

**ENABLING ADAPTIVE OFDM FOR MOBILE RADIO CHANNELS<sup>1</sup>**

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**ABSTRACT**

*Adaptive orthogonal frequency division multiplexing (AOFDM) modulation is a promising technique for achieving high data rates required for wireless multimedia services. To accomplish efficient adaptive channel loading, the channel state information (CSI) needs to be fed back to the transmitter. Since the fading channel varies rapidly for fast vehicle speeds, long range fading prediction (LRP) is required for mobile radio AOFDM to insure reliable adaptation. We use past channel observations to predict future CSI and perform adaptive bit and power allocation for the OFDM system. We derive the minimum mean-square-error (MMSE) long-range channel prediction that utilizes the time and frequency domain correlation functions of the Rayleigh fading channel. Since the channel statistics are usually unknown, robust prediction methods that do not require the knowledge of the correlation functions are developed. Statistical model of the prediction error is created and used in the design of reliable adaptive modulation. In addition, several methods that significantly reduce the feedback load for mobile radio AOFDM systems are developed and compared. We use a standard sum-of-sinusoids model and a novel physical model to test our algorithm. Simulation results demonstrate reliable performance and robustness of the proposed techniques, thus validating feasibility of AOFDM for rapidly varying mobile radio channels.*

**I. INTRODUCTION**

Continued increase in demand for all types of wireless services such as voice, data, and multimedia is fueling the need for higher capacity and data rate. Orthogonal frequency division multiplexing (OFDM) [1] has been proposed for use in high-speed wireless data applications due to its relatively simple receiver structure compared to single carrier transmission in frequency selective fading channels. In a frequency selective fading channel, some subcarriers experience a deep fade while others are subject to channel gain. The spectral efficiency can be improved by allocating more bits to those subcarriers with favorable channel conditions than to those in a deep fade. This is called adaptive OFDM (AOFDM). Several

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practical integer-bit and power allocation algorithms have been addressed in [2–4] that perform the optimum or near-optimum loading of bit and power in an OFDM frame.

AOFDMA requires CSI feedback from the receiver. Since the channel is rapidly time variant for fast vehicle speeds, there is a mismatch between the channel quality that is estimated by the receiver and fed back to the transmitter, and that is actually experienced during the transmission of the following OFDM frame. This degrades the achievable performance gain of AOFDM, especially in rapidly time variant fading. Even in an open-loop system where the CSI is obtained by channel estimation at the transmitter as in time division duplex (TDD) operation [5], current CSI is not sufficient since future channel conditions need to be known to adapt transmission parameters. To realize the potential of AOFDM, the channel variations have to be reliably predicted at least several milliseconds ahead.

Recently, a novel adaptive long-range prediction (LRP) method for flat fading channel was proposed in [6–9]. This algorithm employs an autoregressive (AR) model to characterize the fading channel and computes the minimum mean-square-error (MMSE) estimate of a future fading coefficient based on a number of past observations. The advantage of this algorithm relative to conventional methods is due to its low sampling rate (on the order of twice the maximum Doppler shift and much lower than the data rate), which results in longer memory span and prediction further into the future for a fixed filter length. More recently, the LRP was extended to frequency selective channels. In [12,13], LRP and adaptive modulation using CSI of another carrier was addressed, and in [21], LRP for frequency hopping (FH) systems was investigated. In this work, we develop the long-range prediction algorithms for OFDM systems. An ideal MMSE method that utilizes previous observations in time and frequency domain, and robust adaptive LRP algorithms are developed and compared. The LRP is utilized in adaptive bit and power allocation for the OFDM system. Statistical model of the prediction error is created and used in the design of reliable adaptive modulation.

The fading channel is characterized as the superposition of several scattered components. The accuracy of the LRP algorithm is determined by the rate of change of amplitude, frequency and phase associated with each scatterer [6,9–11]. However, the standard Jakes model or a stationary random process description does not capture the variation of these parameters. To validate the LRP, novel physical channel modeling based on the method of images was proposed in [9–11]. It was demonstrated in [9–11] that this physical model generates data sets that closely resemble measured data, and results of the LRP for the physical model and measured data are similar. In addition, this model can generate different scenarios to classify typical and challenging cases for testing the algorithm. These scenarios are more difficult to identify for the

measured data. Thus, the physical model allows to test robustness and to determine practical constraints of the proposed adaptive transmission methods. In this paper, we employ this physical model to test performance of the LRP for AOFDM.

The transmitter can obtain the knowledge of the CSI to properly adapt the modulation parameters for each subcarrier from different sources. If the communication between the two stations is bi-direction and the channel can be considered reciprocal, as, for example, in TDD systems, then each station can estimate the channel quality on the basis of the received symbols and adapt the parameters to this estimation. This is called open-loop adaptation [5]. If the channel is not reciprocal, the receiver has to estimate channel quality from feedback resulting in closed-loop adaptation. The feedback load consumes power and bandwidth, and the fed back CSI needs to be quantized resulting in degraded performance. (Note that for many adaptive transmission applications, e.g., selective transmitter diversity or fixed power adaptive modulation, it is not necessary to feed back the actual fading coefficient. It is sufficient to send to the transmitter just the antenna selection or modulation index bits derived from the estimates of predicted values at the receiver. However, feedback of complex fading coefficients is required for some adaptive transmission applications and/or if the prediction is performed at the transmitter [9].) For AOFDM, the CSI is required for all subcarriers, resulting in high feedback load that increases for fast vehicle speeds due to high feedback rate. Hence feedback load should be minimized while providing sufficient information for the transmitter to predict the future CSI accurately. In this paper, we investigate reduction of the feedback load for closed loop systems by using the correlation induced by the multipath fading between the subcarriers.

The remainder of this paper is organized as follows. Section II introduces the channel model and statistics used to perform and test our prediction algorithms. In section III, we first briefly describe the adaptive OFDM system, and then present the theoretical MMSE long-range prediction and robust prediction methods that do not require the knowledge of the channel statistics for the AOFDM system. In Section IV, robust adaptive bit and power loading for mismatched channel information is investigated and the reduced feedback techniques are explored.

## II. PROPAGATION MODEL AND CHANNEL STATISTICS

The equivalent lowpass complex fading coefficients at  $K$  subcarriers,  $f^1 < f^2 < \dots < f^K$ , where  $|f^i - f^j| \ll$  the carrier frequency  $f_c$ , can be closely approximated as [17]:

$$c(f^i, t) = \sum_{n=1}^N A(n) \exp \{j(2\pi f_d(n)t + \phi_i(n)\}, i= 1, 2, \dots K \quad (1)$$

In (1), for the  $n^{\text{th}}$  path,  $A(n)$  is the (real) amplitude and  $f_d(n) = f_c \frac{v}{c} \cos(\theta(n)) = f_{\text{dm}} \cos(\theta(n))$  is the Doppler shift, where  $v$ ,  $c$ ,  $f_{\text{dm}}$ , and  $\theta(n)$  are the speed of the mobile, the speed of light, the maximum Doppler shift, and the incident angle of the path to the direction of the mobile, respectively. The phase difference for the  $n^{\text{th}}$  path,  $\phi_i(n) - \phi_j(n) = 2\pi\Delta f\tau(n)$ , where  $\Delta f = f^i - f^j$  is the frequency separation, and  $\tau(n)$  is the excess propagation delay. The gains  $c(f^i, t)$  are distributed approximately as zero mean complex Gaussian random variables. Therefore, the amplitudes  $|c(f^i, t)|$  are Rayleigh distributed. We assume the wide sense stationary uncorrelated scattering (WSSUS) model [15] with  $\theta(n)$  being uniformly distributed on  $[0, 2\pi]$ , and the propagation delay  $\tau(n)$  being exponentially distributed [17] with the probability density function (*pdf*)  $p(\tau) = \frac{1}{\sigma} \exp\{-\tau/\sigma\}$ , where  $\sigma$  is the *rms* delay spread [18]. The *ensemble average correlation function* (EACF) for two fading signals with the time difference  $\Delta t$  and the frequency separation  $\Delta f$  can be factored into the time-domain correlation function  $R_t(\Delta t)$  and the frequency domain correlation function  $R_f(\Delta f)$  as [16,19]:

$$R_E(\Delta t, \Delta f) = E[c(f^1, t) c^*(f^2, t + \Delta t)] = \Omega R_t(\Delta t) R_f(\Delta f) \quad (2)$$

where  $\Omega = E[|c(f^1, t)|^2]$  is the average power of the fading signals. (We normalize  $\Omega$  to 1 throughout the paper),  $R_t(\Delta t) = J_0(2\pi f_{\text{dm}}\Delta t)$  is the zero order Bessel function [17] and  $R_f(\Delta f) = \frac{1}{1+(2\pi\Delta f\sigma)^2} + j\frac{2\pi\Delta f\sigma}{1+(2\pi\Delta f\sigma)^2}$ . We define  $f_{\text{dm}}\Delta t$  and  $\Delta f\sigma$  as the *normalized time difference* (NTD) and the *normalized frequency separation* (NFS), respectively.

To generate the CSI with the desired correlation function (2), Jakes model is employed. In this model,  $N$  equal strength multipath components in (1) are equidistant on the unit circle. The usefulness of this model in testing the long range prediction algorithm is limited due to time-invariant parameters (the amplitude, the shifts and the phase are fixed once they are chosen). We extend the novel physical model in [9-11] to AOFDM channels and use it to test the robustness of the proposed LRP methods to variations of these parameters. Figure 1 demonstrates the scattering configuration and the channel gain for the physical model data set used in this paper. The maximum Doppler shift is 100Hz. The Doppler shifts undergo significant variation in the transition interval between samples 500 and 700. This interval is used to test the robustness of the LRP to parameter variation in the rest of this paper.

### III. SYSTEM MODEL AND LONG RANGE PREDICTION

Consider an OFDM signal with  $K$  subcarriers, symbol (block) duration  $T_s$ , and subcarrier (tone) spacing  $\Delta f_s$ . Assume the channel bandwidth of the each subcarrier is much smaller than the coherence bandwidth and the channel state

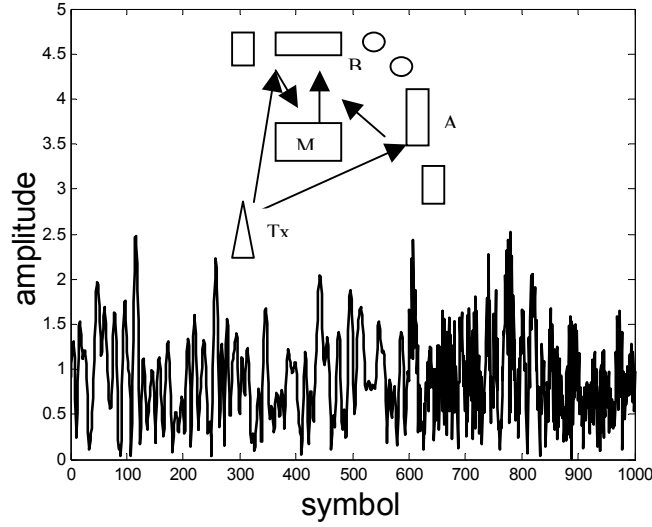


Figure 1. Geometry of the physical modeling and the corresponding data set.

information does not change within one OFDM symbol duration  $T_s$ , but varies from symbol to symbol. The equivalent complex channel gain  $H_s[n, k]$  at  $n^{\text{th}}$  symbol block and  $k^{\text{th}}$  subcarrier can be modeled as the samples of the time-varying frequency selective channel in (1) with the time domain and frequency domain sampling interval  $T_s$  and  $\Delta f_s$ . The ideal EACF (2) for the OFDM symbols with block difference  $\Delta n$  and tone spacing  $\Delta k$  can be expressed as  $R_E(\Delta n T_s, \Delta k \Delta f_s)$ .

The uncoded AOFDM system aided by the LRP and reduced feedback considered in this paper is depicted in Fig. 2. The input data is allocated to the subcarriers according to the CSI fed back from the receiver. The LRP is employed to enhance the CSI accuracy. Let  $a[n, k]$  denote the complex baseband symbols at  $n^{\text{th}}$  block and  $k^{\text{th}}$  tone. The received signal after OFDM demodulation can be expressed:

$$X[n, k] = H_s[n, k]a[n, k] + w[n, k] \quad (3)$$

where  $w[n, k]$  is the additive white Gaussian noise with power spectrum density  $N_0$ . Then frequency domain coherent channel estimation of the complex symbols associated with each of the  $K$  subcarriers is employed. A 2-D minimum mean square error channel estimator was proposed in [19]. Let

$$\tilde{H}_s[n, k] = H_s[n, k] + \tilde{w}[n, k] \quad (4)$$

denote the estimated CSI, where  $\tilde{w}[n, k]$  is the estimation error modeled as white Gaussian noise with power spectrum  $\tilde{N}_0$ .

Define the observation SNR as  $E[|H_s[n, k]|^2] / \tilde{N}_0$ .

We derive the linear MMSE-based channel predictor for the fading samples  $H_s[n, k]$  in (3) characterized by (1). One important parameter for the LRP is the sampling rate. For narrow band single carrier systems, the sampling rate of the

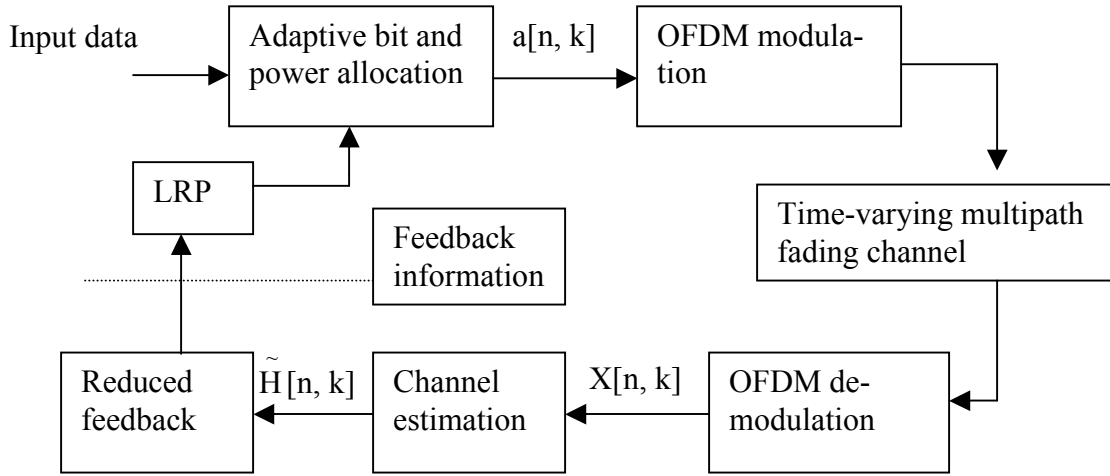


Figure 2. Block diagram of an adaptive OFDM system.

LRP is much lower than the symbol rate [9]. While the symbol interval in OFDM systems is longer, it is still beneficial to choose the sampling rate of the LRP lower than the symbol rate. Let  $\tilde{H}[n, k]$  denote the estimated CSI with the sampling interval  $T_p$  (an integer multiple of the OFDM symbol interval  $T_s$ ). The channel predictor for the CSI at the  $k^{\text{th}}$  tone and the  $n^{\text{th}}$  sample based on the  $p$  previously observed samples at  $K$  subcarriers can be constructed by:

$$\hat{H}[n, k] = \sum_{j=1}^p \sum_{m=1}^K d^*(j, m) \tilde{H}[n-j, m] \quad (5)$$

Provided that the correlation functions (2) are known, the optimal filter coefficients  $d(j, m)$  that minimize the MSE =  $E[|(H[n, k] - \hat{H}[n, k])|^2]$  and the closed form expression for the MMSE  $J_{\min}$  are derived in [16]. This result serves as a theoretical foundation for our prediction problem and will be used in the performance analysis.

In the linear prediction algorithm (5), the optimum MMSE is achieved by observing previous symbols of multiple subcarriers. However, this method is very complex in practice. Moreover, we observed that if the SNR of the observed feedback samples is high, the improvement in the prediction accuracy when non-adjacent subcarriers observations are used relative to observing just past samples of desired and adjacent subcarriers is negligible [16]. In fact, it can further be demonstrated that if the CSI is noiseless and the correlation functions are separable (2), then past samples of the desired subcarrier are sufficient to achieve the optimal MMSE performance [16]. Thus, we propose to simplify the algorithm by using only previously observed samples at subcarrier  $k$  to predict the CSI  $H[n, k]$ :

$$\hat{H}[n, k] = \sum_{j=1}^p d_j^*(n) \tilde{H}(n-j, k), \quad k=1, 2, \dots, K \quad (6)$$

Note that if the observation SNR is low, adjacent subcarriers can be easily incorporated to improve the performance by reducing the noise level at the cost of the system complexity. While in general, the coefficient vector  $\underline{d}(n) = [d_1 \ d_2 \ \dots \ d_p]^T$  in (6) needs to be computed and adapted individually for each subcarrier, for our channel model it is sufficient to employ the same filter coefficient vector  $\underline{d}(n)$  to predict future CSI for each subcarrier. This method is justified by the fact that the flat fading coefficients of different subcarriers have approximately the same Doppler shifts (see (1)). It was shown in [6] that only the Doppler shifts associated with the scattering determine the prediction coefficients  $\underline{d}(n)$  in (6). Hence the filter coefficient vector  $\underline{d}(n)$  should remain tone-invariant resulting in significantly reduced computational complexity and greatly improved tracking ability for the adaptive prediction methods discussed in the following sections since all feedback observations can be used jointly to update the coefficients. We call this method *simplified multiple carriers prediction* (SMCP). Note that this tone invariability can be generalized to the case when observation of several adjacent subcarriers are used for prediction provided that the same number of adjacent subcarriers is employed on each side of the desired subcarrier [16]. This method extends to adaptive transmitter antenna diversity systems since the channels for all antennas have the same Doppler shifts.

The optimum MMSE channel prediction above relies on the knowledge of the time and frequency domain correlation functions (2). However, these correlation functions depend on the particular environment and are usually unknown. In addition, the coefficient vector  $\underline{d}(n)$  in (6) needs to be computed adaptively as the Doppler shifts in (1) vary with time. We employ the adaptive Least Mean Square (LMS) and Recursive Least Squares (RLS) algorithms, which do not require the knowledge of the correlation functions of the channel, to update the prediction filter coefficients for the OFDM system.

The error between the desired response and the predicted CSI at subcarrier  $k$  is  $e[n, k] = H[n, k] - \sum_{j=1}^p d_j^*[n] \tilde{H}[n-j, k]$ ,  $k =$

$1 \dots K$ . The average mean square error (AMSE) over all subcarriers is defined as

$$\text{AMSE} = J(n) = \frac{1}{K} \sum_{k=1}^K E[|e[n, k]|^2] \quad (7)$$

This AMSE is used for updating the coefficients of the LMS and RLS algorithms. Since AMSE is the average of the single carrier prediction error, it is lower-bounded by the MMSE for the single carrier LRP  $J_{\text{amin}}$  given by  $J_{\text{min}}$  for (5) with  $K = k = 1$ . Note that using AMSE in SMCP, we adapt the coefficient vector  $\underline{d}(n)$  jointly using the errors for all subcarriers. This improves accuracy and convergence relative to single carrier adaptive prediction [7,9,11,16].

We use the Jakes (N=34) and the physical model to validate the performance of the LRP for the OFDM system. The prediction filter length  $p$  in (6) is 50. The maximum Doppler shift is 100 Hz and the *rms* delay spread is approximately set to 1 $\mu$ s. To construct an OFDM symbol, assume that the entire channel bandwidth, 800kHz, is divided into 128 subcarriers. The symbol duration is 160 $\mu$ s, and the guard interval is 5 $\mu$ s. Thus, the subcarrier symbol rate is approximately 6KHz. For each subcarrier, the fading signal is sampled at the low rate of 466Hz for the LRP (the prediction range is 1/466Hz  $\approx$  2ms). In this paper, we assume reliable channel estimation and hence the high effective SNR (80 dB) of the observed CSI. While actual SNR of the observed samples might be much lower, it is possible to employ noise reduction techniques due to very low sampling rate of the LRP [7,9]. Interpolation is utilized to predict channel coefficients at the subcarrier symbol rate [7–9].

Figure 3 demonstrates the AMSE (7) for the SMCP method for the Jakes model. When these results are compared with the single carrier prediction, we find that the excess mean square error for the LMS algorithm  $J_{\text{ex}}(n)$  ( $= J(n) - J_{\text{amin}}$ ) of these two approaches is the same given the same step size  $\mu$ . The MSE curve shown for  $\mu=0.005$  corresponds to both methods. However, the single carrier algorithm diverges for large  $\mu$ , while for the SMCP (6),  $\mu$  can be chosen as large as 0.1 without divergence, thus improving the convergence rate. As the NFS increases, larger step size  $\mu$  can be chosen, resulting in faster convergence [16]. The RLS significantly improves on the LMS. For the RLS, the excess mean square error  $J_{\text{ex}}$  for SMCP is derived similarly to that for the single carrier case [20]. It decays almost linearly with  $nK$  (the convergence rate is approximately  $K$  times faster than for single carrier prediction for (6)). For  $\lambda = 1$ ,  $J_{\text{ex}}(n)$  converges to zero, and for  $\lambda$  close to 1, the  $J_{\text{ex}}(\infty) \approx J_{\text{amin}} \frac{(1-\lambda)p}{2K}$ . Hence for large  $K$ ,  $J_{\text{ex}}(\infty) \approx 0$ . Thus, SMCP improves the convergence rate and the steady state MSE for the RLS relative to the single carrier prediction [6–9].

In Fig. 4, the SMCP is explored for the physical model. It is observed that the RLS algorithm converges rapidly with almost no excess MSE for  $\lambda = 0.9$ , whereas the LMS algorithm converges more slowly with significant excess MSE relative to the RLS algorithm. Fig. 4 demonstrates that the RLS algorithm is good at tracking the non-stationary channel. During the transition period (Fig. 1), the forgetting factor  $\lambda = 0.1$  has better tracking ability than  $\lambda = 0.9$ . Hence it is more robust to the non-stationary environment. The tracking results for the LMS algorithm are much poorer with a relatively high MSE during and even after the transition period. We also observed that the proposed prediction algorithm is more robust



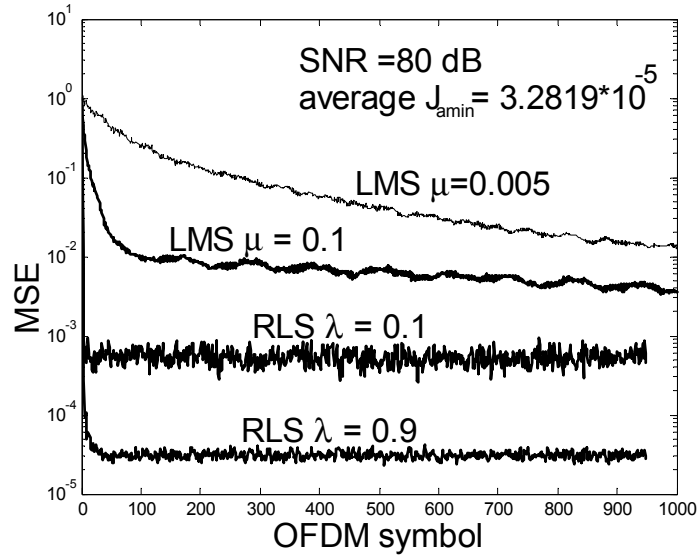


Figure 3. Performance of adaptive simplified multicarrier prediction method for the Jakes model.

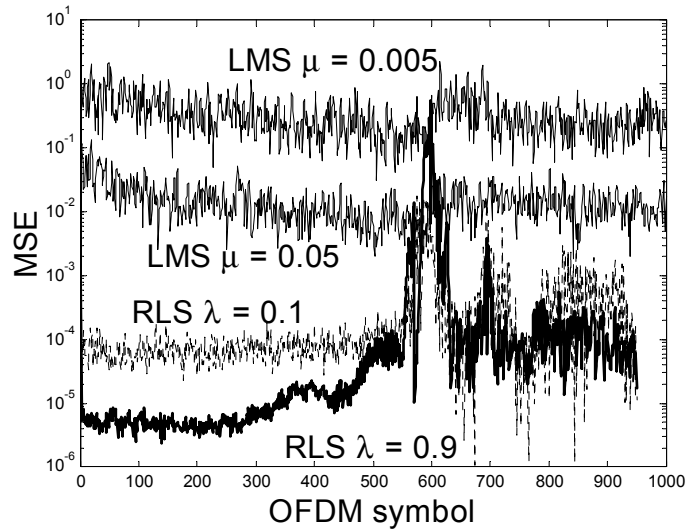


Figure 4. Performance of adaptive simplified multicarrier prediction method for the physical model

to noise in the feedback signals compared to the single carrier prediction [8,9] for both the LMS and RLS algorithms if adjacent subcarriers are employed for prediction.

#### IV. ADAPTIVE OFDM AND REDUCED FEEDBACK

In this paper, we employ channel loading optimization under the *bit rate maximization* (BRM) criterion, where the goal is to allocate the limited energy among the subcarriers to maximize the overall bit rate subject to a target bit error rate constraint [4]. A simplified loading method similar to [3] is compared with the optimal Hughes-Hartogs algorithm [2] in the presence of imperfect CSI that results from prediction errors.

For each subcarrier we employ rectangular  $M(i)$ -QAM modulation [15] where  $M(1)=0$ ,  $M(i)=2^{i-1}$ ,  $i=2\dots 6$ . Let  $\hat{c}$  denote the CSI obtained from the linear prediction algorithm (6) and  $c$  the actual complex gain at a certain subcarrier. Hence  $\hat{c}$  and  $c$  are jointly complex Gaussian and their amplitudes  $\hat{\alpha}$  and  $\alpha$  are both Rayleigh distributed. The SNR  $\gamma_{M(i)}$  required to employ  $M(i)$ -QAM modulation can be found by numerical search to meet the bit error rate constraint

$$\text{BER}_c = \int_0^{\infty} \text{BER}_{M(i)}(\gamma_{M(i)} x^2) p_{\alpha|\hat{\alpha}}(x) dx, \quad (8)$$

where  $\text{BER}_{M(i)}$  is the bit error rate for the  $M$ -QAM modulation on the AWGN channel [15], and  $p_{\alpha|\hat{\alpha}}$  the conditional *pdf* of  $\alpha$  given  $\hat{\alpha}$ , is given by [14,16]  $p(\alpha|\hat{\alpha}) = \frac{2\alpha}{(1-\rho)\Omega} I_0\left(\frac{2\sqrt{\rho}\alpha\hat{\alpha}}{(1-\rho)\sqrt{\Omega\hat{\Omega}}}\right) \exp\left(-\frac{1}{1-\rho}\left(\frac{\alpha^2}{\Omega} + \frac{\rho\hat{\alpha}^2}{\hat{\Omega}}\right)\right)$ , where the parameter  $\rho$  is the correlation coefficient between  $\alpha^2$  and  $\hat{\alpha}^2$ :

$$\rho = \frac{\text{Cov}(\alpha^2, \hat{\alpha}^2)}{\sqrt{\text{Var}(\alpha^2)\text{Var}(\hat{\alpha}^2)}} \quad (9)$$

and  $\Omega = E\{\alpha^2\} = 1$ ,  $\hat{\Omega} = E\{\hat{\alpha}^2\}$  and  $I_0$  is the 0<sup>th</sup> order modified Bessel function. Once the  $\gamma_{M(i)}$  are calculated for each modulation level and each subcarrier, they are used to implement the loading algorithms in the presence of imperfect CSI. The only difference in the implementation (relative to the perfect CSI case) is that the SNR  $\gamma_{M(i)}$  in (8) is used in place of the ideal SNR required to achieve the BER with  $M(i)$ -QAM.

The average bits per symbol (BPS) vs. the correlation coefficient  $\rho$  for different SNR =  $\frac{P_{\text{total}}}{KN_0}$  constraint is shown in Fig. 5, where we assume each subcarrier has the same prediction accuracy  $\rho$  and noise power  $N_0$ , and  $P_{\text{total}}$  is the total power constraint. The BER constraint for each subcarrier is  $10^{-3}$ . The correlation  $\rho=1$  corresponds to perfect prediction, while  $\rho=0$  represents the worst case when the BPS of the adaptive modulation converges to that of the non-adaptive M-QAM for given SNR and bit error rate constraint  $\text{BER}_c$ . It is observed that the simplified algorithm is near-optimal when  $\rho$  is close to 1 and has performance loss less than 0.1 BPS for  $\rho \ll 1$  compared with the optimal Hughes-Hartogs algorithm.

Next we address the problem of feedback load reduction for AOFDM. As discussed in the Introduction, it is desirable to reduce the feedback load for AOFDM channels. We explore several methods for reducing the feedback of the OFDM signal vectors  $\tilde{\mathbf{H}} = [\tilde{H}(n, 1) \dots \tilde{H}(n, K)]$  (4) while insuring accurate reconstruction at the transmitter. Since  $\tilde{\mathbf{H}}$  is modeled as Gaussian, the estimates of reconstructed signals are formed as linear combinations of the signals that are fed back. The

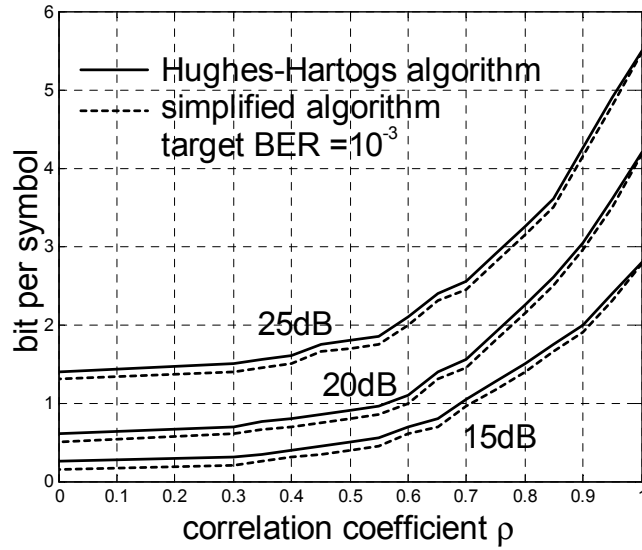


Figure 5. BPS vs.  $\rho$  for different SNR for adaptive OFDM system.  $\text{SNR} = P_{\text{total}}/KN_0$ .

performance is measured by the correlation coefficient  $\rho$  (9) between the reconstructed signals and the actual CSI for each subcarrier and is dependent on the feedback density (FD), which is defined as the number of fed back symbols divided by

the total number of subcarriers  $\text{FD} = \frac{\text{Number of fed back symbols}}{\text{Total number of subcarriers}}$ . We also define the normalized feedback density

(NFD):

$$\text{NFD} = \frac{\text{FD}}{\text{normalized subcarrier frequency separation}} \quad (10)$$

We assume non-quantized channel observations. In practice, the feedback symbols need to be quantized. However, due to the low feedback rate (sampling rate) required for the LRP and the reduced feedback feasible for AOFDM, the quantization level can be chosen large without significantly reducing the achievable bit rate. Thus, the actual performance is expected to be close to that obtained for ideal non-quantized channel observations. The feedback can be reduced by projecting the CSI onto an orthonormal basis and feeding back a subset of projection coefficients. Since the basis of the Karhunen-Loeve (K-L) low rank modeling [20] depends on the knowledge of the channel correlation function  $R_f(\Delta f)$ , we propose to utilize the discrete Fourier basis and transform the CSI  $\tilde{\underline{H}}$  using the inverse discrete Fourier transform (IDFT).

This choice is meaningful since the IDFT corresponds to the channel impulse response. The K-point IDFT of the CSI  $\tilde{\underline{H}}$  is

given by  $I(m) = \frac{1}{K} \sum_{k=1}^K \tilde{H}(n, k) \exp\{j2\pi \frac{k-1}{K}(m-1)\}$ ,  $m=1 \dots K$ . The samples  $I(m)$  are relatively small for  $m > \tau_{\text{max}} \Delta f K$ . In

OFDM channels,  $K$  is chosen larger than  $\tau_{\max}\Delta fK$  ( $\Delta f < 1/\tau_{\max}$ ) to avoid intersymbol interference (ISI). Thus, the transformed signal  $I(m)$  can be truncated, fed back to the transmitter and reconstructed by the DFT. Alternatively, we can directly feed a uniformly sampled subset of the CSI samples  $\tilde{\underline{H}}$  back to the transmitter using a *direct reduced feedback*.

We use the Jakes and the physical model to validate the performance of our AOFDM system aided by the LRP with reduced feedback. The target BER for the adaptive OFDM system is  $10^{-3}$ . The system parameters are described in Section III. The BPS performance for reduced feedback methods is compared in Fig. 6 for the Jakes model. For the ideal KL method, the performance is near optimal when the NFD (10) is larger than 6. This implies from (10) that only 4 symbols need to be fed back for a 128-subcarrier OFDM system with normalized subcarrier frequency separation 0.005. For the practical IDFT method, the performance loss is less than 0.5 BPS at NFD = 6 as opposed to 1 BPS loss for the direct reduced feedback method with linear interpolation. The choice of the feedback density provides a trade-off between the feedback load and the prediction accuracy, and hence the transmission rate.

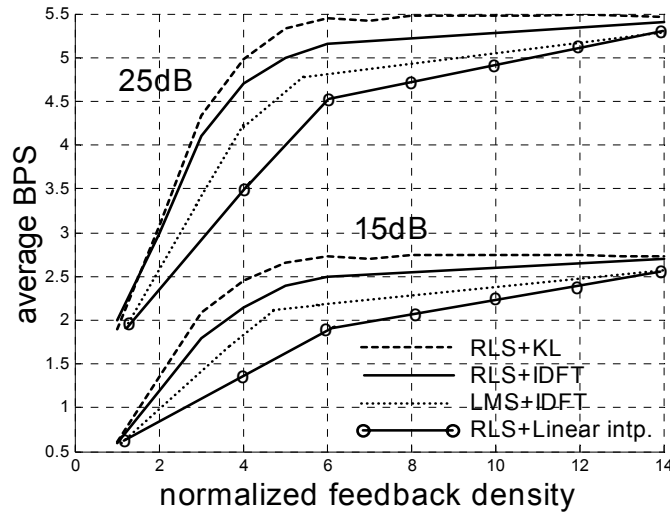


Figure 6. Performance comparison of reduced feedback methods.

The average BPS of the AOFDM for different prediction algorithms for the Jakes and physical channel models is plotted in Fig. 7. Perfect feedback is assumed. Comparison reveals that the RLS has better performance than the LMS algorithm for the Jakes and non-stationary physical model. The performance of the RLS algorithm for the Jakes model is near-optimal (not shown), whereas the loss is less than 0.5 dB for the physical model compared to the perfect knowledge of the CSI. The performance of the AOFDM using the outdated CSI samples [14] (1 ms delay) without prediction for the Jakes

model is also shown in Fig. 7. This results in significant bit rate loss assuming stationary Rayleigh fading channel, while prediction achieves near-optimal BPS for non-stationary channels.

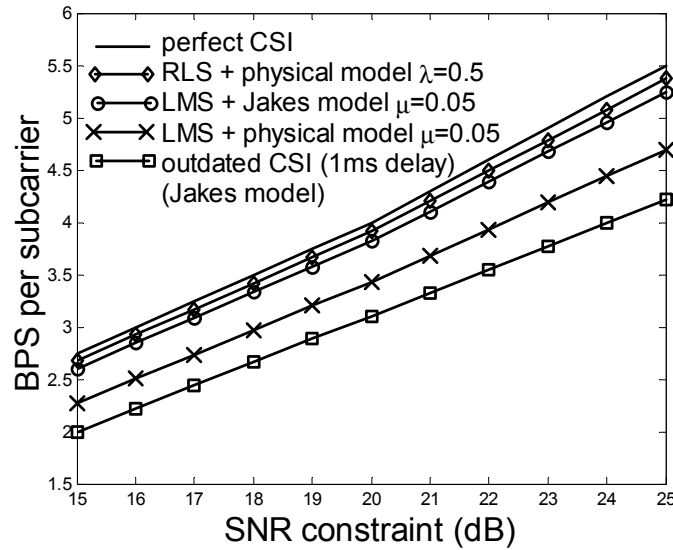


Figure 7. Comparison of average BPS performance for adaptive OFDM aided by different prediction methods for the Jakes and physical model.

## V. CONCLUSION

A mobile radio AOFDM system aided by the long-range prediction and reduced feedback was investigated. A realistic physical model and a stationary random phase model were employed to validate the prediction performance. The simulation results demonstrated that accurate long range prediction is required to achieve the potential of adaptive OFDM system for fast vehicle speeds and realistic delays. Specifically, we introduced the RLS prediction method that is robust to realistic multipath OFDM fading channels. The statistical model of the prediction accuracy distribution was created to perform the bit and power allocation for the AOFDM system. Finally, several methods were developed to reduce the feedback load, and it was shown that the IDFT method offers significant feedback load reduction while maintaining near-optimal spectral efficiency.

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