A Physical Model for Wireless Channels to Understand and Test Long Range Prediction of Flat Fading*

Hans Hallen*, **Shengquan Hu**^, **Ming Lei**+ and **Alexandra Duel-Hallen**+

*Department of Physics, +Department of Electrical and Computer Engineering and Center for Advanced Computing and Communication, North Carolina State University, Raleigh, NC 27695

^Philips Semiconductor, Inc, San Jose, CA 95131

Abstract

Algorithms [1 - 7] that predict the wireless channel for up to a few wavelengths cannot be adequately tested with stationary models, such as the Jakes model [8]. Moreover, ray-tracing or finite difference time domain (FDTD) methods do not provide insights into the relationship between the reflector configurations and the performance of the long-range prediction. A novel model is required to: (1) create non-stationary datasets to test our previously proposed adaptive long range prediction algorithm, which enables practical realization of adaptive transmission techniques, including modulation, adaptive coding, power control, sentient transmitter diversity, etc. (2) provide limits on the speed of adaptation needed for an algorithm to predict the channel significantly into the future, and thereby reveal the timing of future deep fades, etc. (3) classify the reflector geometries that will have the typical or the most severe parameter variations, so that the reflector configurations for test datasets can be appropriately chosen and (4) illuminate the origins of the temporal and statistical properties of measured data. We present a model that satisfies these criteria. It provides insights and test data for fading over relatively small spatial regions, as required for prediction. Therefore, it does not incorporate significant long-range fading or diffusive propagation (although it does utilize diffraction and can handle shadowing). It could be incorporated into the later stages of a long-range propagation model. We validate the performance of our adaptive prediction algorithm using channels given by the physical model or actual measured data. The performance is similar for both types of channel, and different from the performance when the channel is given by the Jakes model. Moreover, we demonstrate improvement of prediction performance when recursive least squares (RLS) adaptive tracking of the model coefficients is utilized, and show that when prediction is employed with adaptive power control, the accuracy depends on the scattering environment.

I. Introduction

The tremendous growth in demand for wireless communications capacity has created a need for new modulation, coding and detection methods that more efficiently use the multipath fading channels encountered in mobile radio. Since the channel

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changes rapidly, the transmitter and receiver are not usually optimized for current channel conditions, and thus fail to exploit the full potential of the wireless channel. Recently, several new adaptive transmission techniques [2,11], such as adaptive modulation and adaptive channel coding, adaptive power control, and adaptive transmitter antenna diversity, have been investigated by many researchers. By taking advantage of the time-varying nature of the wireless fading channel, all these adaptive schemes are trying to use both power and spectrum more efficiently to realize the higher bit rate transmission without sacrificing the Bit Error Rate (BER) performance. To implement these adaptive transmission methods in practice, *channel state information* (CSI) for a future block from tens to hundreds of data symbols long must be available at the transmitter due to feedback delay and other constraints [2]. At realistic mobile speeds, even a small delay will cause a significant degradation of performance, since channel variation for high Doppler shifts usually results in a different received power at the time of transmission than at the time of channel estimation. Therefore, to realize the potential of adaptive transmission methods, the channel variations have to be *reliably predicted* at least several milliseconds ahead. Recently, we investigated a novel adaptive long-range fading channel prediction algorithm [1 - 7]. This method can forecast the wireless channels well beyond the coherence time, and provides enabling technology for adaptive transmission (also, see [2] for a literature review of recent advances in fading channel prediction.) In [2, 4 – 6, 12], we combined channel prediction with the truncated channel inversion (TCI) power control method [11]. In [10, 14], joint adaptive variable rate Multilevel Quadrature Amplitude Modulation (MQAM) [11] with channel prediction was addressed. Combined long-range power prediction and Transmission antenna diversity for Wideband Code Division Multiple Access (WCDMA) was studied in [13, 15, 16]. In this paper, we give physical insights into the nature of the deterministic modeling of the flat fading channel, and verify that this model will generate realistic fading datasets to test both our prediction algorithm and its application in adaptive transmission schemes.

II. The Physical Model

A well-known statistical model that characterizes a flat fading channel is *Rayleigh fading,* in which the fading coefficients are modeled as complex Gaussian random variables [8, 9]. The deterministic *Jakes model* [8] is used as a standard model in computer simulations. Jakes model with a relatively small number of sinusoids (less than nine) can generate a Doppler spectrum that accurately approximates that of the theoretical Rayleigh fading channel. However, neither this stationary model nor the depiction as a stationary Rayleigh random process captures the variation of channel parameters associated with each reflected wave (amplitudes, frequencies and phases). The performance of the long-range prediction algorithm [2] depends on the time-varying parameters associated with the important reflectors -- their relative phases, frequency (direction), amplitudes and number [1, 3, 7]. The rate of change of these parameters significantly affects prediction accuracy [1, 2, 10, 12]. Thus, to test the long-range prediction algorithm and its application in adaptive transmission systems for realistic

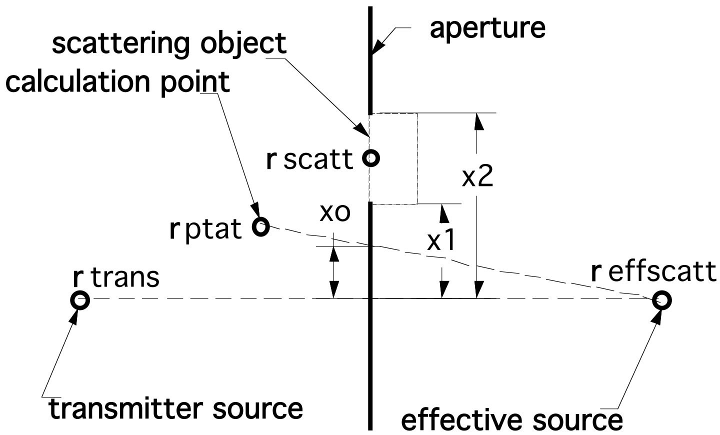

Figure 1. The parameters used to calculate the amplitude from one reflecting object, shown as a dotted rectangle. Also shown is the aperture chosen. The origin is arbitrary since only differences between the vectors are used.

mobile radio channels, non-stationary data sets are necessary. We use such datasets, created with our physical model or measured in the field, to test such an algorithm. Similar performance (that differs from the performance on Jakes model datasets) is obtained for both cases [1, 2, 6].

The physical model used is based upon the method of images combined with diffraction theory. An aperture in the object plane defines the size, large or small, of an object, and acts as a source of diffraction. The placement of the effective (image) source is determined by the object curvature. The amplitude of each effective source is given by the reflectivity times a factor that is required to obtain the intensity of the source at the center of the reflector's aperture. Complex objects can be represented as several flat or curved objects with adjacent apertures. The Fresnel diffraction formalism with point-illumination [17] is used to calculate the field for each reflector in the region of interest. The interference pattern c (coherent sum of the complex electric fields E_j of wavelength λ) generated by N plane-wave reflectors with amplitude A_j, (Doppler) frequency f_j and phase ψ_j, and time averaged over an optical cycle, can be written as:

$$\text{Pattern} = c(t) = \sum_{j=1}^{N} E_j = \sum_{j=1}^{N} A_j\, e^{-2\pi i f_j t + i\psi_j}\,, \qquad (1)$$

$$E_j = \left(\frac{i\Re E_{in} e^{-2\pi i r/\lambda + i\phi}}{2} \frac{|\mathbf{r}_{scatt} - \mathbf{r}_{effscatt}|}{r} [C(w_{x2}) - C(w_{x1}) - iS(w_{x2}) + iS(w_{x1})][C(w_{y2}) - C(w_{y1}) - iS(w_{y2}) + iS(w_{y1})] \right)_j$$

$$\text{with } w_x = \sqrt{\frac{2}{\lambda\rho}}\,(x - x_0),$$

$$\text{C and S the Fresnel integrals } C(w) = \int_0^w \cos(\pi u^2/2)du \ \text{ and } S(w) = \int_0^w \sin(\pi u^2/2)du\ ,$$

$$\text{and } \frac{1}{\rho} = \frac{1}{|\mathbf{r}_{scatt} - \mathbf{r}_{effscatt}|} + \frac{1}{|\mathbf{r}_{ptat} - \mathbf{r}_{scatt}|}.$$

All variables refer to the j-th reflector. The parameters and position vectors $\mathbf{r}_{scatt\ j}$, $\mathbf{r}_{effscatt\ j}$, $\mathbf{r}_{ptatj}$, x_{1j}, x_{2j} and $r_j = |\mathbf{r}_{ptat} - \mathbf{r}_{effscatt}|_j$ are defined in Figure 1. The reflector at $(\mathbf{r}_{scatt})_j$ has reflectivity $\Re_j$, and incident power from the transmitter $(E_{in})_j$. The phase factor, $e^{-2\pi i r/\lambda + i\phi}$, contains the propagation term proportional to $\tilde{\mathbf{r}}_j$ and the phase from the reflection process, ϕ_j. The propagation term $\tilde{\mathbf{r}}_j$ is simply $\mathbf{r}_j$ for a flat reflector, but needs to be increased by $|\mathbf{r}_{trans} - \mathbf{r}_{scatt}|_j$ – (curvature radius)$_j$ for a curved reflector. The phase ϕ_j could be calculated with the Fresnel formulae, [17], but we treat as a constant. It depends upon the details of the object such as its complex index of refraction, and tends to slightly compress or expand the pattern, so its variations have the same effect as small changes in vehicle speed. We do not insert the spatial variation of this contribution to the phase. We assume an infinite aperture in the y-direction so that the Fresnel integral term for the y direction in square brackets reduces to $\sqrt{2}$.

To create a dataset, the user of the model specifies the location of the transmitter and the centers of the apertures for each object. The orientation of the aperture, object reflectivity, object curvature, and reflection phase shift are also specified for each object. An aperture is specified for the transmitter so that shadowing can be modeled. Other inputs to the modeling program include the carrier frequency and region of interest (location, size and number of points for each of the two dimensions). The region of interest may be any rectangular array of points from a square to a single line in either direction. The position of the image source for a flat reflector, Fig. 2(a), is the location opposite from the transmitter (across the aperture plane) on the line perpendicular to the aperture plane. This line need not pass through the aperture. We assume that the transmitter is much further from the aperture than the object's radius of curvature, and apply the paraxial approximation to position an image source for the uniformly curved objects, Fig. 2(b). The image source is placed at half the radius of curvature from the aperture plane. The object is assumed to intersect the aperture plane at the midpoint of aperture. The model calculation running on a Macintosh G3 computer takes a few seconds for several thousand points in the region of interest with ~10 reflectors, or a few minutes for ~100,000 points in the region of interest and ~100 reflectors.

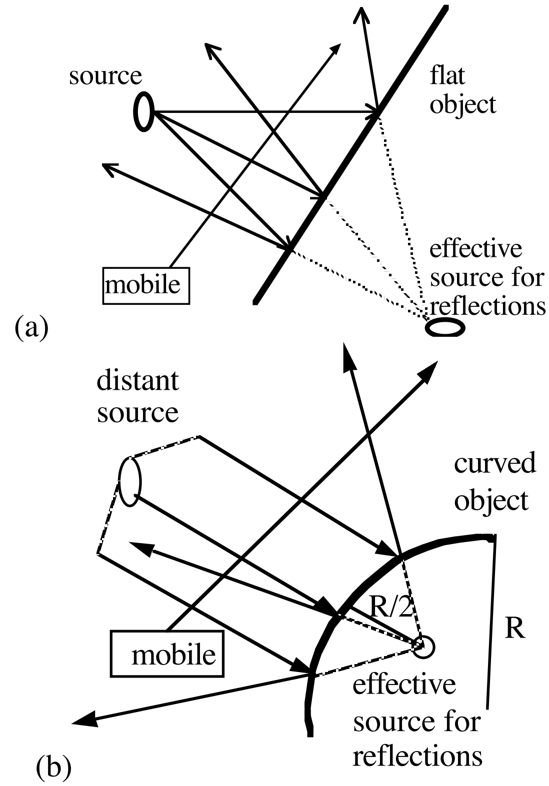

Figure 2. (a) A schematic of reflection from a flat object. The specular reflection can be modeled as emanating from an effective source, which is the mirror image of the source with the large object as the mirror. (b) The curved object's reflected rays diverge more quickly, due to the nearby effective source.

The physical model has the advantage of giving significant insights for determination of typical and challenging-case reflector geometry. This information is useful for constructing test datasets for algorithms, because it allows a sentient choice of object placement. The insights also can be used to improve siting of base stations, for systems that use long range prediction. In these systems, base station position affects not only the average intensity, which is calculated well by augmented ray tracing models [18], but also the parameter variation rates, or ease of tracking. Long range prediction only requires a local model of the flat fading, so even cases for which a weak diffracted signal serves as the source, such as a canyon-like street, can be accurately considered with this image-source, diffraction-through-aperture model.

The insights derive from the simple relation between the field contribution from each component and the (effective) point source and aperture response in the model. For a specific example, consider one large flat and five curved reflecting objects creating an interference pattern with the source. The source is 105m to the left of the center of the 10m square region shown in Figure 3(a). A large object 10 m to the right of the region does not run perpendicular to it, so its effective source is 130 m to the right of the region's bottom (think of it as a hill or building. Its amplitude reflection coefficient is 2/3. The five spherical reflectors to the right are evenly spaced on a 10 m long line as shown and with effective sources 1.8 m to the right. Think of them as five spherical cars parked along the road. The interference pattern (route 2) shown in Figure 3(b) is complex with narrow, deep fades which are ~1/100 the average power. The Doppler shifts f_j in Eqn. 1 are easy to calculate as a function of position with the image method. The Doppler frequency is proportional to the cosine of the angle between the direction of the mobile and the Poynting vector (ray direction or wave-front normal) of the signal. The change in angle towards the effective source, hence Doppler frequency variation rate, is slow (< 18 Hz/second) for the reflection from the flat object, since the image source is distant. Conversely, the proximity of the effective sources for the curved objects causes faster variations. Route 2 in Figure 3(a) passes close to the curved objects, so those components of the interference pattern will have relatively rapid Doppler frequency variations (up to 890 Hz/second).

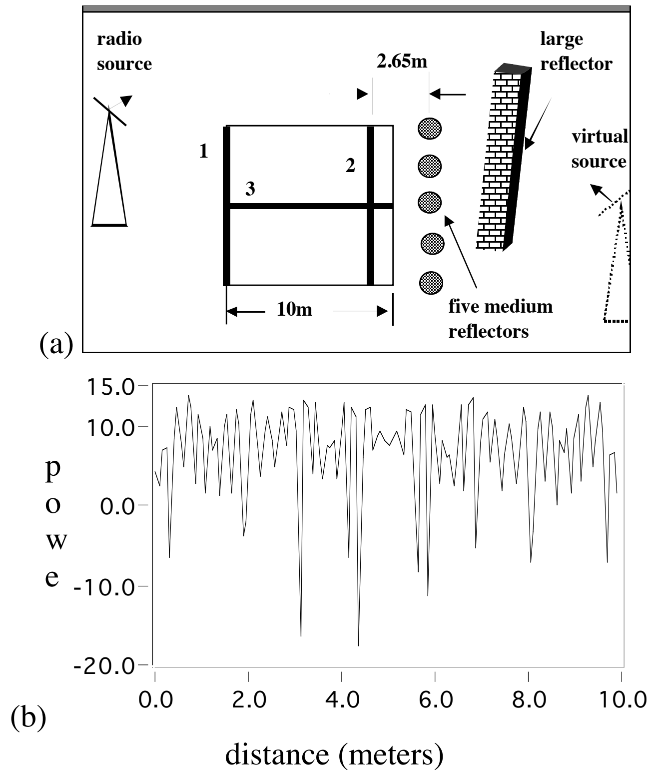

Figure 3 (a) Geometry used for the physical channel model calculation, with one large and five curved reflecting objects. (b). Line cut from the region shown in (a) (route 2, in dB with arbitrary zero). Divide the abscissa by the mobile's speed to get time.

This variation causes this route to be a challenging case. In contrast, the rate of Doppler frequency variation along route 1 is <200 Hz/second, which is more typical in practice. The amplitudes, A_j in Eqn. 1 and as in Fig. 1, also vary more quickly along route 2, due to the 1/r dependence of Eqn. 1 and diffraction effects.

III. Long Range Prediction of Model and Measured Data

The ultimate purpose of the model is to provide a testbed for our long-range prediction algorithm. In this section, we show the importance of using our nonstationary model, and show that the performance of the prediction algorithm is similar for the physical model 'data' and measured data. In Figure 4, we show the importance of using a nonstationary channel model for testing the prediction algorithm. In all cases, the complex fading coefficients are predicted using the adaptive long-range prediction jointly with least mean squares (LMS) tracking [2, 5]. The prediction algorithm uses an autoregressive (AR) model

$$\hat{c}_n = \sum_{j=1}^{p} d_j c_{n-j} , \tag{2}$$

where $\hat{c}_n$ is the predicted sample, and c_{n-j} are the observed samples of c(t) in Eqn. (1). When the channel is given by the sum of several important reflectors, Eqn. (1), the AR model coefficients d_j in Eqn. (2) that are tracked will be related to the Doppler frequencies associated with reflectors, whereas the amplitude and phase of each reflector are accounted for through the use of the prior data in the prediction. The mean square error vs. prediction range is shown for the measured data, our physical model, and the Jakes model. The measured data were collected by a van along a route in low density urban Stockholm. During the measurement, the speed of the van varied between 0 and 50 km/h, though mostly at 30km/h or below. The frequency of the radio wave was 1877.5 MHz. The data set contains 100,000 samples of the flat fading signal sampled at the rate of 1562.5Hz. The three (Jakes, physical model, measured) data sets have similarly shaped autocorrelation functions. Also shown in Figure 4 are the simulation results of mean square error (MSE) vs. prediction range for the Jakes model at a lower sampling rate f_s=521Hz for the c_n in Eqn. 2. We found that the prediction of the stationary Jakes model data set can be improved by using a lower sampling rate [7]. However, the prediction for the non-

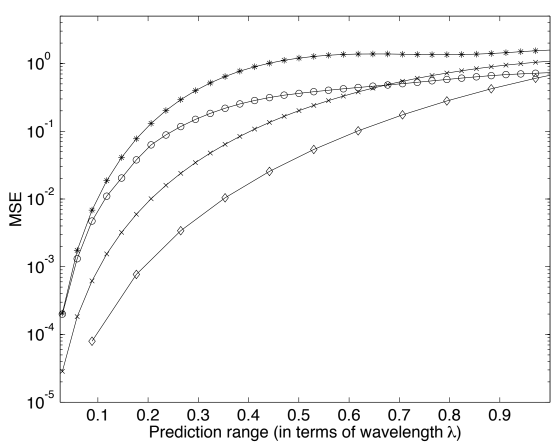

Figure 4. Mean square error of the prediction for Jakes model, physical data and measured data are given as a function of prediction range in wavelengths. (p = 40, the maximum Doppler shift f_{dm} = 46 Hz, and the sampling rate is 1562.5 Hz).

stationary measured and modeled data is not improved, while it still benefits from the sampling rate that is much lower then the data rate given fixed model order [2,7]. The significant degradation of the MSE for two realistic data sets relative to the Jakes model at shorter prediction lengths is due to the non-stationarity encountered in mobile radio channels. Prediction at the longer ranges depends strongly on the number of important reflectors (fixed in Jakes model, varies for the physical model and measured data) and their variations. One expects an improvement in performance when recursive least squares (RLS) is used for adaptation rather than LMS, since it is known to converge faster. This should improve convergence to the correct model and tracking of parameter variations. We show in Figure 5 the improvements one obtains when using RLS. Improvements for both the stationary Jakes model and nonstationary physical model indicate that convergence rate is important.

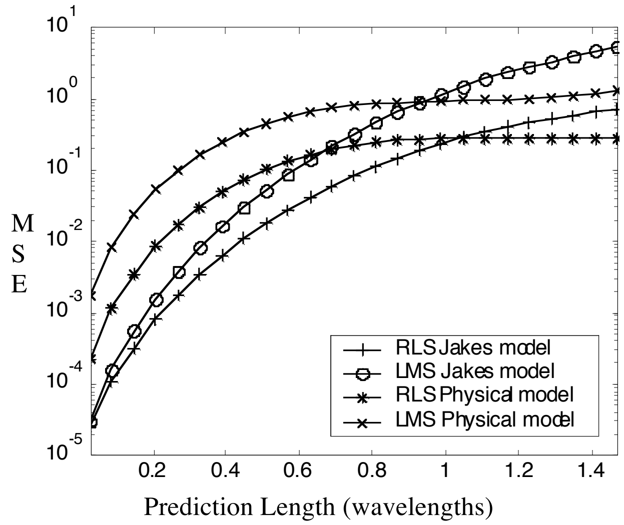

Figure 5. Comparison of prediction mean square error for RLS and LMS with Jakes model and physical model data. The initial observation interval is 500 samples during which LMS is pre-trained [19] to aid convergence. Maximum Doppler shift is 46 Hz, sampling frequency is 1562.5 Hz, and the model order, Eqn. 2, is p=40.

We compared the BER performance of the truncated channel inversion adaptive power control method (TCI) [4, 11] with long range prediction between typical and challenging cases in Figure 6. Two thresholds, 0.4 and 0.1, are used for the TCI as described in [4, 5]. The fading signals generated along the equivalent of routes 1 and 2 in Figure 3(a) are considered as typical and challenging cases, respectively. The channel sampling rate is 1000 Hz and the Maximum Doppler shift 67 Hz, corresponding to a vehicle speed of 45 miles/h for the carrier frequency f_c = 1GHz. The data rate is 50 Kbps. The simulation utilized 2-step (2 ms) ahead prediction. The performance difference shows that our physical model insights can help us create different mobile radio environments that both test the limits of our prediction method and validate its application in adaptive power control, for a range of environments.

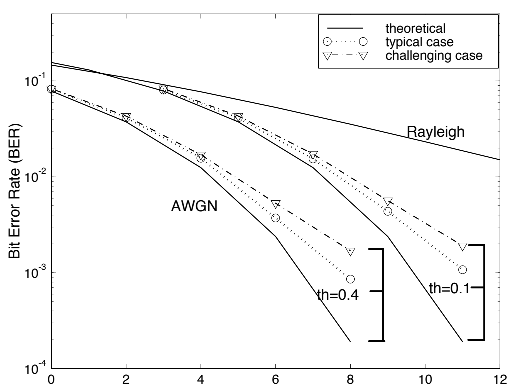

Figure 6. BER performance of TCI for typical and challenging case mobile radio environments is compared. (2ms ahead prediction, f_{dm}=67Hz)

IV. Conclusions

We have given an overview of a physical model that generates realistic, non-stationary data for long-range prediction testing, and provides expectations of the degree of prediction difficulty for various environments. This physical model can be used to gain insights into the interference patterns that give rise to flat fading in mobile communications. It allows calculation of the rate at which reflected signal powers and frequencies will vary, and hence the adaptive tracking speed required to accurately predict future channel properties. The parameters vary much more slowly than the actual channel. The model can be used to determine the nature of the environments in which measured data were acquired, and can be used to test channel prediction methods. The channel prediction method tested here performs similarly with both the non-stationary channel generated by the model and with measured channel data. The RLS tracking of model parameters is shown to improve accuracy of the long-range prediction. The application of the channel prediction method for adaptive power control algorithm is validated with our physical model for typical and challenging propagation environments.

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Author Biographies:

Hans Hallen received his B.S. degree in engineering physics (1984), and M.S. (1986) and Ph.D. (1992) degrees in Applied Physics from Cornell University. During 1991-1993, he was a postdoctoral member of the technical staff in the Physics Division of AT&T Bell Laboratories at Murray Hill, NJ. He joined the North Carolina State University Physics faculty in 1993, as a Visiting Assistant Professor until 1995, then as an Assistant Professor. Dr. Hallen's research interests include Near-field scanning optical microscopy of condensed matter systems and novel uses of the near-field probe, gradient-field Raman spectroscopy, biophysics and cellular signaling processes, particulate scattering, and wireless communications.

Shengquan Hu received a B.S. in 1987 and an M.S. in 1992, both in mathematics from NanKai University, Tianjin, China. He worked for Shenyang Automation Research Institute, the Chinese Academy of Sciences, from 1987 to 1989. In 1992-1996, he was with Shindengin Electric Mfg. Co. Ltd, Japan, as a systems engineer. In 1997, he started his Ph.D. degree study at North Carolina State University, Raleigh, and received the degree in 2000. He is currently employed by Phillips Semiconductor in San Jose, CA.

Ming Lei graduated from Beijing University in 2000. He is currently graduate student at North Carolina State University in Raleigh, NC.

Alexandra Duel-Hallen received B.S. degree in mathematics from Case Western Reserve University in 1982, M.S. degree in Computer, Information and Control Engineering from the University of Michigan in 1983, and Ph.D. in Electrical Engineering from Cornell University in 1987. During 1987-1990 she was a Visiting Assistant Professor at the School of Electrical Engineering, Cornell University, Ithaca, NY. In 1990-1992, she was with the Mathematical Sciences Research Center, AT&T Bell Laboratories, Murray Hill, NJ. She is an Associate Professor at the Department of Electrical and Computer Engineering at North Carolina State University, Raleigh, NC, which she joined in January 1993. Dr. Duel-Hallen's current research interests are in equalization, wireless communications and multiuser detection.