov framework to obtain *SSR aware* Markov models for residue errors. Further, it is shown that the proposed SSR aware Markov framework provides significant performance benefits and can characterize the residue error traces even across varied WLAN setups. This leads to the design of *non-homogenous Markov models* that can vary the transition matrix on the basis of using SSR indication as side-information. We deploy such a non-homogenous Markov model and show that it can characterize the error process significantly better than Markov models that are derived by ignoring SSR values.**

***Index Terms*—Channel Modeling, Wireless**

## I. Introduction

Recent years have seen an increased deployment of 802.11b based Wireless LANs (WLAN) in home and office setups. Concurrent with this trend has been an increased demand for multimedia applications. The above two synergistic growths have in turn led to an increased demand for seamless availability of multimedia content over wireless media. However, often in practical deployments of 802.11b WLANs, it has been observed that the number of packet drops due to bit corruption of the MAC frames can be significant. This decrease in throughput can adversely affect the performance of network applications and especially multimedia applications over the wireless network. As a result, some of the recent studies have advocated a cross-layer error-control strategy that can recover data even from the corrupted packets [3]-[8] and improve throughput.

The utility/feasibility of data recovery from corrupted MAC frames is a function of the "residue error" patterns observed at the link-level[1]. In this paper we analyze and model the behavior of the actual residue error patterns observed at the 802.11b link-level based on crucial parameters and side information that can be collected at the physical layer. The proposed work thus has important implications for design of future error control protocol and deduction of performance bounds.

Previous attempts at modeling 802.11b (WLAN) residual errors have typically not taken into consideration packet boundaries and attempt to characterize the entire residue error traces on the basis of a single set of model parameters (e.g. the author's previous work [10]-[14]). In addition previous modeling techniques employed at the link-level do not incorporate any Channel State Information (CSI) that can be associated with a residue error trace during the data collection step of the experimentation. In this work, we show that modeling techniques such as the above are inherently attempting to model a non-stationary process and thus can often lead to conclusions that are not broadly applicable. In particular, as evidence, in section III we show that the observations about long-range dependence of the residue error process, as was concluded in [12], can vary from one experimental setup to another.

The behavior of a residue error process and in fact the wireless channel can be influenced by many factors, such as presence of interfering sources, receiver mobility and terrain ( which in the context of the home/office setup considered in this paper corresponds to presence of walls etc). Thus it's natural to expect the behavior of the error process to vary from one environment to another and correspondingly also with time, if the surroundings are even slightly dynamic. Thus it is hard to characterize the channel behavior in a manner that would be independent of the above mentioned environmental /infrastructural biases. Signal to Silence Ratios (SSR) can be used as a representation of the overall Signal to Interference/Noise Ratio (SINR)[2] and thus the error process when "conditioned" on a SSR can be expected to behave similarly across different environments. Thus the SSR indications, that a typical 802.11b radio hardware is capable of providing, can be used very practically for link-layer model adaptation.

[1] Here, *residue error* represents bit errors that are not corrected by the physical layer, and consequently they appear within (corrupted) packets at the link-layer and possibly at other higher layers.
[2] In this paper we often use the terms SNR and SSR interchangeably.

In most theoretical studies and emulations of wireless channels, the relationship of the bit error probability to SSR indication is assumed to be constant. It is common knowledge in theoretical and purely simulation/emulation based studies that the performance of a model and in particular entropy of a sequence reduces when the physical layer Signal to Noise/Silience/Noise+Interfernce is used as side-information or CSI. Thus for such studies the presented work may seem almost trivial; yet there exists experimental evidence that the prediction (i.e. apriori assumptions) made on the basis of SSR indications are not always robust (see e.g. [15]). Based on our own experimental studies, the authors do not find the predictive utility of SSR indications an immediately obvious fact and thus believe that it is important to establish all the evidence for the proposed work even if it may seem trivial/obvious to some of the readers.

Thus in section III we observe that the average bit error rate in a corrupted MAC frame, when expressed as a function of SSR, indeed has a constant relationship across different environments. The invariance of this first-order relationship is essential for invariance in higher order relationships to exist. Invariance in higher order relationships is essential for a single Markov model associated with a particular SSR to characterize all residue errors in packets with that particular SSR. Thus the above result is used as a motivation for the remainder of the work. We also quantify, on the basis of mutual information, the variations in the temporal correlation of the residue error process with respect to the SSR range. It is observed that the amount of temporal correlation can vary as a function of SSR, thus providing further motivation for the proposed work.

Based on the above motivation, we focus on developing SSR aware Markov models. In section IV we provide description of the Markov states. We also quantify in terms of conditional entropy the utility of Markov modeling at various SSR values. We then investigate the ability of the full-state Markov chains (FSM) to capture various features in the residue error process. In particular with the help of Entropy Normalized Kullback-Liebler (ENK) distance, we show that the SSR aware Markov models can capture the features such as the (i) Inter-arrival rate of error bursts and (ii) Frequency of error in a corrupted packet, significantly better than a SSR unaware model.

In section V we utilize the above developed SSR aware models to realize a *non-homogenous Markov model*. The performance of the SSR aware Non-Homogenous Markov model in replicating the residue error process is shown to be significantly better than the other models. Finally in section VI we summarize the key conclusions of the proposed work.

## II. Trace Collection Methodology

Our experimental setup envisaged collecting 802.11b frames at in various work environments. The setup consisted of 802.11b Access Point (AP) operating in Distributed Coordination Function mode with RF output power set at 18dBm. A station is connected to the AP using 100Mbps Ethernet and acts like a server, while a wireless station serves as a Line Of Sight (LoS) client. A third wireless station serves as "sniffer" machine. We used DWL 122 wireless card based on Prism 2.5 chipset with linux-wlan-ng-0.2.1pre21 device driver [1]-[2] for all "sniffer" machines, to avoid any fluctuations due to receiver sensitivity. The Prism based card enables operation in "monitor" mode which enables delivery of all the MAC frames without any filtering, including those with failed Frame Check Sequence (FCS).

For the trace collection, the AP transmits packets over the wireless medium to the LoS client at 11Mbps and the "sniffer" sniffs these transmissions from various locations with different link quality. The source code of the "sniffer" device driver was modified to dump all the corrupted/uncorrupted frames from the kernel buffer space. The Prism2.5 device also measures received signal strength indication (RSSI) value and "silence" value at the antenna of the radio hardware. The RSSI is measured for 10µs while receiving the frame and provides total power observed, including signal, interference and background noise. The "silence" value measures total power before the start of the frame. Both these values are collected per-frame basis and reported as Signal-to-Silence ratio of that particular frame. In this paper all references to Signal-to-Noise Ratio (SNR) also imply the RSSI to silence value ratio. Packets that correspond to the LoS Client were recovered from the packet dump at a later stage and the XOR images of the LoS Client and the sniffer are used as error traces.

The work environments where traces were collected have been broadly classified into two groups. The first setup (*Home Setup*) consisted of a relatively interference-free Home environment. The second setup (*Office Setup*) consisted of an office environment with 2 to 3 "Rogue" (i.e. interfering) APs on a single channel. In this study we only consider the 802.11 PHY bitrate of 11Mbps. We collected about 1.5 million packets in *Home Setup* at a packet transmission rate of 384packets/sec and another set of 1.5 million packets in *Office Setup* at a packet transmission rate of *almost* 1000 packets/sec. For both the Office and Home setup, the A.P and the sniffer had atleast one wall between them. The size of the rooms in which the data was collected, varied approximately from a 10 *by* 10 feet room in a house to a 30 *by* 30 feet office space. The sniffer machine was not necessarily static; the mobility was completely determined by the arbitrary slow/occasional movement of a human subject collecting the traces.

## III. Motivation

**Long Range Dependence:**

Let $\{z_i\}$ be a random process defined on the error trace, such that $z_i$ represents the total number of packet errors in the $i^{th}$ data packet. The data process $\{z_i\}$ can be aggregated at a

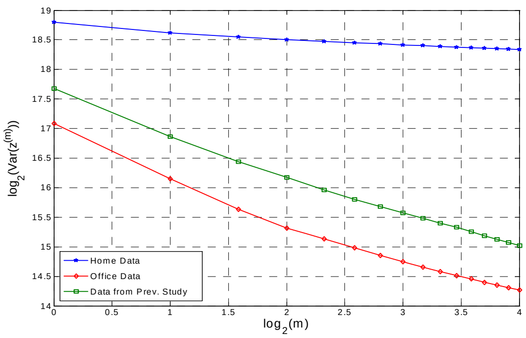



**Figure 1** Variance of number of bit errors per packet as function of different aggregation scales[3]

scale $m$ by defining a random process $z_i^{(m)} = \sum_{j=(i-1)\cdot m+1}^{i\cdot m} z_j$ such that, the sequence length of $\{z_i^{(m)}\}$ is $1/m$ time's length of $\{z_i\}$. The variance of $z_i^{(m)}$, derived from the actual wireless trace data can be used to deduce whether the process $\{z_i\}$ is Long Range Dependent (LRD). In [12] on the basis of the slope of the curve defining the relationship between $\log_2\left(\mathrm{var}(z^{(m)})\right)$ and $\log_2(m)$ it had been deduced that the process $\{z_i\}$ is LRD. We conduct a similar analysis, with the traces collected in this work.

Figure 1 shows the log-variance plots for the *Home* and *Office* data. It can be observed that the slope of the plot varies, depending on the environment in which the traces were collected. A process is LRD if the *Hurst parameter* lies between 0.5 and 1. From the Figure 1 it can be deduced that $H = 0.9375$ corresponds to the *Home_Data* and $H = 0.3125$ corresponds to the *Office_Data*. Thus based on the observation in one wireless infrastructure one might conclude that $\{z_i\}$ is LRD (as done by [12]) and based on another infrastructure we could get a completely different conclusion. Hence, unless the radio-link parameters are taken into account, a model may be ignoring the fact that the "*source/cause*" for the residue errors has been altered and thus the process is non-stationary.

**Promise of an SSR based approach:**

***Loss Rate:***

Figure 2 shows the probability of receiving a completely uncorrupted packet at a particular SSR. The SSR values 0-7dB, 7-14dB and 14db-above form the SSR ranges bad, transition and good respectively. The probability of receiving an uncorrupted packet varies as 0-0.1 in the "Bad Range", 0.1-0.9 transition range and 0.9-1.0 in the "Good Range". For SSR values above 14dB, corrupted packets are rare and thus the confidence in the relationships presented for this Range is low. Explicit attempts at collecting large quantities of bad packets in the "Good Range" haven't been made due to lack

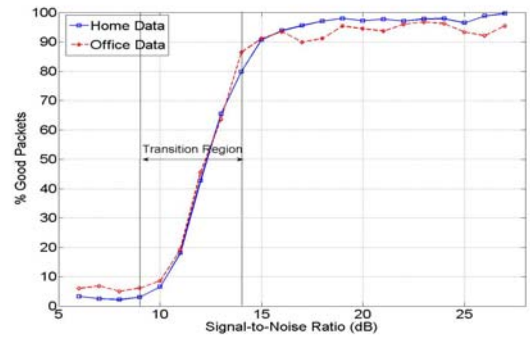



**Figure 2** Probability of receiving an uncorrupted packet

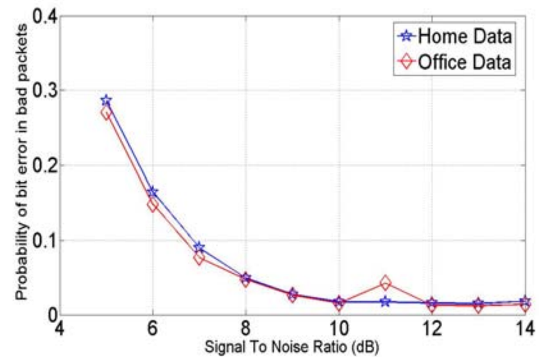



**Figure 3** $\overline{\varepsilon(SSR)}$ v/s Signal-to-Silence Ratio

of utility of data recovery from corrupted packets in extremely good channel conditions.

Also note, that we often refer to corrupted packets as "Bad Packets" and uncorrupted packets as "Good Packets".

***Bit Error Rate*:**

We evaluated the relationship of SSR and the average bit error rate in a corrupted packet received with the corresponding SSR indication. The value of $\overline{\varepsilon(SNR)}$ was obtained by measuring the average percentage of corrupted bits in all corrupted MAC frames for a given SSR value. Figure 3 shows the plots based on such an evaluation. It can be observed that the distribution for *Home_Data* fits *Office_Data* pretty well. Thus if SSR is taken into consideration, a single model can be expected to represent atleast the first order statistic of residue errors over different environments.

***Mutual Information as a function of lag*:**

To quantify the amount of memory in the residue errors of corrupted packets we calculated the sample mutual information as a function of lag $\eta$. The sample mutual information can be calculated by considering the sequence of errors in a packet $\{x_i\}$ and then evaluating the mean frequency $f\{x_i, x_{i+\eta}\}$ of each possible combination of $\{x_i, x_{i+\eta}\}$. The frequency $f(x_i)$ is nothing but the average probability of error $\overline{\varepsilon}$. Thus the mutual information is then calculated using the standard mutual information formula

[3] "Data from previous study" was obtained by utilizing some of the packet traces used for [12].

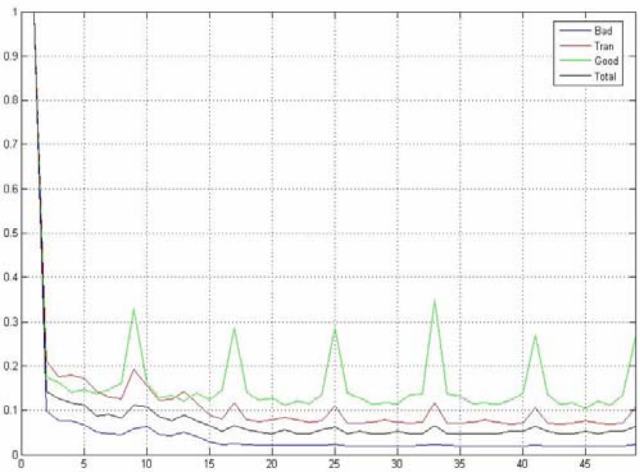



**Figure 4** Normalized Mutual Information between bits in a corrupted packet with lag $\eta$

$$I(\eta)=\sum f\left(x_i,x_{i+\eta}\right)\log_2\left(\frac{f\left(x_i,x_{i+\eta}\right)}{f\left(x_i\right)\cdot f\left(x_{i+\eta}\right)}\right)$$

Figure 4 shows the SSR range wise mutual information normalized by the sample entropy

$$H\left(X_i\right)=\sum f\left(x_i\right)\log_2\left(\frac{1}{f(x_i)}\right)$$

It can be seen that the mutual information decays faster as function of lag when the SSR values are low. As the SSR values increases the memory increases. Thus naturally implying the need for different models at different SSR ranges

Ideally the length of the channel model should be varied as a function of SSR. However in order to simplify the analysis and make a more fluent presentation in this paper we focus on models that have equal memory length for all SSR values. Thus unlike a traditional approach of modeling, where the memory length of a process is identified before choosing a model, we choose a specific model order and then try to evaluate the utility of the model. The utilty of the model should thus be expected to vary as a function of SSR.

## IV. FULL STATE MARKOV MODEL

**Order and State Definitions:**

For a memory length $k$, the bit errors $\bar{x}=[x_1,x_2\cdots x_k]$ have $2^k$ possible error patterns. The states of the Markov model we employ here are described by the bit error pattern of the previous $k$ bits. Since we formulate a distinct state for each possible error pattern, the Markov model used in this paper can be referred to as a full-state Markov (FSM) chain. The Markov chain we employ is auto-regressive in nature, such that for each state transition $[x_1,x_2\cdots x_k]\rightarrow[x_2,\cdots x_k,x_{k+1}]$, the output is a single error bit $x_{k+1}$. Thus the state transition probabilities provide us with the probability of error at a particular bit location, conditioned on the error pattern of the previous $k$ bit locations. Such a modeling approach is particularly useful in practical setups.

In this section we consider 2 models, both these models are obtained by evaluating the transition probabilities only over the corrupted packets. Let $Z$ be an indicator random variable (obtained from the Frame Check Sequence) that can indicate whether a packet is corrupted ($Z$=1) or uncorrupted ($Z$=0). Thus,

SSR_Unaware: model is obtained by evaluating the transition probability $p\left([x_2,\cdots x_k,x_{k+1}]/([x_1,x_2\cdots x_k],Z=1\right)$ for each possible pattern

SSR_aware: model is obtained by evaluating the transition probability $p\left([x_2,\cdots x_k,x_{k+1}]/([x_1,x_2\cdots x_k],Z=1,SSR\right)$ for each possible pattern

**Conditional Entropy:**

In Figure 5 the conditional entropy for a particular value of *SSR* has been calculated as

$$H\left(X_{k+1}\big/ SSR=c,\left[X_i,\cdots X_k\right]\right)=$$
$$-\sum_{SSR=y}\left(\begin{array}{l} f\left(x_{k+1}\big/ SSR=c,\left[x_i,\cdots x_k\right]\right)\\ \cdot\log_2\left(f\left(x_{k+1}\big/ SSR=c,\left[x_i,\cdots x_k\right]\right)\right)\end{array}\right)$$

Thus the conditional entropy measures the uncertainty associated with the error process if the SSR value is known and the previous $k$ values are known. It can be seen that increasing the memory length of the model is beneficial at all SSR values, however at very low SSR values the entropy of the error process may be too high to provide any useful information even when a high order Markov model is used. As against that in a transition region the benefits of increasing the order of the model starts diminishing as the size of the order starts equaling the memory length of the process. For high SSR values, increased memory can provide significant performance benefits. Thus it can be clearly observed that different strategies may have to be adopted to model residue error processes in different SSR ranges.

**Efficiency In Capturing Features**

We measure the performance of the full-state Markov chains (FSM) in terms of the ability of the synthesized data to replicate the *features* of the actual error process. The *features* are defined in terms of random variables such as inter-arrival rate $I$ and the frequency of errors per packet $p$. The performance of the model is quantified in terms of *Entropy*

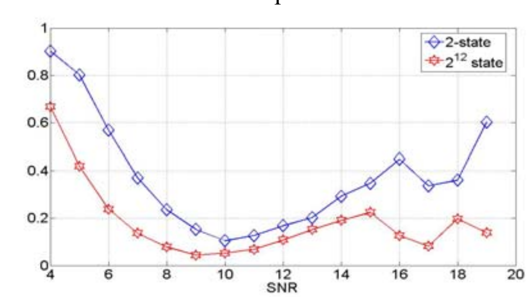



**Figure 5** Conditional Entropy for varied model orders as a function of SSR

*Normalized Kullback-Leibler* (ENK [11]) *Divergence* between the probability distributions of the various random variables.

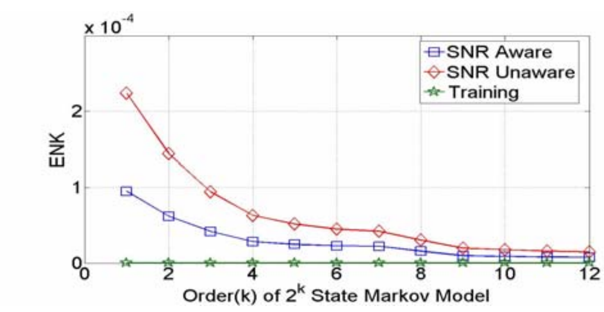
The Kullback-Leibler distance [9], gives approximately the difference in bits required to code a single symbol for the two probability distributions. If the probability distributions are close to each other the distance should be close to zero. However the Kullback-Leibler distance does not portray the complete picture, for e.g. a distance of 1 bit represents a smaller distance from the original distribution if the number of bits required to represent a symbol is 10 compared to case when the original distribution required 1 bit. We can improve the measure by normalizing the Kullback-Leibler distance with entropy. Thus the expression for ENK is given by

$$ENK\left(p\left(\overline{X}\right)\middle\|q\left(\overline{X}\right)\right)=\frac{D\left(p\left(\overline{X}\right)\middle\|q\left(\overline{X}\right)\right)}{H\left(p\left(\overline{X}\right)\right)}$$

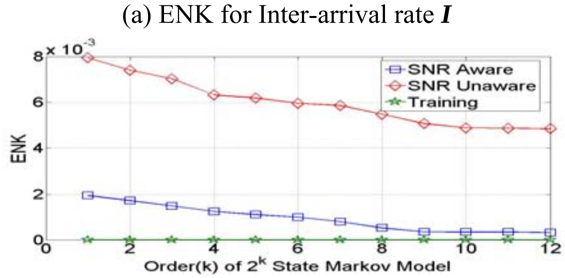
where $p\left(\overline{X}\right)$ is obtained from the actual trace data and $q\left(\overline{X}\right)$ is obtained from the synthesized data.

The *training set* for the Markov models was formed by randomly choosing 70% of the corrupted packets from the *Home_Data*. The remaining 30% was used as *test data*. The transition probabilities for the Markov models were determined based on this training data. Once the training was done, the transition matrix was used to synthesize the data. The relative entropy of the synthesized data with the test data was compared with the relative entropy of the training data with the test data. This allows us to compare the performance of the model vis-à-vis the ability of the source to model itself.

Figure 6 (b) shows the result of the above explained experiments. At low model order the ability of an SSR aware model to capture the inter-arrival rate feature was significantly better than that that of an SSR unaware model. As the memory

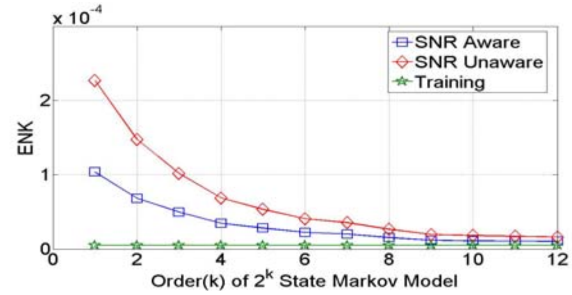



(a) ENK for Inter-arrival rate ***I***




(b) ENK for frequency of bit errors per packet ***p***

Figure 6 ENK for test data chosen from *Home_Data*




(a) ENK for Inter-arrival rate ***I***


(b) ENK for frequency of bit errors per packet ***p***

Figure 7 ENK for test data chosen from *Office_Data*

length increased, the relative entropy of the synthesized data for both the models was almost equal to that of the training data from the source. Hence to appropriately illustrate the utility of *SSR_aware* modeling (especially because the performance measure ENK is feature dependent) we consider the ability of the model to capture another feature, ***p*.** In many practical error control mechanisms the distribution of *p* can play a pivotal role. Thus if a model is unable to extract this feature, simulations based on such a model may lead to conclusions that are not applicable over actual networks. It can be observed in Figure 6 (c) that an SSR aware scheme can provide performance close to that of the training data even by using low order Markov model. However, an SSR unaware Markov model provides drastically worse performance even for large memory lengths.

To further test the utility of an SSR aware modeling approach, we consider test data that was drawn from a completely different environment. For this purpose we consider the *Office_data*. The synthesized data was still generated on the basis of the transition matrix obtained by training on *Home_data*. Figure 7 shows the performance in terms of ENK. It can be seen that the ENK between training data and test data is greater than before, thus underlining the significance of utilizing test data from a foreign environment. It can be observed that the *SSR_aware* model can characterize residue error traces from a distinct infrastructural setup also very well.

## V. NON-HOMOGENOUS MARKOV MODEL

Till this point our analysis has been completely based on analyzing the residue error traces in a piece-wise manner. In the collected traces, corrupted packets do not necessarily occur continuously and similarly consecutive packets do not necessarily have identical SSR indications associated with them. Thus to test our belief that the work presented in the previous sections may be useful for development of future predictive tools in dynamic environments, in this section we consider the 802.11b residue error traces as a continuous process. We use various models to synthesize data. For some models the FCS and SSR traces associated with the actual residue error trace is provided as side-information. We evaluate the ability of the various models to replicate the features of the actual residue error traces. Thus for the purpose of data synthesis we consider.

(i) **FSM model:** This corresponds to the modeling approach employed in [11], and is packet boundary unaware and SSR unaware, thus the model parameters are obtained by training the model on the entire residue error trace.

(ii) **PA-FSM**: This corresponds to a modeling scheme that is *SSR_unaware* but is packet boundary aware. Thus we leave the decision of whether a packet is uncorrupted or not to the FCS. If the FCS indicates that a packet is corrupted then the data in that location is synthesized on the basis of the SSR_unaware Markov model

(iii) **SAPA-FSM:** This corresponds to a modeling scheme that is *SSR_aware* and packet boundary aware. Thus we leave the decision of whether a packet is uncorrupted or not to the FCS. If the FCS indicates that a packet is corrupted then the data in that location is synthesized on the basis of the SSR_aware Markov model .

For the data synthesized using each of the above models we calculated the log-variance plots, similar to Figure 1. Figure 8 shows the result of such a experiment. The closer the log-variance plot of a synthetic data to the actual data, better would be the performance of a model as a predictive tool. Thus it can be observed that, even when a process is long-range dependent, very efficient prediction and channel characterization can be achieved if the CSI provided by the FCS and SSR indications is utilized in conjunction with a *SSR_aware* Markov Model.

The significance of the results presented in Figure 8 can be

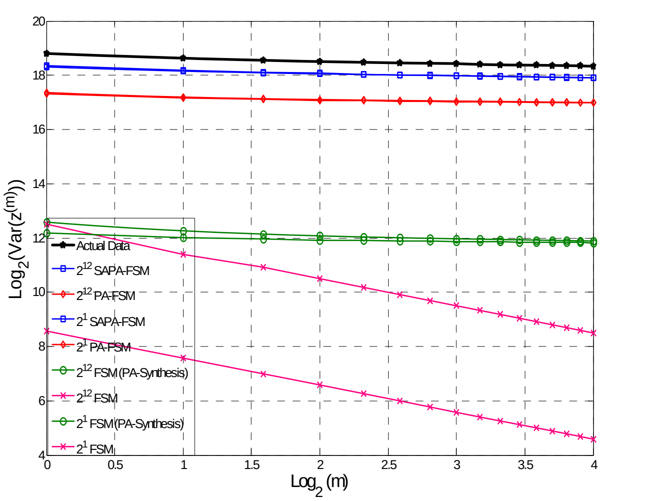



**Figure 8** Variance of number of bit errors per packet as function of different aggregation scales for actual data from *Home_Setup* and for data synthesized using methods (i), (ii), (iii)

brought forth by highlighting its implications. Note, if a process is concluded to be LRD, then a long history may be essential to achieve good channel/process characterization. Results in Figure 8 show that, in a practical system we could get efficient performance with zero history, as long as we do not ignore the CSI.

## VI. Conclusions

In this paper it has been shown that the ability of Markov models to characterize the residue errors in 802.11b can be greatly enhanced by making them SSR aware. We show that the overall behavior of link-level residue errors is a function of the environment in which the wireless traces are collected. SSR indications can be useful in unbiasing the environmental and infrastructural biases. SSR_aware Markov models were shown to provide excellent performance in foreign environments also; and thus should prove useful for developing future error control, simulation/emulation applications.

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