

FEASIBILITY OF ADAPTIVE TRANSMISSION FOR MULTICARRIER AND FREQUENCY HOPPING MOBILE RADIO SYSTEMS

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ABSTRACT

We address feasibility of adaptive transmission for rapidly varying fading channels encountered in mobile communication systems. Due to rapid channel variations and the feedback delay, implementation of adaptive transmission in these channels requires accurate prediction of future channel conditions. We describe the design and performance of adaptive transmission methods enabled by the Long Range Fading Prediction algorithms (LRP) for Orthogonal Frequency Division Multiplexing (OFDM) and slow Frequency-Hopping Spread Spectrum (FH/SS) systems. The LRP algorithms are tested with a modified Jakes model and our realistic physical model. To enable channel loading for adaptive OFDM (AOFDM), robust adaptive prediction methods that track channel parameter variations are developed and compared. Feasibility of AOFDM for rapidly varying mobile radio channels is demonstrated, with bit rates approaching those for channels with ideal knowledge of the channel state information (CSI). For FH/SS systems that employ coherent detection, we utilize correlated fading to predict future CSI for the upcoming frequency based on channel observations of other frequencies. This LRP method is utilized in adaptive modulation to mitigate the effects of fading. Analysis and simulation results show that while prediction is not as reliable for FH/SS as for AOFDM, significant performance gains are achieved relative to non-adaptive methods.

KEY WORDS

Adaptive Modulation and Coding, OFDM, Frequency Hopping Spread-spectrum.

1. Introduction

In mobile wireless communications, system performance is severely degraded due to rapidly time-variant multipath fading. Traditional communication systems designed for the worst-case channel conditions use a fixed link margin to maintain acceptable performance when the channel quality is poor, resulting in low bandwidth and power efficiency. Since high-speed data transmission is desired in future wireless communication systems, it is important to improve the bandwidth efficiency while maintaining the low power constraint. To realize this goal, one

solution is to adapt the parameters of the transmitted signal to the channel conditions [1-3].

However, the performance of the adaptive transmission systems depends on the availability of the accurate Channel State Information (CSI). In the adaptive transmission systems, the CSI is estimated by the receiver and sent to the transmitter through a reliable feedback channel. Due to the delay associated with channel estimation and feedback, and the transmission format constraints, the CSI at the time of transmission is usually different from the CSI at the time of channel estimation. Thus, the outdated CSI is not sufficient for the adaptive transmission. For rapidly varying mobile radio channels, even a small delay will result in significant performance degradation. To realize the potential of adaptive transmission, it is necessary to predict the channel several milliseconds ahead [4-8].

In this paper, we investigate feasibility of adaptive transmission for frequency selective channels. First, we focus on Orthogonal frequency Division Multiplexing (OFDM) [9] that has been proposed for use in high-speed wireless data applications. Adaptive OFDM (AOFDM) system, similarly to adaptive modulation for single carrier flat fading channel [1,2], involves optimizing the modulation level and the transmit power over the entire frequency band to maximize the spectral efficiency. Several practical integer-bit and power allocation algorithms addressed in [10-13] perform the optimum or near-optimum loading of bit and power in an OFDM frame. We investigate the potential of AOFDM for rapidly varying mobile channels with the adaptive Long Range Prediction algorithm (LRP) [4,5,7].

Furthermore, we explore adaptive transmission aided by the LRP for slow frequency hopping (SFH) systems that employ coherent detection [14-16]. We adapt the modulation level and the transmission power to rapidly varying short-term channel variations using the LRP for FH channels. The objective is to increase the spectral efficiency subject to the power and reliability constraints. We also compare performance of LRP for OFDM and FH systems, and discuss limitations of LRP for FH channels.

The remainder of this paper is organized as follows. Section 2 introduces the channel model and statistics used to perform and test our prediction algorithms. In Section 3, we briefly describe the adaptive OFDM and FH systems, and the long-range prediction methods. In Section 4, adaptive bit and power loading aided by the LRP is discussed. Numerical results and comparisons are presented in Section 5.

2. Propagation Model

The equivalent low-pass complex fading coefficients at K frequencies (or subcarriers), $f^1 < f^2 < \dots < f^K$, where $|f^i - f^j| \ll$ the carrier frequency f_c , is closely approximated as [17]:

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

In (1), for the n^{th} path, $A(n)$ is the (real) amplitude and $f_d(n) = f_c (v/c) \cos(\theta(n)) = f_{dm} \cos(\theta(n))$ is the Doppler shift, where v , c , f_{dm} , and $\theta(n)$ is 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^{th} path, $\phi_i(n) - \phi_j(n) = 2\pi \Delta f \tau(n)$ where $\Delta f = f^j - f^i$ is the frequency separation, and $\tau(n)$ is the excess propagation delay. Let $\{A, \theta, \tau, \phi_i\}$ denote the set $\{A(n), \theta(n), \tau(n), \phi_i(n), n=1 \dots N\}$ that parameterizes this channel model. The $c(f^i, t)$ are distributed approximately as a zero mean complex Gaussian random variables. Therefore, the amplitudes $|c(f^i, t)|$ are Rayleigh distributed.

For $c(t)$ characterized as wide sense stationary uncorrelated scattering (WSSUS) [18], the ensemble average correlation function (EACF) for two fading signals with frequencies f^i and f^j with the time difference Δt and the frequency separation $\Delta f = f^j - f^i$ is defined as $R_E(\Delta t, \Delta f) = E[c(f^i, t)c^*(f^j, t + \Delta t)]$. It represents the statistical average of the correlation function of the channel coefficient in (1) with randomized phase $R_E(\Delta t, \Delta f) = E_{\{A, \theta, \tau\}} \{E_{\{\phi_i\}} [c(f^i, t)c^*(f^j, t + \Delta t) | \{A, \theta, \tau\}] \}$ [7, 19, 20]. It can be factored into the time-domain correlation function $R_t(\Delta t)$ and the frequency domain correlation function $R_f(\Delta f)$ as [21]:

$$R_E(\Delta t, \Delta f) = \Omega R_t(\Delta t) R_f(\Delta f) \quad (2)$$

where $\Omega = E[|c(f^i, t)|^2]$ is the average power of the fading signals. (We normalize Ω to 1 throughout the paper.)

Assume $\theta(n)$ is uniformly distributed around 2π , and the propagation delay $\tau(n)$ is exponentially distributed [17] with the probability density function (pdf) $p(\tau) = 1/\sigma \exp\{-\tau/\sigma\}$, where σ is the rms delay spread [22]. The Jakes model [17] is widely used to model the fading channel. In this paper, we modify the Jakes model by observing that it is more realistic to model $\theta(n)$ as randomly distributed on the unit circle. We refer to this model as the random phase model (RPM). In the Jakes and RPM models discussed above, the parameters

associated with the reflectors (the amplitudes, the Doppler shifts and the delays) are fixed once they are chosen. Thus, the correlation function does not vary in time. In real mobile radio environments, the correlation function is time-variant and is affected by many factors such as the number and locations of the reflectors, carrier frequency, vehicle speed, distance between the transmitter and the receiver, etc. The LRP predicts the channel far ahead, and requires large observation interval and memory span [5]. Therefore, the performance of this algorithm is affected by the variation in time of the parameters associated with the reflectors. In practice, this variation has to be taken into account in the estimation of the correlation function. Thus, realistic non-stationary modeling is necessary.

A novel physical model based upon the method of images combined with diffraction was proposed [5, 23]. This model can provide physical insights into the nature of the signal fading that affect the performance of the LRP algorithm. For testing the robustness of the LRP, we have created a data set where the CSI is dominated by different groups of reflectors for the first and second time intervals, respectively. The dominant amplitudes and phases undergo significant variation during the transition period. We use this transition interval to test the robustness of the LRP to parameter variation in the rest of the paper.

3. Long Range Prediction for OFDM and FH/SS Channels

Consider an OFDM signal with K subcarriers, symbol (block) duration T_s , and adjacent subcarrier (tone) spacing Δf_s . Assume the channel bandwidth of the each subcarrier is much smaller than the coherence bandwidth and the channel state 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^{th} symbol block and k^{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 Δf_s .

In the uncoded AOFDM system aided by the LRP and reduced feedback, 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^{th} block and k^{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 complex additive white Gaussian noise with variance $E[|w[n, k]|^2] = N_0$. 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 [21]. 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 . We define the observation SNR as $E[|H_s[n, k]|^2]/\tilde{N}_0$. The estimated CSI $\tilde{H}[n, k]$, $k=1\dots K$, can be reduced and fed back to the long-range predictor at the transmitter at low rate [7,19,20]. Alternatively, the predictor can be placed at the receiver between the channel estimation and the reduced feedback blocks.

The optimum linear Minimum Mean Square Error (MMSE) prediction algorithm that utilizes previous symbols of multiple subcarriers [7,19] is very complex in practice. It can be shown that the following simplified approach is near-optimal [19]. For predicting the CSI $H[n, k]$, we use only previously observed samples of subcarrier k :

$$\hat{H}[n, k] = \sum_{j=1}^p d_j^*(n) \tilde{H}(n-j, k) \quad k = 1, 2, \dots, K \quad (5)$$

While in general, the coefficient vector $d(n) = [d_1 \ d_2 \ \dots \ d_p]^T$ in (5) needs to be computed and adapted individually for each subcarrier, for our channel model, it is sufficient to employ the same filter coefficient vector $d(n)$ to predict future CSI for each subcarrier [7]. Hence the filter coefficient vector $d(n)$ 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).

The MMSE channel prediction in (5) relies on the knowledge of the time and frequency domain correlation functions. However, these correlation functions depend on the particular environment and usually are unknown. In addition, the coefficients $d(n)$ need 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:

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

The average mean square error (AMSE) over all subcarriers is

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

This AMSE is used for updating the coefficients of the LMS and RLS algorithms described in [7,19], and a lower bound on AMSE tends to the conditional MMSE for the single carrier LRP J_{smmin} [19]. Note that using AMSE in SMCP, we adapt the coefficient vector $d(n)$ jointly using the errors for all subcarriers. As discussed below, this improves accuracy and convergence relative to single

carrier adaptive prediction [5]. We also observed that the prediction algorithm is more robust to noise in the feedback signals compared to the single carrier prediction for both the LMS and RLS algorithms if the adjacent subcarriers are employed for prediction.

It is shown in [7,19] that the learning curve of the RLS method decays almost linearly with nK (the convergence rate is approximately K times faster than for single carrier prediction). Thus, SMCP improves the convergence rate and the steady state MSE for the RLS relative to the single carrier prediction. While the RLS has higher computational complexity than the LMS algorithm, its learning curve and the excess MSE $J_{\text{ex}}(n) = J(n) - J_{\text{smmin}}$ (where $J(n)$ is given by (7) and J_{smmin} is a lower bound on AMSE) are significantly improved relative to the LMS. The RLS algorithm converges rapidly with almost no excess MSE, whereas the LMS algorithm converges more slowly with significant excess MSE relative to the RLS algorithm. The SMCP aided by the RLS algorithm is good at tracking the non-stationary channel. It remains robust during the transition period described in section 2 [7,19]. The tracking results for the LMS algorithm are much poorer with a relatively high MSE throughout the physical model data set.

Next, we investigate LRP for slow frequency hopping systems that employ coherent detection. Assume that the total number of frequencies is q and the hopping rate is f_h . Denote the frequency separation between adjacent frequencies as Δf . In this paper, we employ a randomly chosen periodic hopping pattern with length $N=q$, although the proposed methods are also applicable to non-periodic hopping patterns.

Let $c(f(t), t)$ be the equivalent lowpass complex sample of the fading channel at time t and frequency $f(t)$, where $f(t)$ is the carrier frequency occupied at time t . Assume fading is flat for each frequency and is described by (1). We employ the MMSE linear prediction method. Assume the channel coefficients in (1) are sampled at the rate $f_s = 1/T_s$, and for an integer n , define $c(f(n), n) = c(f(nT_s), nT_s)$. The prediction $\hat{c}(f(n+\tau), n+\tau)$ (τ is a positive integer) of the future channel coefficient $c(f(n+\tau), n+\tau)$ based on p past observations $c(f(n), n), \dots, c(f(n-p+1), n-p+1)$ is formed as

$$\hat{c}(f(n+\tau), n+\tau) = \sum_{j=0}^{p-1} d_j(n) c(f(n-j), n-j). \quad (8)$$

The optimal prediction coefficients are computed as $d(n) = R(n)^{-1} r(n)$, where $d(n) = [d_0(n) \ \dots \ d_{p-1}(n)]^T$, $R(n)$ is the autocorrelation matrix with $R_{ij}(n) = E\{c(f(n-i), n-i) c^*(f(n-j), n-j)\}$, and $r(n)$ is the autocorrelation vector with $r_j(n) = E\{c(f(n), n) c^*(f(n-j), n-j)\}$. The resulting instantaneous MMSE of this prediction method is $\text{MMSE}(n) = 1 - d(n)^T r(n)$ [5]. Because the hopping pattern is a random frequency sequence, a single prediction filter does not exist. The prediction coefficients, determined by the sampling time and the hopping pattern, need to be re-

computed at the sampling rate. The MMSE for FH systems is computed as the average over all LP filters. When the channel correlation functions are not known at the transmitter, $R_t(\tau)$ and $R_t(\Delta f)$ in [1] must be estimated and updated as new observations become available. In our investigation, pilot symbol aided channel estimation is used to estimate the channel correlation functions [24].

The optimal MMSE LRP described above is complex, because it requires inversion of large matrices at the sampling rate. In [15,24], a recursive matrix update method was proposed. It significantly reduces the computation of the optimal LRP. Moreover, in [14], low complexity prediction methods were studied, and it was demonstrated that the optimal LRP method is required to achieve reliable prediction. In practice, $c(f(n),n)$ are observed in the presence of noise. The prediction error can be easily modified to include the effect of the noise, and noise reduction methods can be utilized to reduce the noise present in the observations [5,6].

4. Adaptive Channel Loading Aided by LRP

For AOFDM, 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 [13]. In particular, we utilize a simplified loading method similar to [12] (see [19] for the detailed description).

For each subcarrier we employ rectangular $M(i)$ -QAM modulation [2] 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 (5) 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 α are both Rayleigh distributed. For subcarrier k , let P ($= E[|a[n, k]|^2]$) (3) denote the transmitted signal power of the complex $M(i)$ -QAM symbol that is determined by allocation algorithm. (Note the sum of the allocated powers for all subcarriers does not exceed the total power constraint P_{total}). Assume each subcarrier has the same noise power N_0 (see (3)). The SNR $\gamma_{M(i)}$ ($= P/N_0$) required to employ $M(i)$ -QAM modulation given the predicted channel gain $\hat{\alpha}$ at the k^{th} subcarrier can be found by numerical search to meet the target bit error rate BER_{tg} (set to 10^{-3} in this paper):

$$\text{BER}_{\text{tg}} = \int_0^{\infty} \text{BER}_{M(i)}(\gamma_{M(i)}x^2) p_{\alpha|\hat{\alpha}}(x) dx \quad (9)$$

where $\text{BER}_{M(i)}$, calculated from [25], is the bit error rate for the M -QAM modulation on the AWGN channel, and $p_{\alpha|\hat{\alpha}}$, the conditional probability density function of α given $\hat{\alpha}$, is given by [3,19]:

$$p(\alpha|\hat{\alpha}) = \frac{2\alpha}{(1-\rho)\Omega} I_0\left(\frac{2\sqrt{\rho}\alpha\hat{\alpha}}{(1-\rho)\sqrt{\Omega\hat{\Omega}}}\right) \exp\left(-\frac{1}{1-\rho}\left(\frac{\alpha^2}{\Omega} + \frac{\rho\hat{\alpha}^2}{\hat{\Omega}}\right)\right),$$

where the parameter ρ is the correlation coefficient between α^2 and $\hat{\alpha}^2$:

$$\rho = \frac{\text{Cov}(\alpha^2, \hat{\alpha}^2)}{\sqrt{\text{Var}(\alpha^2)\text{Var}(\hat{\alpha}^2)}} \quad (10)$$

and $\Omega = E\{\alpha^2\} = 1$, $\hat{\Omega} = E\{\hat{\alpha}^2\}$ and I_0 is the 0th order modified Bessel function. Once the $\gamma_{M(i)}$ are calculated for each modulation level and each subcarrier, they are used to implement the simplified loading algorithm 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 (9) is used in place of the ideal SNR required to achieve the BER with $M(i)$ -QAM [25]. It is shown in [7,19] that there is negligible performance difference between the optimal loading method and our simplified approach.

Similarly, in FH/SS, we employ the same adaptive modulation scheme. It is aided by LRP described in Section 3 in each dwell interval.

5. Numerical Results

We use the RPM and the physical model to validate the performance of the LRP for the OFDM system. To test the performance of our prediction algorithm on the fading channel modeled by the RPM, $N = 34$ is chosen and multiple deterministic channel realizations are generated by using independent angles $\{\theta\}$ and propagation delays $\{\tau\}$. The near-optimal prediction filter length p in (5) is 50 for all LRP results in this paper [19,24]. The maximum Doppler shift of 100 Hz is used in both models. The rms delay spreads is approximately 1 μ s in both channel models. To construct an OFDM symbol, assume that the entire channel bandwidth, 800kHz, is divided into 128 subcarriers. The symbol duration is 160 μ s. An additional 5 μ s guard interval is used to provide protection from ISI due to channel multipath delay spread. Thus the total block length is 165 μ s and 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 high effective SNR (80 dB) of the observed CSI. While the actual SNR of the observed samples is usually much lower, noise reduction techniques can be employed to decrease the estimation error greatly [5,6,21]. Moreover, our investigation in [19] shows that degradation due to lower effective SNR values (above 40 dB) is negligible. Therefore, accurate channel estimation assumed in this paper is realistic and is not a limiting factor in the performance of adaptive prediction. Interpolation is utilized to predict channel coefficients at the subcarrier symbol rate [5].

The average Bits per Symbol (BPS) of the AOFDM for different prediction algorithms for the RPM and physical channel models is plotted in Fig. 1. Perfect feedback is assumed. Comparison reveals that the RLS has better

performance than the LMS algorithm for the RPM and non-stationary physical model. The performance of the RLS algorithm for the RPM is near-optimal (not shown), whereas the loss is less than 0.5 dB for the physical model compared to the perfect knowledge of CSI. The performance of the AOFDM using the outdated CSI samples (1 ms delay) without prediction for the RPM is also shown in Fig. 1. Calculation of thresholds for this case was studied in [3]. We found that even very small delay causes significant loss of the bit rate for fast vehicle speeds when accurate LRP is not utilized.

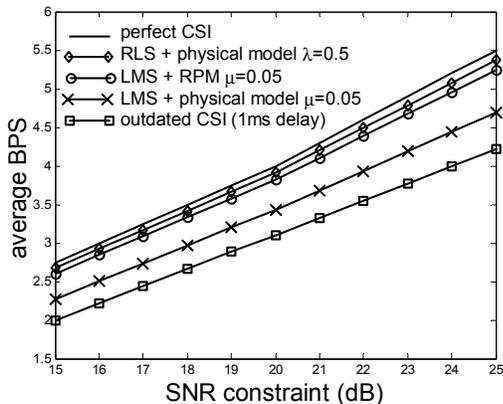


Fig. 1. Comparison of average BPS performance for adaptive OFDM aided by different prediction methods for the RPM and physical model.

For FH systems, we predict the channel coefficients of the next dwell interval. We assume a typical hopping rate of SFH systems of 500 hops/second. Thus, the prediction range $\tau T_s=2\text{ms}$ is desirable. The sampling rate $f_s=2\text{kHz}$ is employed due to its best performance for the system parameters used in the simulations. Since the sampling rate is much lower than the symbol rate, interpolation is performed within a dwell interval to predict fading coefficients for all data points. We assume channel observations with $\text{SNR}=100\text{dB}$. We first use the standard Jakes model with $N=34$ to validate the performance of the proposed adaptive modulation method. The maximum Doppler shift is $f_{dm}=50\text{Hz}$. A random hopping pattern with length of 32 is employed. The BPS of adaptive modulation as a function of normalized adjacent frequency separation $\Delta f\sigma$ is plotted in Figure 2. We observe that the spectral efficiency degrades as $\Delta f\sigma$ increases. The SFH benefits from adaptive transmission primarily when $\Delta f\sigma$ does not significantly exceed 0.1. As $\Delta f\sigma$ grows, the spectral efficiency saturates and approaches that of non-adaptive modulation. Thus, for large $\Delta f\sigma$, the SFH will not benefit from adaptive transmission. However, the benefit of frequency diversity is greater as $\Delta f\sigma$ increases.

For example, assume a typical value of the delay spread of $1\mu\text{s}$ microsecond for outdoor radio channels [22] and a typical adjacent frequency separation of less than 100Hz [16]. Adaptive transmission aided by the proposed channel prediction method is feasible for these systems. It

was also demonstrated in [14,15,24] that adaptive transmission is beneficial for other typical SFH parameters and moderate to high Doppler shifts.

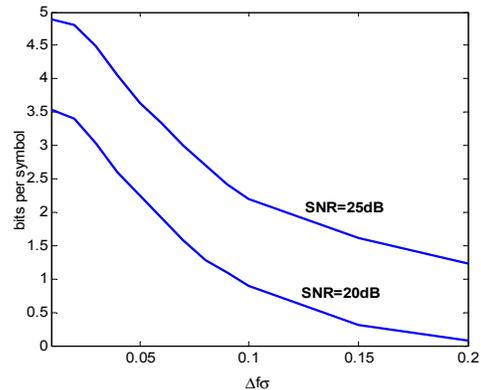


Figure 2. BPS of adaptive modulation vs. $\Delta f\sigma$ for SFH system.

Next, we use our physical model to investigate the performance in realistic non-stationary fading channels. A typical scenario and a challenging scenario are created to test the performance. The delay spread σ changes slowly in the typical case, while in the challenging case, σ changes rapidly over a wide range. The performance comparison is presented in Figure 3. Since the channel correlation functions vary faster in the challenging scenario than in the typical scenario, the prediction accuracy is worse in the challenging case. While the BPS gain is lower for the physical model than for the Jakes model due to the channel parameter variations, significant improvement is still obtained relative to non-adaptive modulation.

We observe significant loss in the bit rate of adaptive modulation aided by the LRP for FH channels relative to OFDM and narrowband channels. This loss is observed despite reduced maximum Doppler shift, and is further enhanced when our realistic physical model is employed rather than the Jakes model. For OFDM and flat fading channels, the observations are at the same frequency, and thus much greater prediction accuracy is achieved, enhanced by the SMCP method for OFDM systems (by comparing with Fig. 1, observe that this BPS is close to the “perfect CSI” curve in Fig. 3.) Moreover, in OFDM channels, we employ fast adaptive tracking combined with LRP to achieve almost the same prediction accuracy for the physical model as for the Jakes model. The reason why we have not achieved similar gains for FH systems is that the observations were constrained by the hopping pattern, and thus distributed in frequency. This constraint results in suboptimal sampling in frequency domain, and precludes utilization of fast adaptive tracking techniques.

6. Conclusion

Mobile radio AOFDM and adaptive FH systems aided by the long-range prediction were investigated. The simulation results demonstrated that accurate long range

prediction is required to achieve the potential of these adaptive mobile radio systems for fast vehicle speeds and realistic delays. For AOFDM, the RLS LRP that uses combined observations of all carriers was shown to enable adaptive loading for the physical model and practical system parameters. For FH channels, the optimal MMSE long range channel prediction algorithm was introduced and shown to enable adaptive modulation for SFH. It was demonstrated that prediction capability of the LRP for FH systems is limited relative to the OFDM channels, since the observations in FH systems are constrained by the hopping pattern.

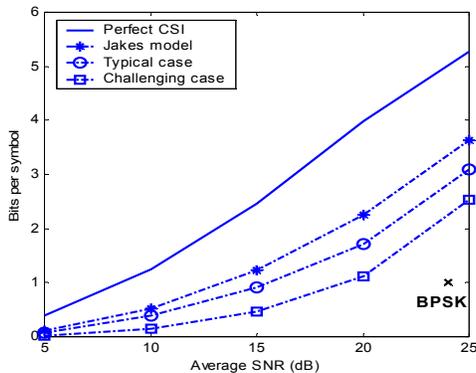


Figure 3. Performance comparison for the Jakes model and the physical model for SFH system. $\Delta f\sigma=0.05$

Acknowledgements

This research was supported by NSF grant CCR-0312294 and ARO grant W911NF-05-1-0311

References

[1] A.J. Goldsmith and S.G. Chua, "Variable-Rate Variable-power MQAM for Fading Channels", *IEEE Trans. Comm.*, 45 (10), 1997, 1218-1230.

[2] A. J. Goldsmith and S. G. Chua, "Adaptive Coded Modulation for Fading Channels," *IEEE Trans. Commun.*, 46 (5), 1998, 595 - 601.

[3] D.L. Goeckel, "Adaptive Coding for Time-Varying Channels Using Outdated Channel Estimates," *IEEE Trans. Comm.*, 47 (6), 1999, 845-855.

[4] S. Hu, A. Duel-Hallen, H. Hallen, "Long Range Prediction Makes Adaptive Modulation Feasible for Realistic Mobile Radio Channels," *Proc. of CISS'2000, 1*, March 2000, WP4-7 ~ WP4-13.

[5] A. Duel-Hallen, S. Hu and H. Hallen, "Long Range Prediction of Fading Signals: Enabling Adaptive Transmission for Mobile Radio Channels," *IEEE Signal Processing Mag.*, 17 (3), 2000, 62 - 75.

[6] S. Falahati, A. Svensson, T. Ekman, and M. Stenard, "Adaptive Modulation Systems for Predicted Wireless Channels." *IEEE Trans on Comm*, 52 (2), 2004.

[7] T.S. Yang, A. Duel-Hallen, H. Hallen, "Enabling Adaptive OFDM for Mobile Radio Channels", *Proc. of MILCOM'04*.

[8] S. Semmelrodt, R. Kattenbach, "Investigation of different fading forecast schemes for flat fading radio channels," *Proc. IEEE VTC, vol.1*, 2003, 149-153

[9] J. A. C. Bingham, "Multicarrier Modulation for Data Transmission: An idea whose time has come," *IEEE Commun. Mag.*, May 1990, 5-14.

[10] D. Hughes-Hartogs, *Ensemble Modem Structure for Imperfect Transmission Media*. U. S. Patent No. 4,833,706 (July 1987).

[11] B. S. Krongold, K. Ramchandran, and D. L. Jones, "Computationally Efficient Optimal Power Allocation Algorithms for Multicarrier Communication Systems," *IEEE Trans. Comm.*, 48 (1), 2000, 23-27.

[12] A. Czylik, "Adaptive OFDM for Wideband Radio Channels," *Proc. IEEE GLOBECOM'96*, 713-718.

[13] J. Campello, "Practical Bit Loading for DMT," *Proc. IEEE ICC '99*, 2, 6-10 June, 1999, 801-805.

[14] M. Lei, A. Duel-Hallen, "Long Range Channel Prediction and Adaptive Transmission for Frequency Hopping Communications," *Proc. 41st Annual Allerton Conf. on Comm., Control, and Comput.*, Oct. 2003.

[15] L. Ming, A. Duel-Hallen, H. Hallen, "Enabling Adaptive Modulation and Interference Mitigation for Slow Frequency Hopping Communications," *Proc. SPAWC'05*, June 5-8, 2005.

[16] S. Tomisato, K. Fukawa, "Coherent Frequency Hopping Multiple Access (CFHMA) with Multiuser Detection for Mobile Communication Systems", *IEEE Trans. Vehic. Tech.*, 49 (2), 2000, 531-539.

[17] W. C. Jakes, *Microwave Mobile Communications* (New York, Wiley, 1974).

[18] J. G. Proakis, *Digital Communications. 4th Edition* (McGraw-Hill, 2000).

[19] T.-S. Yang, "Performance Analysis of Adaptive Transmission Aided by Long Range Channel Prediction for Realistic Single-and Multi-Carrier Mobile Radio Channels," Ph.D. Thesis, NC State Univ, 2004.

[20] T.-S. Yang, A. Duel-Hallen, H. Hallen, "Reliable Adaptive Modulation Aided by Observations of Another Fading Channel", *IEEE Trans. on Comm.*, 52 (4), 2004, 605-611.

[21] Y. Li, L. J. Cimini, and N. R. Sollenberger, "Robust Channel Estimation for OFDM Systems with Rapid Dispersive Fading Channel," *IEEE Trans. Commun.*, 46, 1998, 902-915.

[22] T. S. Rappaport, *Wireless Communications: Principles and Practice, 2nd edition* (Prentice-Hall, 2000).

[23] H. Hallen, A. Duel-Hallen, S. Hu, T. S. Yang, M. Lei, "A Physical Model for Wireless Channels to Provide Insights for Long Range Prediction," *Proc. MILCOM'02*, Oct. 7-10, 2002.

[24] M. Lei, "Performance Analysis of Reliable Adaptive Transmission for Mobile Radio Slow Frequency Hopping Channels Aided by Long Range Prediction", Ph.D. Dissertation, NC State University, Fall 2004.

[25] K. Cho, D. Yoon, "On the General BER Expression of One- and Two-Dimensional Amplitude Modulations," *IEEE Trans. Comm.*, 50, 2002, 1074-1080.