A Real-time Algorithm for Long Range Signal Strength Prediction in Wireless Networks

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Abstract— **Prediction of rapidly time variant fading channel conditions enables adaptive data transmission in wireless systems, which in turn improves the quality of service for end users and reduces the power consumption for data transmissions. In this paper, we construct an accurate, low-complexity, on-line prediction mechanism for the *long range* prediction of wireless link quality. Our method is independent of the propagation environment and distance between user nodes and the access points. The proposed method uses past measurements of the received signal strength as its input, and uses a combination of segmentation, filtering and regression to predict the future trend in the received signal strength. An adaptive windowing mechanism is designed to adapt to abrupt changes in the data trace, which considerably reduces the prediction error. The algorithm is tested on real life networks in diverse environments. The prediction results are compared with one of the best existing channel prediction algorithm. We show that our algorithm can be used as a robust and comparatively more accurate predictor.**

I. Introduction

Efficiency in data transmission and energy consumption in wireless systems can be enhanced via adaptive data transmission based on current and future wireless channel conditions. Consequently, wireless link quality estimation and prediction tools are very useful for users or designers of wireless systems. Prediction methods for fast fading channels have received considerable attention in the literature and many schemes exist that can predict fast fading channel coefficients, at a time horizon of several milliseconds, for wireless nodes moving at vehicular speeds. However, in many scenarios and applications, predictions on a longer time scale, such as that in the order of hundreds of milliseconds may be desirable. For example, dynamic route selection methods based on link quality in multi-hop wireless networks require abundant time to explore and select new paths when the signal to noise ratio on the previous route degrades. In this paper, we consider the problem of signal strength prediction for scenarios with such long range prediction requirements.

The work in this paper specifically addresses the problem of online, long range prediction of signal strength in wireless networks. Our work is motivated by the need to develop real-time and accurate tools that can predict wireless link quality many hundreds of milliseconds ahead in adaptive data transmission wireless systems for mobile users. In addition to aiding MAC, routing and other application layer protocols that adapt to changing link conditions, the prediction mechanism developed in this paper is also applicable to scenarios with slow node movements, such as users walking in a campus or office environment etc. In our work, we assume that the mobile node moves with a speed of $v = d$ meters/s where d is much larger than the radio signal's wavelength.

The link quality prediction scheme proposed in this paper uses the received signal strength as the metric for link quality and uses measurements of the received signal strength as the input to the prediction scheme. The problem of long range signal strength prediction is quite challenging due to a number of reasons. First, the received signal strength trace may not be ergodic since the wireless medium is time varying in nature. At a given site, the channel is susceptible to variations caused by noise, multipath fading (also called small scale fading) and shadow fading (medium scale fading). Second, the mobile nodes move along unknown traces. It's thus hard to forecast abrupt changes caused by a mobile node moving into a shadowing area. The impediments in the channel caused by path loss (large scale fading) change over time in unknown ways also. To address these challenges, we divide the data into small segments. We smooth the segment data and filter it from multipath fading and measurement noise. For purposes of prediction, instead of using the error prone fixed window schemes, this paper develops an adaptive window based mechanism which dynamically chooses the window size to adapt to abrupt changes in the data trace to improve the prediction performance. We then predict future trend of measured data in segments, which is caused by path loss and shadow fading. In our work, we are interested in the prediction of large and medium scale fading only. Although small scale fading is also difficult to predict, fortunately there already exist many methods to characterize it [13].

Extensive tests in real life wireless networks with mobile nodes were used to validate the prediction methodology developed in this paper. These tests were carried out in a number of geographical locations, both indoors and outdoors, with different channel characteristics and user movement patterns. Our results show that the proposed prediction methodology successfully predicts the signal strength in all these scenarios with very low errors and also outperforms existing prediction methods. We also note that unlike many of the existing prediction methods that are site specific or based on extensive ray tracing of a given site, the proposed methodology does not depend on site specific information.

The rest of the paper is organized as follows: Section II presents the related work. Section III presents the experimental setup. Section IV describes the proposed methodology for signal strength prediction. In Section V we compare our prediction results with predictions from a existing autoregressive (AR) based wireless channel prediction tool. Finally, Section VI presents the concluding remarks.

II. Related Work

Many of the current works on link quality estimation for wireless networks use the rate of successful reception of packets as the means for estimation and prediction. Such methods include temporal trace based approaches such as Exponentially Weighted Moving Average (EWMA) and Window Mean with EWMA (WMEWMA) estimators [2]. In [3] the authors develop a more accurate estimator than WMEWMA by exploring spatial correlation for link quality estimation. However, the rate of successful reception of packets itself is a crude and biased (since the probability of successful reception depends on the transmission rate as well as the coding mechanism used) measurement for the quality of wireless links. In our work, we use the more representative and versatile received signal strength as the metric for link quality.

The deterministic channel model and an AR signal model with its parameter estimation schemes for predicting the mobile radio channel are compared in [10]. Based on realistic simulation data and measurements, the authors show that the AR model performs best. In [1], the authors present a mechanism for reliable prediction of fast fading channel coefficients several milliseconds in advance using an AR model. They assume that the signal is stationary with slowly varying parameters. In [4] the authors show that the better performance of the AR based prediction algorithms is due to their lower sampling rate relative to the conventional (data rate) methods. However, the prediction for more realistic non-stationary data is not improved significantly by the lower sampling rate. What's more, the iterative AR models used in their method have the problem of error propagation for prediction steps larger than one. In [5] an adaptive channel prediction algorithm using Kalman filtering is proposed. A mechanism based on Recurrent Least Squares Support Vector Machines and nonlinear regression for long range prediction of fading channels is proposed in [7]. However, the prediction range in all the above methods is only about a wavelength or few milliseconds ahead and cannot be used in applications such as dynamic route selection in multi-hop networks where we need predictions hundreds of milliseconds ahead.

A prediction algorithm based on multi-layer perception (MLP) is proposed in [6]. However, this requires measured and pre-processed channel data consisting of up to 6072752 patterns to be first developed for a given site, making it computationally complex for on-line deployments.

III. Signal Strength Measurement Methodology

In this section we outline the methodology applied to obtain the signal strength traces for the purposes of the prediction algorithm developed in this paper. We also describe the various locations in which the measurements were carried out.

It is well known that the performance of a wireless system depends on the environment in which it operates. This dependence on the environment mainly comes from the variation in radio channel behavior in different sites. One of the main aims of this paper is to develop a non site-specific prediction mechanism for wireless link quality and validate its performance in different environments. For this reason, measurements were carried out in multiple, diverse locations. Both outdoor and indoor scenarios were considered in our measurements. The measurements were conducted in various buildings and locations in the RPI campus. More specifically, the indoor measurements were carried out in three different buildings. The first is the Johnsson Engineering Center which primarily consists of rooms for faculty and space for laboratories. In the floors of this building where the measurements were conducted, concrete walls were the main cause of signal obstruction and attenuation. The second building was the campus library where the large number of metallic bookshelves were the primary source of attenuation and shadowing. The third indoor setting was the Student Union dining hall where there were lesser obstructions. In addition to these, outdoor measurements were also conducted at various locations in the campus. In addition to the measurements carried out at the university campus, a set of measurements were also carried in home settings, in an apartment. In all these measurement scenarios, multiple traces for the signal strength were collected as the user walked around inside the building or outside. More than 40 signal strength measurement traces were collected with the receiver moving at walking speed at 13 different environments.

In each of the measurement scenarios described above, signal strength measurements were done using the LINKSYS Wireless-G Broadband Router as the access point (AP) and IBM T42 laptop, running Linux Feroda core 5, with built in PH12127-E IBM 802.11a/b/g Wireless LAN Mini PCI adapter as receiver. The signal strength measurements were directly provided from the card by the `madwifi`-0.9.2 driver used for the card. The driver uses RSSI as the basic measure for signal strength which is converted to dBm. The driver assumes a constant noise level of -96dBm since this is the thermal noise for 20MHz OFDM signals, plus an additional 5dBm noise from the amplifiers. The SNR levels are then obtained by SNR(dBm)=Signal(dBm)-Noise(dBm). The actual signal strength measurements were conducted while the laptop received packets from the AP. The packets were from an UDP video data stream transmitted at a data rate of 30$\sim$35Kbps. We collected signal strength measurement every 0.25 seconds.

IV. Methodology

A. Overview

The aim of the proposed methodology is to predict the future trend in the wireless link quality as indicated by the signal strength, caused by path loss and shadowing for a prediction range much longer than a wavelength. Since the prediction range in this case is in the order of several hundreds of milliseconds and small scale fading is not of interest here, we first apply kernel smoothing on the raw measured signal strength traces in order to remove data variations due to small scale fading and measurement noise. The smoothing filter is designed to remove variations caused by multipath fading while keeping the variations caused by shadowing related fading. In the next step, we divide the data into small segments and predict the future trend in the received signal strength, using a dynamic window scheme. A linear regression model is then used to model and predict the signal attenuation trend caused by path loss and shadowing. Before presenting the details of the proposed methodology, we first describe the underlying communication model assumed in this paper.

B. Propagation Model

Wireless radio channels experience attenuations due to multipath fading, shadow fading and path loss fading. Multipath fading causes changes in the received signal strength within the order of one wavelength. Shadow fading is influenced by the spatial movements in the order of tens of wavelengths and creates random variations in the average power of the received signal. Path loss is caused by spatial movements in the order of hundreds of wavelengths making the average power level vary in power-law fashion with path length. The above three fading components are mutually independent of each other. In our work, we use the following commonly used statistical model from [8]. The ratio of the received and transmitted powers, P_r and P_u respectively, in dBm is given by

$$\frac{P_r}{P_u}(\text{dBm}) = 10log_{10}K - 10\gamma log_{10}\frac{d}{d_0} + \varphi_{\text{dBm}} + \phi_{\text{dBm}} \quad (1)$$

where $10\gamma log_{10}\frac{d}{d_0}$ models the path loss fading as a linear function of the distance d between the transmitter and receiver, with d_0 being the reference distance. Also, γ is the path loss exponent and K is a unitless constant which depends on the antenna characteristics. The attenuation from shadowing, φ_{dBm}, is normally distributed with zero mean and variance σ_φ^2. Finally, ϕ_{dBm} represents the variation caused by multipath fading and can be modeled as a Raleigh (for non-LOS channels) or Rician (for LOS channels) distribution with appropriate parameters.

In our work, we assume that the node is moving with a walking speed of $v = d$ meters/s. We assume that v is less than 5 miles/hour (2.22m/seconds). Our sampling interval for obtaining the measurement traces is 0.25 seconds. At 2.437GHz frequency (channel 6 in IEEE 802.11g), the radio wavelength λ is 0.1231m. Thus, for example, predicting the signal strength sample 2 index steps ahead corresponds to 0.5 seconds (1.11m ahead, which is about 10λ). In [1] it is shown that fast fading is predictable about a wavelength ahead. In our mechanism, we predict the trend of data caused by large and medium scale fading including path loss and shadowing. Since we are not concerned with small scale fading in this paper, to improve the quality of long range prediction, we remove the variations in the measurement data caused by small scale fading. This is the next step in the proposed methodology.

TABLE I
CHOICE OF SMOOTHING KERNELS

kernel	normal	uniform	epanechnikov	triangular
MISE	3.8947	3.0078	2.4655	2.1810
NMSE	0.0251	0.0260	0.0241	0.0225
kernel	triweight	quartic	cosinus	
MISE	1.9921	2.1759	2.4056	
NMSE	0.0223	0.0230	0.0238	

C. Data Smoothing

The first step in the proposed prediction methodology is to smooth the raw signal strength measurement trace in order to eliminate the variations caused by small scale fading and measurement noise. While many approaches are possible for signal smoothing, in this paper we use a kernel-based method. Kernel-based smoothing methods are the most popular non-parametric signal estimators and can uncover structural features in the data which a parametric approach might not reveal. The kernel bandwidth h controls the smoothness or roughness of an estimate and the performance of kernel smoothing is measured by MISE (mean integrated squared error) or AMISE (asymptotic MISE) [9].

In order to choose the right smoothing function, we tested the performance of a number of kernel-based smoothing methods on the measured data traces. The performance of seven kernel functions in terms of their MISE is shown in Table I. The equations governing each of these seven functions may be obtained from [9]. Our experimental results showed that the optimal value of the kernel bandwidth h is 2 for the data traces that we collected. Note that 2 samples correspond to distances 1.11m apart, which is about length of 10λ. This matches the results in [12] that on the average, "10λ window length provides the best compromise between removing multipath fading without distorting shadow fading patterns". The results shown in Table I are for the kernel functions at their optimal bandwidth. We note that the triweight kernel has the smallest MISE for our traces and is therefore chosen as smoothing kernel. The table also shows the error in the final prediction results (using the method shown the next subsection) when we use the different kernel functions. We again note that the triweight kernel leads to the smallest normalized mean square prediction error (NMSE) in the final results. The triweight kernel function is given by

$$K(x,p) = \frac{(1-x^2)^p}{2^{2p+1}B(p+1,p+1)}, \qquad |x| < 1 \quad (2)$$

with $p = 3$ and

$$B(a,b) = \Gamma(a)\Gamma(b)/\Gamma(a+b) \quad (3)$$

where Γ is the Gamma function.

D. Prediction Algorithm

In this section we describe the details of the prediction algorithm, an outline of which is given in Algorithm 1. We first note that even after smoothing, the signal strength trace may not be easily trackable because of the random movement of the user and the accompanying abrupt changes such as

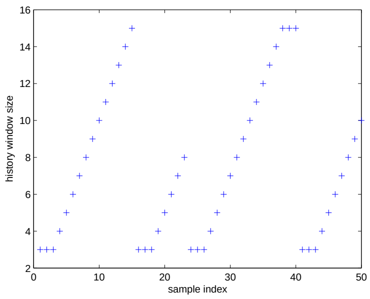

Fig. 1. History window size vs sample sequence in the adaptive windowing mechanism

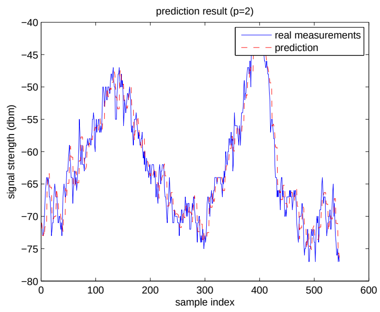

Fig. 2. Predicted vs measured signal strength

when the node moves in and out of a shadowing region etc. In order to make the data more predictable, a dynamic window is utilized to deal with abrupt changes. Predictions on the future values of the signal strength are then made by analyzing the trend of data within the sliding window. We now describe this prediction mechanism in detail.

The prediction mechanism is based on observing the trend in the past measurements. In the proposed mechanism, the past measurements $y_1, \cdots, y_n$ (after smoothing) are stored in a sliding history window. A linear regression model, $\widehat{Y}$=a+bX, is used to fit the data $y = (y_1, \ldots, y_n)$ with $x = (1, \cdots, n)$. The parameters of this regression model are given by

$$b = \frac{S_{xy}^2}{S_x} = \frac{\Sigma_{xy} - \overline{y} \cdot \overline{x}}{\Sigma_x^2 - n\overline{x}^2} \tag{4}$$

$$a = \overline{y} - b\overline{x} \tag{5}$$

where Σ_{xy} is the cross covariance of variable X and Y. $\overline{x}$ and $\overline{y}$ are the means of X and Y respectively. Σ_x^2 is the variance of X. The regression model is then used to predict future signal strength, $\widehat{y}_{n+p}$, according to

$$\widehat{y}_{n+p} = a + bp \tag{6}$$

where p is the prediction step.

A main feature of the proposed prediction mechanism is that instead of using a fixed window, we propose a dynamic windowing scheme to adapt to the abrupt variations in the signal strength. At initialization, the history window size is set at a default value. At each prediction step, the prediction errors are monitored and the window size is modified according to the observed error. If the prediction error is within an error threshold, the history window size is additively increased until it reaches the defined maximum window size. On the other hand, if the prediction error exceeds the error threshold, the window size is immediately decreased to its default initial value. This dynamic window scheme is designed to adapt to the abrupt change points in data trace. When sudden variations such as those caused by entering or leaving shadowing areas, old history data would not reflect the current trend and is thus discarded by reducing the window size. However, correct predictions increase our confidence in the trend shown by the past data, motivating the increase in the window size. Figure 1 shows the dynamic window size when the prediction mechanism is applied to one of the collected data traces while Figure 2 shows the accuracy of our prediction mechanism and its ability to closely follow the measured data trace at a prediction step of $p = 2$. Our experimental results show that this dynamic window scheme improves prediction performance by significantly reducing the prediction error as compared to fixed window size scheme.

Algorithm 1 Prediction Algorithm

p: `prediction step;`
$\widehat{y}_{i+p}$: `prediction of` $(i+p)_{th}$ `sample;`
w: `window size;`
w_{start}: `starting window size;`
w_{max}: `maximum window size;`
e: `prediction error;`
INITIALIZATION
$w = w_{start}$;
prediction lag for w;
$i = w$;{i is a loop control index}
PREDICTION
while (1) **do**
  read new incoming measurement as input of smoothing filter and output smoothed data y_i;
  calculate LR parameters a and b using $[y_{i-w+1}, \cdots, y_i]$;
  $\widehat{y}_{i+p} = a + bp$;
  $e = |(\widehat{y}_i - y_i)|$;
  if $(e > e_{max})$ **then**
    $w = w_{start}$;
  else if $(w < m_{max})$ **then**
    $w++$;
  else
    $w = w_{max}$;
  end if
  $i++$;
end while

V. Performance Evaluation

In this section we design and report on a set of measurement based experiments to validate our proposed prediction methodology. The parameters used in our mechanism are the experiment factors and we estimate the contribution of each factor and its values on the performance. We also compare our

TABLE II
2^K FACTORIAL DESIGN

	A_1		A_2	
	B_1	B_2	B_1	B_2
C_1	2.8076	2.8076	4.8599	4.8599
C_2	3.5337	3.4534	4.3783	4.4543

methodology with one of the most popular schemes that have been proposed in the literature. The performance metrics used are prediction accuracy and computational complexity. We use the normalized mean square error (NMSE), defined as

$$NMSE = \frac{1}{M}\sum_{j=1}^{M}\frac{\sum_{i=1}^{N}(y_i-\widehat{y}_i)^2}{\sum_{i=1}^{N}(y_i^2)} \tag{7}$$

to measure the prediction accuracy. In Equation (7) N is the sample size and y_i and $\widehat{y}_i$ for $i = 1 \ldots N$ are the measured and predicted data, respectively. M represents the number of traces collected at a given location with the user following the same path and $M = 3$ in our experiments.

A. Parameter Optimization

For a given signal strength trace, the performance metric NMSE depends on three parameter settings including the starting window size, the maximum window size, the error threshold and the interactions between these three factors. The smoothing window size is optimized to be 10λ for all data trace as an independent parameter shown in Section IV-C and is not discussed here. Each of these factors and their interactions has a range of values and can be optimized to achieve the best performance metrics. Optimizing the parameters by full factorial design is impractical since it requires too many experiments. Thus 2^K factorial designs, where the K factors ($K = 3$ in our case) each have 2 levels with extreme values, were used to obtain the optimal parameter settings. The allocation of variations of the 2^K factors were then used to estimate the contribution of each factor on the performance variation and then adjust the most important factors and ignore the trivial ones to achieve the "best" prediction performance.

We first set the range for each of the three factors with the window size $A \subseteq [3, 10]$, maximum window size $B \subseteq [10, 100]$, error threshold $C \subseteq [0.5, 5]$. For a signal strength trace, $2^K = 8$ factorial designs experiments are then conducted with the parameters set as extreme values in their range. The output NMSE of the eight experiments are shown in Table II. where

A_1: start window size = 3
A_2: start window size = 10
B_1: maximum window size = 10
B_2: maximum window size = 100
C_1: error threshold = 0.5
C_2: error threshold = 5

The performance metric NMSE has a variation, which is caused by the varying values of factors and their interactions. Importance of factor is explained as the proportion of variation caused by that factor. From Table II we can calculate that the variation caused by start window size (A), maximum window size (B) and error threshold (C) is 48.92%, 43.64% and 0.32% respectively. The interaction between start window size and error threshold (AC) explains 7.05% for the variation. The interaction between maximum window size and start window size (AB) counts for only 0.3% for the variation. The interaction between maximum window size and error threshold (BC) causes almost 0% variation. The interaction of the three factors together (ABC) causes 0.3% variation. Therefore we can conclude that start window size and maximum window size are the major factors. Although error threshold itself is not an important factor, its interaction with start window size has some influence on the prediction accuracy. Maximum window size can be optimized independently since its interaction between the other two factors has little or no contribution on the results. So for each data trace, first we search for the optimal value of the maximum window size by method of exhaustion, since the range of this parameter is discrete and limited. Then, similarly we search for the optimal value of start window size and its combination with proper error threshold. In our experiments, for each of the 13 wireless environments, we use one signal strength trace as training data and get the optimal parameters for that environment. We then use the other traces collected in that environment as testing data. Our experimental results show that the optimized parameters achieve minimum NMSE on the testing data also.

The assumption of 2^K factorial design is that errors are statistically independent, additive and normally distributed. To prove the validity of our experimental design, we use D'Agostino-Pearson's K_2 test [11] for assessing normality of prediction. The hypothesis test is given in as follows:

- $\mathcal{H}_0$[null]: Z is normal with unknown mean and variance.
- $\mathcal{H}_1$[alternate]: Z is not normal.

where Z represents the prediction error. If $\mathcal{H}_0$ is true, the Pearson statistic χ_2 for the tested data Z has Chi Square distribution with 2 degrees of freedom. For the prediction error obtained from our data trace in Figure 2, $\chi_2 = 11.5712$, p-value (probability that Chi Square random value with 2 degrees of freedom is greater than χ_2) is 0.1156 while significance level α is chosen to be 0.05. Since p-value is larger than α, the Null Hypothesis $\mathcal{H}_0$ is taken, which assumes that prediction error is normal.

B. Prediction Accuracy

The results from our prediction mechanism are compared with an AR based channel estimator provided and implemented in [13]. The authors of [13] also provide a SALP (Spectral Analysis and Linear Prediction)-Toolbox, which is a collection of MATLAB m-files developed for analyzing stationary and non-stationary signals. Linear prediction methods are investigated for adaptive transmission techniques in mobile communications in [13]. But since our data has trend, the AR model estimator has very poor performance when directly applied on our data. In order to make the comparison fair, we removed the trend of the data before it is input to the AR model by removing the average of the segment data along the sliding window. This average value is then added to

TABLE III

PREDICTION PERFORMANCE AND COMPARISON WITH AR MODEL

$NMSE \times 10^{-5}$ for trace 1 (RPI JEC Building)					
prediction step	1	2	3	4	5
AR	0.1945	0.3213	0.4425	0.5030	0.5764
line fit	0.1810	0.2189	0.2552	0.2977	0.3341
prediction step	6	7	8	9	10
AR	0.664	0.812	1.065	1.564	2.432
line fit	0.3693	0.3979	0.4407	0.4783	0.5049

$NMSE \times 10^{-5}$ for trace 2 (RPI Library)					
prediction step	1	2	3	4	5
AR	0.23	0.4019	0.5558	0.6195	0.6838
line fit	0.2137	0.2794	0.3198	0.3621	0.3805
prediction step	6	7	8	9	10
AR	0.726	0.781	0.828	0.929	1.066
line fit	0.4415	0.4625	0.4897	0.4888	0.4842

$NMSE \times 10^{-5}$ for trace 3 (RPI Student Union Dinning Hall)					
prediction step	1	2	3	4	5
AR	0.292	0.45	0.58	0.68	0.85
line fit	0.2756	0.3376	0.3800	0.3925	0.4170
prediction step	6	7	8	9	10
AR	1.13	1.84	3.07	5.65	11.59
line fit	0.4321	0.4344	0.4577	0.4938	0.5094

$NMSE \times 10^{-5}$ for trace 4 (Home)					
prediction step	1	2	3	4	5
AR	0.271	0.437	0.530	0.567	0.644
line fit	0.2138	0.2819	0.3522	0.4116	0.4185
prediction step	6	7	8	9	10
AR	0.698	0.811	0.925	1.138	1.441
line fit	0.4452	0.4688	0.4794	0.5800	0.5953

$NMSE \times 10^{-5}$ for trace 5 (Outdoor RPI Campus Road)					
prediction step	1	2	3	4	5
AR	0.2710	0.4368	0.5302	0.5669	0.6437
line fit	0.2705	0.3506	0.3920	0.4225	0.4597
prediction step	6	7	8	9	10
AR	0.698	0.811	0.925	1.138	1.441
line fit	0.4805	0.5170	0.5693	0.6226	0.6632

the prediction result obtained from the AR model. Prediction results generated by [13] and our algorithm for ten different prediction steps $p = 1, \cdots, 10$ are shown in Table III. The NMSE for the two methods is tabulated for five different locations, both indoors and outdoors, and the methodology of this paper is labeled “line fit”. Parameters for both methods were optimized using the 2^K factorial design. We note that the proposed method has very good prediction accuracy and outperforms the AR based model. We also see that in the AR model, the prediction error increases quickly when the prediction step increases. This is because [13] uses iterative AR model for multiple steps prediction, which lead to error propagation. In our methodology, the increase in the error is much smaller, especially for longer prediction horizons. Our experimental results show that above observations are true for all the data collected in 13 environments, where different floors of JEC building, library and student union are also included. This indicates that although AR model is a good predictor for small scale fading [10], it’s not the best one for large and medium scale fading prediction.

C. Computational Complexity

The proposed prediction methodology has significantly lower computational complexity as compared to the AR based model of [13]. The AR model parameters require large matrix inverse calculations if the AR order is large. Also, its computational complexity increases as the prediction step increases. In the proposed method, the computational complexity is independent of the prediction step, since our prediction is only dependent on the calculations of the regression parameters a and b. Also, the computations involved in determining the values of a and b is much lower that the calculations required for the matrix inversion in the AR based model.

VI. CONCLUSIONS

We proposed an accurate, on-line prediction mechanism for link quality in wireless networks. The prediction mechanism is based on a regression model of smoothed past measurements of the received signal strength and has the advantage of being location-independent. Experimental results were conducted in a number of settings, both indoors and outdoors. Our method can predict at long ranges (up to a few seconds) at walking speeds and outperforms AR based channel prediction models in terms of both the accuracy and the computational complexity. Our predictor can be used in adaptive transmission applications such as dynamic route selection in multi-hop networks, where predictions are needed many hundreds of milliseconds in advance.

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