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**STOCHASTIC SIGNAL PROCESSING AND POWER
CONTROL FOR WIRELESS COMMUNICATION
SYSTEMS**

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Mohammed Mohsen Olama

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Dedication

This dissertation is dedicated to whom I treasure above all on this earth, and who have given meaning to my life: To my beloved mother and my great father, my lovely wife Suzan and my cute 9 month-old son Omar. Without their understanding, encouragement and support, this work would not have been possible. I also dedicate this dissertation to my sister Heba, my brothers Mostafa and Muhannad, my brother in-law Sameh, my young nephew Zaid and my niece Sara. The motivation, endurance, patience, and understanding of my family, all crowned by their devotion had contributed substantially to my success.

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Abstract

This dissertation is concerned with dynamical modeling, estimation and identification of wireless channels from received signal measurements. Optimal power control algorithms, mobile location and velocity estimation methods are developed based on the proposed models.

The ultimate performance limits of any communication system are determined by the channel it operates in. In this dissertation, we propose new stochastic wireless channel models which capture both the space and time variations of wireless systems. The proposed channel models are based on stochastic differential equations (SDEs) driven by Brownian motions. These models are more realistic than the time invariant models encountered in the literature which do not capture and track the time varying characteristics of the propagation environment. The statistics of the proposed models are shown to be time varying, and converge in steady state to their static counterparts. Cellular and ad hoc wireless channel models are developed.

In urban propagation environment, the parameters of the channel models can be determined from approximating the band-limited Doppler power spectral density (DPSD) by rational transfer functions. However, since the DPSD is not available on-line, a filter-based expectation maximization algorithm and Kalman filter to estimate the channel parameters and states, respectively, are proposed. The algorithm is recursive allowing the inphase and quadrature components and parameters to be estimated on-line from received signal measurements. The algorithms are tested using experimental data, and the results demonstrate the method's viability for both cellular and ad hoc networks.

Power control increases system capacity and quality of communications, and reduces battery power consumption. A stochastic power control algorithm is developed using the so-called predictable power control strategies. An iterative distributed algorithm is then deduced using stochastic approximations. The latter only requires each mobile to know its received signal to interference ratio at the receiver.

Several methods for tracking a user based on wave scattering models and particle filtering are presented. These algorithms cope with nonlinearities in order to estimate the mobile location and velocity. They take into account non-line-of-sight and multipath propagation environments. To show that the algorithms are robust numerical results are presented to evaluate their performance of the algorithms in the presence of parametric uncertainties.

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Chapter 1

Introduction

1.1 Overview

Recent advances in wireless communications and electronics, such as wireless micro-sensor networks, internet technologies and standards, home networking, and sensor devices in micro-scale, pose new challenges and require innovative and multidisciplinary solutions. These technologies have tremendous applications in health, chemical, and biological monitoring. On the other hand, these advances have enabled the development of new low cost, low power multifunctional micro-sensors, which communicate over small distances [1].

A micro-sensing device consists of a sensing unit, a data processing unit, a transceiver unit, and a power unit. These micro-sensor devices make up micro-sensor networks comprised of hundreds or thousands of ad hoc tiny sensor nodes, which spread across a geographical area, and collaborate among themselves to create a sensing network. These devices are preparing the ground for the emergence of new applications, and the development of new technologies, which can provide access of information anytime anywhere by collecting, processing and disseminating information data. Internet, satellite, ad hoc networks and wireless media in general, are becoming the neural system for a global community providing the means of sharing information collected by micro-sensing devices. These infrastructures-less networks consist mostly of heterogeneous wireless mobile devices with various capabilities, *power constraints* and *mobility characteristics*.

Wireless communication networks are constrained by available bandwidth, but the user population continues to grow. Wireless systems adapt to these pressures through more

efficient use of bandwidth; code division multiplexing (CDMA) and transmitter power control (PC) are two examples. Adaptive transmission methods including modulation, PC, and channel coding require models of the communication channels and noise sources. In this dissertation we are concerned with cellular and ad hoc wireless communication systems, which deal with *large amount of aggregate non-homogeneous traffic information*, under very diverse operational conditions such as different propagation environments and transmission technologies. The operational success of such wireless systems depends on the *correct characterization of the input-output response* of the fading channel statistics and its realization through *state space models*. The efficient utilization of bandwidth allocation and in general the system performance relies on the deployment of dynamic quality of service (QoS) measures, which are *robust* to the channel characteristic and the aggregate non-homogeneity of the traffic [2, 3].

The ultimate performance limits of any communication system are determined by the channel it operates in [78]. Realistic channel models are thus of utmost importance for system design and testing. In this dissertation, *new stochastic time varying models* for cellular and ad hoc networks are presented. These models capture the *spatio-temporal variations* of wireless channels, which are due to the relative mobility of the receiver and/or transmitter and scatterers. Unlike existing models of wireless networks that are mainly static in the sense that their statistics do not vary as functions of time [4-6], our work target the *dynamic behavior* of the propagation environment. The random variables characterizing the instantaneous power in static channel models are generalized to dynamical models including random processes with time varying (TV) statistics. Inphase and quadrature components of the TV wireless channel and their statistics are derived from the stochastic state space models.

Since these models are based on state space representations, we propose to estimate with small finite parameter set the channel parameters and state variables, which represent the inphase and quadrature components directly from received signal level measurements. The latter are usually available or easy to obtain in any wireless network. A filter-based expectation maximization (EM) algorithm [79, 80] and Kalman filter [81] are employed in the estimation process. These filters use only the first and second order

statistics and are recursive and therefore can be implemented on-line. Experimental testing of the proposed models and estimation algorithms is carried out using received signal level measurement data collected from cellular and ad hoc wireless environments.

Wireless networks are subject to time spread (multipath), Doppler spread (time variations), path loss, and interference seriously degrading their performance, *power control* is crucial to compensate for these factors for an acceptable performance in both ad hoc and cellular systems. The control of the transmitted power provides for an *efficient and optimal performance* of wireless systems [2, 3, 7, 8]. It increases system capacity and quality of communications, and reduces battery power consumption. Co-channel interference caused by frequency reuse is the most restraining factor on the system capacity. The correct usage of any power control algorithm (PCA) and thereby the *power optimization* of the channel models, require the use of such channel models that capture both temporal and spatial variations in the channel, which exhibit *more realistic* behavior of wireless communication systems [2, 3, 9-16]. Since few temporal or even spatio-temporal dynamical models have so far been investigated with the application of any PCA, the suggested dynamical models result in new PCAs that provide a far *more realistic* and efficient optimum control for wireless channels.

The third aspect of this dissertation is location based services (LBS), also known as location services (LCS), and mobile or wireless location-based services. This is an innovative technology that *provides information or making information available based on the geographical location of the user*. The ability to pinpoint the location of an individual has an obvious and vital value in the context of emergency services [17]. Pinpointing the location of people, sensor devices, and other valuable assets also open the door to a new world of previously unimagined information services and m-commerce possibilities. In this new world, facilitations as “Where is the nearest ATM?”, “Check traffic conditions on the highway on my route”, “Find a parking lot nearby”, as well as answers to “Where is my advisor?”, “Where is my car?” will be an everyday rule in our lives. Mobile location has also obvious applications in wireless micro-sensor networks, for e.g., in military applications where sensors are dropped by thousands in hostile terrain to probe movement of enemy troops. Several market studies predicted that mobile

location services will grow highly in the next few years [18]. Some estimate that LBS will be the next “Golden Child”.

1.2 Related Literature Review

1.2.1 Wireless Channel Modeling

The wireless communications channel constitutes the basic physical link between the transmitter and the receiver antennas. Its modeling has been and continues to be a tantalizing issue, while being one of the most fundamental components based on which transmitters and receivers are designed and optimized.

In addition to the exponential power path-loss, wireless channels suffer from stochastic short term fading (STF) due to multipath, and stochastic long term fading (LTF) due to shadowing depending on the geographical area. STF corresponds to severe signal envelope fluctuations, which occur in densely build-up areas that filled with lots of objects like buildings, vehicles, etc. On the other hand, LTF corresponds to less severe mean signal envelope fluctuations, which occur in much larger sparsely populated or suburban areas [5, 6, 19]. In general, LTF and STF are considered as superimposed and may be treated separately [19].

Ossanna [49] was the pioneer to characterize the statistical properties of the signal received by a mobile user, in terms of interference of incident and reflected waves. His model was better suited for describing fading occurring mainly in suburban areas. The LTF model is described by the average power loss due to distance and power loss due to reflection of signals from surfaces, which when measured in dB's give rise to normal distributions which implies that the channel attenuation coefficient is log-normally distributed [19]. Furthermore, in mobile communications, the LTF channel models are also characterized by their special correlation characteristics which have been reported in [97-99].

Clarke [50] introduces the first comprehensive scattering model describing STF occurring mainly in urban areas. An easy way to simulate Clarke's model using a computer simulation is described in [114]. This model is later expanded to three-

dimensional (3D) by Aulin [44]. An indoor STF is first introduced in [115]. Most of these STF models provide information on the frequency response of the channel, described by the Doppler power spectral density (DPSD). Aulin [44] presented a methodology to compute the Doppler power spectrum by computing the Fourier transform of the autocorrelation function of the channel impulse response with respect to time. A different approach, leading to the same Doppler power spectrum relation was presented by Gans [116]. These STF models suggest various distributions for the received signal amplitude such as Rayleigh, Ricean, or Nakagami.

The majority of research papers in this field use time invariant (static) models for the wireless channels [4-6, 19, 60]. In time invariant models, channel parameters are random but do not depend on time, and remain constant throughout the observation and estimation phase. This contrasts with time varying (TV) models, where the channel dynamics become TV stochastic processes [20, 21, 46-48]. TV models take into account the relative motion between transmitters and receivers and temporal variations of the propagating environment such as moving scatterers.

Mobile-to-mobile (or ad hoc) wireless networks comprise nodes that freely and dynamically self-organize into arbitrary and/or temporary network topology without any fixed infrastructure support [90]. They require direct communication between a mobile transmitter and a mobile receiver over a wireless medium. Such mobile-to-mobile communication systems differ from the conventional cellular systems, where one terminal, the base station, is stationary, and only the mobile station is moving. As a consequence, the statistical properties of mobile-to-mobile links are different from cellular ones [91], [92].

Copious ad hoc networking research exists on layers in the open system interconnection (OSI) model above the physical layer. However, neglecting the physical layer while modeling wireless environment is error prone and should be considered carefully [93]. The experimental results in [94] show that the factors at the physical layer not only affect the absolute performance of a protocol, but because their impact on different protocols is non-uniform, it can even change the relative ranking among

protocols for the same scenario. The importance of the physical layer is demonstrated in [95] by evaluating the Medium Access Control (MAC) performance.

Most of the research on mobile-to-mobile channel modeling, such as [52], [53], [91], [92], [96], deals mainly with deterministic wireless channel models. In these models the speed of nodes are assumed to be constant and the statistical characteristics of the received signal are assumed to be fixed in time. The Doppler power spectral density (DPSD) is then fixed from one observation instant to the next. But in reality, the propagation environment varies continuously due to mobility of the nodes at variable speeds causing network topology to dynamically change, the angle of arrival of the wave upon the receiver can vary continuously, and objects or scatterers move in between the transmitter and the receiver resulting in appearance or disappearance of existing paths from one instant to the next.

The measurements provided in [117] are performed using both narrow-band and wide-band signals in order to obtain both LTF and STF characteristics. Measurements using narrow-band signals provide information on the statistics of power loss as a function of distance and the Doppler spread. These measurements confirm that the power loss due to distance is log-normally distributed and provide values for the mean and variance. Measurements of the DPSD are made by transmitting a single tone frequency, and measuring the fluctuations on the received signal in time. On the other hand, wide-band measurements [117] are useful in determining the number of paths and the power-delay profile, which is a measure of the received power for different delays.

In this dissertation, *new stochastic time varying models* for LTF, STF, and ad hoc environments are presented. These models capture the *spatio-temporal variations* of wireless channels, which are due to the relative mobility of the receiver and/or transmitter and scatterers. The traditional models are special case of our developed models.

1.2.2 Optimal Power Control

Power control (PC) is important to improve performance of wireless communication systems. The benefits of power minimization are not just increased battery life, but also

increased overall network capacity and improved call quality. Users only need to expand sufficient power for acceptable reception as determined by their QoS specifications that is usually characterized by the signal to interference ratio (SIR) [22]. Power control algorithms (PCAs) can be classified as centralized and distributed. The centralized PCAs require global out-of-cell information available at base stations. The distributed PCAs require base stations to know only in-cell information, which can be easily obtained by local measurements. The power allocation problem has been studied extensively as an eigenvalue problem for non-negative matrices [12, 13], resulting in iterative PCAs that converge each user's power to the minimum power [2, 9, 14-16, 23, 24], and as optimization-based approaches [7]. Much of this previous work deals with static time invariant channel models. The scheme introduced in [7, 11], whereby the statistics of the received SIR are used to allocate power, rather than an instantaneous SIR. Therefore, the allocation decisions can be made on a much slower time scale. Previous attempts at capacity determinations in CDMA systems have been based on a "load balancing" view of the PC problem [25]. This reflects an essentially static or at best quasi-static view of the PC problem, which largely ignores the dynamics of channel fading as well as user mobility.

Stochastic PCAs (SPCAs) that use noisy interference estimates have been introduced in [10], where conventional matched filter receivers are used. It is shown in [10] that the iterative SPCA, which uses stochastic approximations, converges to the optimal power vector under certain assumptions on the step-size sequence. These results were later extended to the cases where a nonlinear receiver or a decision feedback receiver is used [26]. However, the channel gains are assumed to be fixed ignoring the effects of time variations on the performance of the system. Other results that attempt to recognize the time-correlated nature of signals are proposed in [27], where blocking is defined via the sojourn time of global interference above a given level. Downlink PC for fading channels is studied in [28] by a heavy traffic limit where averaging methods are used. Stochastic control approach for uplink lognormal fading channels is studied in [29], in which a bounded rate power adjustment model is proposed. Recent work on dynamic PC with stochastic channel variation can be found in [30-32].

In this dissertation, various PCAs are developed based on the TV channel models. A centralized and deterministic PCA based on predictable power control strategies (PPCS) is first introduced. PPCS simply means updating the transmitted powers at discrete times and maintaining them fixed until the next power update begins. The interference or outage probability (OP) is used as a performance measure. A distributed version of this algorithm is derived. The latter helps in allowing autonomous execution at the node or link level, requiring minimal usage of network communication resources for control signaling. Subsequently, an iterative and distributed SPCA based on stochastic approximations, which requires less information than the SPCAs described in the literature, is proposed. It only requires the received SIR at its intended receiver, while the received matched filter output (received SIR) at its intended receiver and the channel gain between the transmitter and its intended receiver are required in the SPCA presented in [10, 33].

1.2.3 Location Based Services

The problem of estimating the location and velocity of a mobile station (MS) has been the subject of much research work over the last few years. The current literature and standards in estimating the location and velocity are based mostly on time signal information, such as time difference of arrival (TDOA), enhanced observed time differences (E-OTD), observed time difference of arrival (OTDOA), global positioning system (GPS), etc., [34-38]. However, not all of these methods meet the necessary requirements imposed by specific services. In addition, most of them require new hardware since localization is not inherent in the current wireless systems, for instance, GPS demands a new receiver and TDOA, E-OTD, OTDOA require additional location measurement units in the network [39]. Adding extra hardware means extra cost for implementation, which can be reflected on both consumers and operators. Researchers have also suggested several MS location methods based on signal power measurements such as in [40] and [41], where a certain minimization problem is solved numerically to get an initial estimate of the MS position, and then a smoothing procedure such as linear regression [40], or the Kalman filter [41] are applied to obtain a more accurate estimate.

In this dissertation, several MS tracking methods based on maximum likelihood estimation (MLE) [72], and recursive nonlinear Bayesian estimation (RNBE) algorithms such as the extended Kalman filter (EKF) [42], the particle filter (PF) [43], and the unscented particle filter (UPF) [75] are proposed. The MLE algorithm employs the average received power measurements based on the lognormal propagation channel model to obtain an initial MS location estimate [86]. These measurements are readily available through network measurement reports or radio measurements, in idle or active mode, for any MS unit in 2G and 3G cellular networks. The RNBE algorithms employ the instantaneous electric field measurements based on the 3D multipath channel model of Aulin [44] to account for multipath and non-line-of-sight (NLOS) characteristics of the wireless channel as well as the dynamicity of the MS. The received instantaneous electric field in this model is a nonlinear function of the position and velocity of the MS. The EKF approach is based on linearizing the nonlinear system model around the previous estimate, and therefore is very sensitive to the initial state. This motivates the use of the ML estimate of the MS location as an initial state to the EKF. Particle filtering approaches approximate the optimal solution numerically based on the physical model, rather than applying an optimal filter to an approximate model such as in the EKF. They provide general solutions to many problems where linearization and Gaussian approximations are intractable or yield low performance. The more nonlinear the model is or the more non-Gaussian the noise is, the more potential PFs have, especially in applications where computational power is rather cheap and the sampling rate is moderate. In this dissertation, particle filtering is implemented for the generic PF and the more recent UPF.

Aulin's model in [44] postulates knowledge of the instantaneous received field at the MS, which is obtained through the circuitry of the mobile unit. The proposed RNBE algorithms take into account NLOS condition as well as multipath propagation environments. They require only one base station (BS) to estimate the MS location instead of at least three BSs as found in the literature [41], [86]. However, an initial MS location estimate that requires at least three BSs, such as the MLE and triangulation method, will improve the convergence of the RNBE filter. Particle filtering has been used

in several tracking wireless applications [62], [87]-[89], but the channel models used do not take into account the multipath properties of the wireless channel. To the best of our knowledge, the utilization of the PF and/or the UPF together with the classical wireless channel model to extract the MS location and velocity is new. The performance of the proposed algorithms is computed numerically and in the presence of parameters uncertainty. Numerical results indicate that the proposed UPF algorithm is highly accurate and superior to other approaches.

1.3 Main Contributions

The main contributions of our research can be described as follows:

1. Development of dynamical wireless channel models, which capture the space-variant and time-variant characteristics of cellular and ad hoc wireless networks. These models are based on state space and SDEs, and are in accordance with the physical principles of electromagnetic wave propagation; they are parametric and can describe diverse propagation environments. They allow the tools of system theory, identification, and estimation to be applied to this class of problems.
2. Development of estimation and identification algorithms based on the EM algorithm and Kalman filtering to estimate the channel model parameters and states, respectively, from received signal measurements for LTF, STF, and ad hoc wireless networks. These filters use only the first and second order statistics and are recursive and therefore can be implemented on-line. The proposed models and estimation algorithms are tested using received signal level measurement data collected from cellular and ad hoc experimental setups.
3. Development of PCAs based on the proposed models to compensate for path losses, multipath, Doppler spread, and interferences affecting the transmitted signal. Centralized, distributed, deterministic and stochastic PCAs are considered. The benefits of such PCAs include: Minimize power consumption and prolong

battery life of communicating nodes, mitigate interference and increase network capacity, and maintain link QoS by adapting to node movements in ad hoc networks and random channel variations by reducing the probability of outage.

4. Development of MS location and velocity estimation algorithms based on the 3D multipath scattering channel model of Aulin. The choice of this model is to account for the multipath properties and NLOS of wireless networks. The instantaneous electric field is a nonlinear function of the position and velocity of the MS. The EKF, PF, and UPF are employed for the estimation process. These estimation algorithms are recursive and can be implemented on-line. They also support existing network infrastructure and channel signaling.
5. Development of experimental and simulation set-ups demonstrating the flexibility and applicability of the proposed channel models in capturing the dynamics of diverse propagation environments, and determining the accuracy of the proposed estimation and identification algorithms in estimating the channel model parameters and states. The experimental and numerical results show the improvement in performance of the developed PCAs over the traditional PCAs, and signify the high accuracy and robustness of the proposed MS location and velocity estimation algorithm using particle filtering.

1.4 Dissertation Outline

This dissertation is structured as follows:

In Chapter 2, we present modeling of dynamical wireless channels for cellular and ad hoc networks. Lognormal shadowing or LTF channel models are discussed first. New dynamical spatial and temporal models for the power path loss and attenuation coefficient of the channel are presented. These models use specific type of SDEs whose solution at every instant represents the correlation properties both in time and space of the channel and corresponds to the statistics of the static lognormal channel. After that, analysis of STF dynamical channel models describing the received signal envelope of each multipath

component is presented. These models are based on the temporal characteristics of the channel, namely the Doppler power spectral density. The dynamics of each multipath component are captured using stochastic state-state models. Finally, ad hoc dynamical channel models are presented in a similar way as the STF channel modeling, except that the deterministic ad hoc DPSD is considered.

Chapter 3 introduces the filter-based EM algorithm combined with the Kalman filter, to estimate the channel parameters and states from received signal measurements. These filters use only the first and second order statistics. The algorithm is recursive allowing the inphase and quadrature components and parameters to be estimated on-line from measurements. The proposed algorithm is tested using received signal level measurement data collected from experiments for both the cellular and ad hoc channels.

Chapter 4 presents several PCAs based on the dynamical models described in Chapter 2. The centralized deterministic PCA is introduced first. The solution of the optimal PC is obtained through path-wise optimization, which is solved by linear programming using PPCS. The PPCS are proven to be effectively applicable to such dynamical models for an optimal PC. The algorithm can be implemented using an iterative distributed scheme. A distributed SPCA based on stochastic approximations and which uses only measured SIR is introduced. Numerical results are provided to evaluate the performance of the proposed PCAs.

Chapter 5 presents MS location and velocity estimation algorithms based on particle filtering. First, we introduce the mathematical models employed for the MS location and velocity estimation algorithms, which are the lognormal channel model and the 3D multipath scattering model of Aulin. The received instantaneous electric field in Aulin's model is a nonlinear function of the position and velocity of the MS. Thus, the MLE, the EKF, the PF, and the UPF are employed to estimate the MS location and velocity. A brief review of the theory of these algorithms is then introduced. Next, numerical results illustrating the accuracy and evaluating the robustness of the proposed estimation algorithms to uncertainties due to random variations in the channel parameters are presented.

Finally, Chapter 6 provides concluding remarks and presents a discussion on the applicability of these models and algorithms in design and analysis. It also provides an opening to emanating future work.

Chapter 2

Stochastic Wireless Channel Modeling

The ultimate performance limits of any communication system are determined by the channel it operates in. Realistic channel models are thus of utmost importance for system design and testing. In this chapter, we propose new stochastic wireless channel models which capture both the space and time variations of wireless systems. The proposed channel models are based on stochastic differential equations (SDEs) driven by Brownian motions and represented in stochastic state space form. Long-term fading (LTF), short-term fading (STF), and ad hoc wireless channel models are developed. These models are more realistic than the time invariant ones usually encountered in the literature, which do not capture and track the time varying characteristics in the environment. In contrast with the traditional models, the statistics of the proposed models are shown to be time varying, but converge in steady state to their static counterparts. Thus, the traditional models are special case of our models. Parts of the results presented here have been published in [21, 46-48, 68, 105, 107, 109, 110].

2.1 The General TV Wireless Channel Impulse Response

The impulse response of a wireless channel is typically characterized by time variations and time spreading [5]. Time variations are due to the relative motion between the transmitter and the receiver and temporal variations of the propagation environment. Time spreading is due to the fact that the emitted electromagnetic wave arrives at the receiver having undergone reflections, diffraction and scattering from various objects along the way, at different delay times. At the receiver, a random number of signal components, copies of a single emitted signal, arrive via different paths thus having

undergone different attenuation, phase shifts and time delays, all of which are random and time varying. This random number of signal components add vectorially giving rise to signal fluctuations, called multipath fading, which are responsible for the degradation of communication system performance.

The general time varying (TV) model of wireless fading channel is typically represented by the following multipath low-pass equivalent impulse response [5]

$$C_l(t; \tau) = \sum_{n=1}^{N(t)} r_n(t, \tau) e^{j\Phi_n(t, \tau)} \delta(\tau - \tau_n(t)) = \sum_{n=1}^{N(t)} (I_n(t, \tau) + jQ_n(t, \tau)) \delta(\tau - \tau_n(t)) \quad (2.1)$$

where $C_l(t; \tau)$ is the response of the channel at time t , due to an impulse applied at time $t - \tau$, $N(t)$ is the random number of multipath components impinging on the receiver, while the set $\{r_n(t, \tau), \Phi_n(t, \tau), \tau_n(t)\}_{n=1}^{N(t)}$ describes the random TV attenuation, overall phase shift, and arrival time of the different paths, respectively. $\{I_n(t, \tau), Q_n(t, \tau)\}_{n=1}^{N(t)} \triangleq \{r_n(t, \tau) \cos \Phi_n(t, \tau), r_n(t, \tau) \sin \Phi_n(t, \tau)\}_{n=1}^{N(t)}$ are defined as the inphase and quadrature components of each path. Letting $s_l(t)$ be the low-pass equivalent representation of the transmitted signal, then the low-pass equivalent representation of the received signal is given by [5]

$$y_l(t) = \int_{-\infty}^{\infty} C_l(t; \tau) s_l(t - \tau) d\tau = \sum_{n=1}^{N(t)} r_n(t, \tau_n(t)) e^{j\Phi_n(t, \tau_n(t))} s_l(t - \tau_n(t)) \quad (2.2)$$

and the multipath TV band-pass impulse response is given by [5]

$$\begin{aligned} C(t; \tau) &= \text{Re} \left\{ \sum_{n=1}^{N(t)} \left[r_n(t, \tau) e^{j\Phi_n(t, \tau)} \right] e^{j\omega_c t} \delta(\tau - \tau_n(t)) \right\} \\ &= \sum_{n=1}^{N(t)} (I_n(t, \tau) \cos \omega_c t - Q_n(t, \tau) \sin \omega_c t) \delta(\tau - \tau_n(t)) \end{aligned} \quad (2.3)$$

where ω_c is the carrier frequency, and the band-pass representation of the received signal is given by

$$y(t) = \sum_{n=1}^{N(t)} \left(I_n(t, \tau_n(t)) \cos \omega_c t - Q_n(t, \tau_n(t)) \sin \omega_c t \right) s_t(t - \tau_n(t)) \quad (2.4)$$

In general, wireless communication networks are subject to time-spread (multipath), Doppler spread (time variations), path-loss, and interference seriously degrading their performance. In addition to the exponential power path-loss, wireless channels suffer from stochastic STF due to multipath, and stochastic LTF due to shadowing depending on the geographical area. If the mobile happens to be in sparsely populated area with few buildings, vehicles, mountains etc., its signal will undergo LTF. Whereas in case the environment is filled with lots of objects like buildings, vehicles etc., then due to increase in scattering of the signal, the type of fading will be STF [5, 6, 19]. LTF is usually modeled by lognormal distributions and STF is modeled by Rayleigh, Ricean, or Nakagami distributions [19]. In general, LTF and STF are considered as superimposed and may be treated separately [19].

There exist many factors that define the randomness and the changing conditions with respect to time and/or space (stochastic) within the wireless medium. Static models do not take into account the time varying behavior of the channel and therefore do not represent a realistic picture of the communication medium. In static models, channel parameters are random but do not depend on time, and remain constant throughout the observation and estimation phase. Therefore, their statistics are time invariant. An alternative is to develop a new approach based on stochastic dynamical channel models to investigate the true behavior of the wireless communication networks. In TV models, the channel dynamics become TV stochastic processes [20, 21]. TV models take into account the relative motion between transmitters and receivers and temporal variations of the propagating environment such as moving scatterers. TV LTF, STF, and ad hoc dynamical channel models are considered in this chapter. The stochastic TV LTF channel modeling is discussed first in the next section.

2.2 Stochastic TV LTF Channel Modeling

2.2.1 The traditional (Static) LTF Channel Model

In this section we discuss the existing static models and introduce our approach on how to derive dynamical models. Before introducing the dynamical TV LTF channel model that captures both space and time variations, we first summarize and interpret the traditional lognormal shadowing model, which serves as a basis in the development of the subsequent TV model. The traditional (time invariant) power loss (PL) in dB for a given path is given by [19]

$$PL(d)[\text{dB}] := \overline{PL}(d_0)[\text{dB}] + 10\alpha \log\left(\frac{d}{d_0}\right) + \tilde{Z}, \quad d \geq d_0 \quad (2.5)$$

where $\overline{PL}(d_0)$ is the average PL in dB at a reference distance d_0 from the transmitter, the distance d corresponds to the transmitter-receiver separation distance, α is the path-loss exponent which depends on the propagating medium, and $\tilde{Z}$ is a zero-mean Gaussian distributed random variable, which represents the variability of PL due to numerous reflections and possibly any other uncertainty of the propagating environment from one observation instant to the next. The average value of the PL described in (2.5) is

$$\overline{PL}(d)[\text{dB}] := \overline{PL}(d_0)[\text{dB}] + 10\alpha \log\left(\frac{d}{d_0}\right), \quad d \geq d_0 \quad (2.6)$$

It can be seen in (2.5) and (2.6) that the statistics of the PL do not depend on time, and therefore these models treat PL as static (time invariant). They do not take into consideration the relative motion between the transmitter and the receiver, or variations of the propagating environment due to mobility.

Such spatial and time variations of the propagating environment are captured herein by modeling the PL and the envelope of the received signal as random processes that are functions of space and time. Moreover, and perhaps more importantly, traditional models do not take into consideration the correlation properties of the PL in space and at

different observation times. In reality, such correlation properties exist, and one way to model them is through stochastic processes, which obey specific type of SDEs.

2.2.2 Stochastic LTF Channel Models

In transforming the static model to a dynamical model, the random PL in (2.5) is relaxed to become a random process, denoted by $\{X(t, \tau)\}_{t \geq 0, \tau \geq \tau_0}$, which is a function of both time t and space represented by the time-delay τ , where $\tau = d/c$, d is the path length, c is the speed of light, $\tau_0 = d_0/c$ and d_0 is the reference distance. The signal attenuation is defined by $S(t, \tau) \triangleq e^{kX(t, \tau)}$, where $k = -\ln(10)/20$ [19]. For simplicity, we first introduce the TV lognormal model for a fixed transmitter-receiver separation distance d (or τ) that captures the temporal variations of the propagating environment. Next, we generalize it by allowing both t and τ to vary as the transmitter and receiver, as well as scatters, are allowed to move at variable speeds. This induces spatio-temporal variations in the propagating environment.

When τ is fixed, the proposed model captures the dependence of $\{X(t, \tau)\}_{t \geq 0, \tau \geq \tau_0}$ on time t . This corresponds to examining the time variations of the propagating environment for fixed transmitter-receiver separation distance. The process $\{X(t, \tau)\}_{t \geq 0, \tau \geq \tau_0}$ represents how much power the signal loses at a particular location as a function of time. However, since for a fixed distance d , the PL should be a function of distance, we choose to generate $\{X(t, \tau)\}_{t \geq 0, \tau \geq \tau_0}$ by a mean-reverting version of a general linear SDE given by [45-48]

$$\begin{aligned} dX(t, \tau) &= \beta(t, \tau)(\gamma(t, \tau) - X(t, \tau))dt + \delta(t, \tau)dW(t), \\ X(t_0, \tau) &= \mathcal{N}(\overline{PL}(d)[dB]; \sigma_{t_0}^2) \end{aligned} \tag{2.7}$$

where $\{W(t)\}_{t \geq 0}$ is the standard Brownian motion (zero drift, unit variance) which is assumed to be independent of $X(t_0, \tau)$, $\mathcal{N}(\mu, \kappa)$ denotes a Gaussian random variable

with mean μ and variance κ , and $\overline{PL}(d)[dB]$ is the average path-loss in dB. The parameter $\gamma(t, \tau)$ models the *average* time varying PL at distance d from transmitter, which corresponds to $\overline{PL}(d)[dB]$ at d indexed by t . This model tracks and converges to this value as time progresses. The instantaneous drift $\beta(t, \tau)(\gamma(t, \tau) - X(t, \tau))$ represents the effect of pulling the process towards $\gamma(t, \tau)$, while $\beta(t, \tau)$ represents the speed of adjustment towards this value. Finally, $\delta(t, \tau)$ controls the instantaneous variance or volatility of the process for the instantaneous drift.

Let $\{\theta(t, \tau)\}_{t \geq 0} \triangleq \{\beta(t, \tau), \gamma(t, \tau), \delta(t, \tau)\}_{t \geq 0}$. If the random processes in $\{\theta(t, \tau)\}_{t \geq 0}$ are measurable and bounded [101], then (2.7) has a unique solution for every $X(t_0, \tau)$ given by [20, 46-48]

$$X(t, \tau) = e^{-\beta([t, t_0], \tau)} \left(X(t_0, \tau) + \int_{t_0}^t e^{\beta([u, t_0], \tau)} (\beta(u, \tau) \gamma(u, \tau) du + \delta(u, \tau) dW(u)) \right) \quad (2.8)$$

where $\beta([t, t_0], \tau) \triangleq \int_{t_0}^t \beta(u, \tau) du$. Moreover, using Ito's stochastic differential rule [101]

on $S(t, \tau) = e^{kX(t, \tau)}$ the attenuation coefficient obeys the following SDE

$$dS(t, \tau) = S(t, \tau) \left[\left(k\beta(t, \tau)[\gamma(t, \tau) - \frac{1}{k} \ln S(t, \tau)] + \frac{1}{2} k^2 \delta^2(t, \tau) \right) dt + k\delta(t, \tau) dW(t) \right] \quad (2.9)$$

$$S(t_0, \tau) = e^{kX(t_0, \tau)}$$

This model captures the temporal variations of the propagating environment as the random parameters $\{\theta(t, \tau)\}_{t \geq 0}$ can be used to model the TV characteristics of the channel for the particular location τ . A different location is characterized by a different set of parameters $\{\theta(t, \tau)\}$.

Now, let us consider the special case when the parameters $\theta(t, \tau)$ are time invariant, i.e., $\theta(\tau) \triangleq \{\beta(\tau), \gamma(\tau), \delta(\tau)\}$. In this case we need to show that the expected value of the dynamic PL $X(t, \tau)$, denoted by $E[X(t, \tau)]$, converges to the traditional average PL in (2.6). The solution of the SDE model in (2.7) for the time invariant case satisfies

$$X(t, \tau) = e^{-\beta(\tau)(t-t_0)} X(t_0, \tau) + \gamma(\tau) \left(1 - e^{-\beta(\tau)(t-t_0)}\right) + \delta(\tau) \int_{t_0}^t e^{-\beta(\tau)(t-u)} dW(u) \quad (2.10)$$

where for a given set of time invariant parameters $\theta(\tau)$ and if the initial $X(t_0, \tau)$ is Gaussian or fixed, then the distribution of $X(t, \tau)$ is Gaussian with mean and variance given by [101]

$$\begin{aligned} E[X(t, \tau)] &= \gamma(\tau) \left(1 - e^{-\beta(\tau)(t-t_0)}\right) + e^{-\beta(\tau)(t-t_0)} E\{X(t_0, \tau)\} \\ Var[X(t, \tau)] &= \delta^2(\tau) \left(\frac{1 - e^{-2\beta(\tau)(t-t_0)}}{2\beta(\tau)}\right) + e^{-2\beta(\tau)(t-t_0)} Var(X(t_0, \tau)) \end{aligned} \quad (2.11)$$

Expression (2.11) of the mean and variance shows that the statistics of the communication channel vary as a function of both time t and space τ . As the observation instant, t , becomes large, the random process $\{X(t, \tau)\}$ converges to a Gaussian random variable with mean $\gamma(\tau) = \overline{PL}(d)[\text{dB}]$ and variance $\delta^2(\tau)/2\beta(\tau)$. Therefore, the traditional lognormal model in (2.5) is a special case of the general TV LTF model in (2.7). Moreover, the distribution of $S(t, \tau) = e^{kX(t, \tau)}$ is lognormal with mean and variance given by

$$\begin{aligned} E[S(t, \tau)] &= \exp\left(\frac{2kE[X(t, \tau)] + k^2 Var[X(t, \tau)]}{2}\right) \\ Var[S(t, \tau)] &= \exp\left(2kE[X(t, \tau)] + 2k^2 Var[X(t, \tau)]\right) \\ &\quad - \exp\left(2kE[X(t, \tau)] + k^2 Var[X(t, \tau)]\right) \end{aligned} \quad (2.12)$$

Now, lets go back to the more general case in which $\{\theta(t, \tau)\}_{t \geq 0} \triangleq \{\beta(t, \tau), \gamma(t, \tau), \delta(t, \tau)\}_{t \geq 0}$. At a particular location τ , the mean of the PL process $E[X(t, \tau)]$ is required to track the time variations of the average PL. This can be seen in the following example.

Example 2.1: Let

$$\gamma(t, \tau) = \gamma_m(\tau) \left(1 + 0.15 e^{-2t/T} \sin\left(\frac{10\pi t}{T}\right) \right) \quad (2.13)$$

where $\gamma_m(\tau)$ is the average PL at a specific location τ , T is the observation interval, $\delta(t, \tau) = 1400$ and $\beta(t, \tau) = 225000$ (these parameters are determined from experimental measurements as will be shown at the end of this section), where for simplicity $\delta(t, \tau)$ and $\beta(t, \tau)$ are chosen to be constant, but in general they are functions of both t and τ . The variations of $X(t, \tau)$ as a function of distance and time are represented in Figure 2.1. The temporal variations of the environment are captured by a TV $\gamma(t, \tau)$ which fluctuates around different average PLs γ_m 's, so that each curve corresponds to a different location. It is noticed in Figure 2.1 that as time progresses, the process $X(t, \tau)$ is pulled towards $\gamma(t, \tau)$. The speed of adjustment towards $\gamma(t, \tau)$ can be controlled by choosing different values of $\beta(t, \tau)$. In Chapter 3, we propose to recursively estimate the channel parameters directly from received signal measurements, using the EM algorithm combined with the Kalman filter.

Next, the general spatio-temporal lognormal model is introduced by generalizing the previous model to capture both space and time variations, using the fact that $\gamma(t, \tau)$ is a function of both t and τ . In this case, besides initial distances, the motion of mobiles, i.e., their velocities and directions of motion with respect to their base stations are important factors to evaluate TV PLs for the links involved.

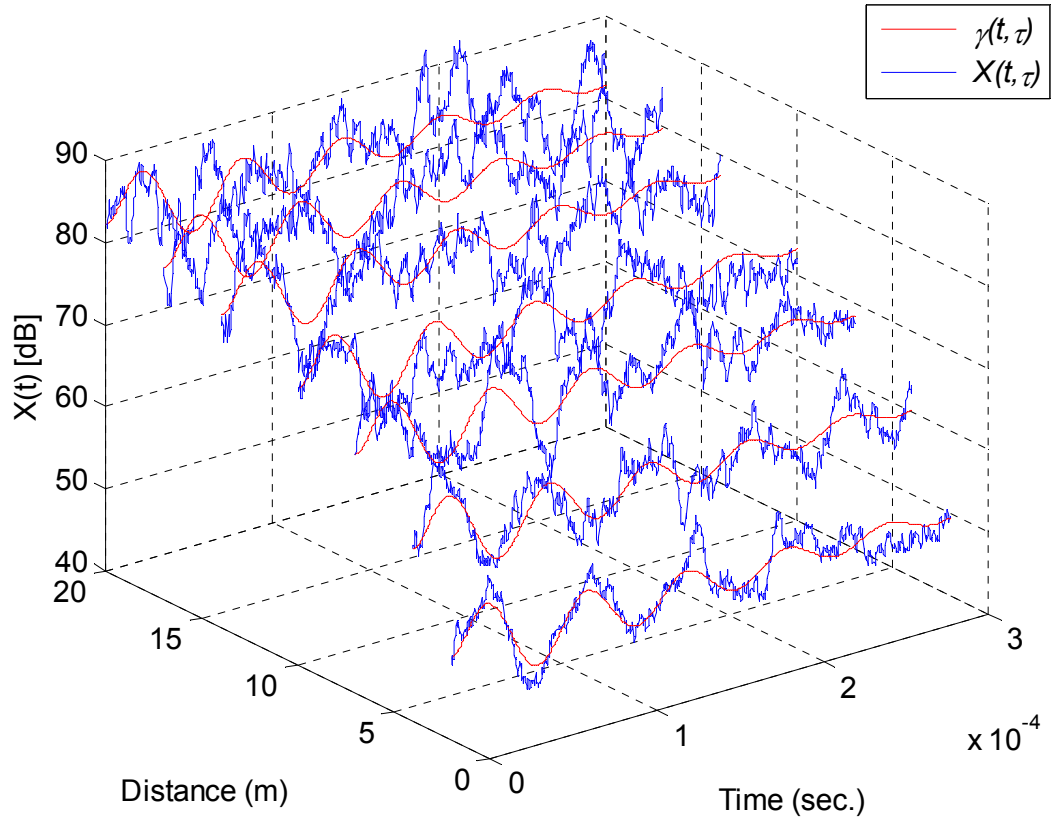


Figure 2.1: Mean-reverting power path-loss as a function of t and τ , for the time varying $\gamma(t, \tau)$ in Example 2.1.

This can be illustrated in a simple way for the case of a single transmitter and a single receiver as follows: Consider a base station (receiver) at an initial distance d from a mobile (transmitter) that moves with a certain constant velocity v in a direction defined by an arbitrary constant angle θ , where θ is the angle between the direction of motion of the mobile and the distance vector that starts from the receiver towards the transmitter as shown in Figure 2.2. At time t , the distance from the transmitter to the receiver, $d(t)$, is given by

$$d(t) = \sqrt{(d + tv \cos \theta)^2 + (tv \sin \theta)^2} = \sqrt{d^2 + (vt)^2 + 2dvt \cos \theta} \quad (2.14)$$

Therefore, the average PL at that location is given by

$$\gamma(t, \tau) = \overline{PL}(d(t)) [dB] = \overline{PL}(d_0) [dB] + 10\alpha \log \frac{d(t)}{d_0} + \xi(t), \quad d(t) \geq d_0 \quad (2.15)$$

where $\overline{PL}(d_0)$ is the average PL in dB at a reference distance d_0 , $d(t)$ is defined in (2.14), α is the path-loss coefficient and $\xi(t)$ is an arbitrary function of time representing additional temporal variations in the propagating environment like the appearance and disappearance of additional scatters. Now, suppose the mobile moves with arbitrary velocity, $(v_x(t), v_y(t))$, in the x-y plane, where $(v_x(t), v_y(t))$ denote the instantaneous velocity components in the x and y directions, respectively.

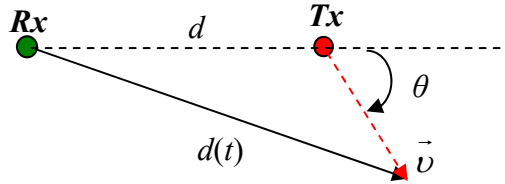


Figure 2.2: A mobile (transmitter) at a distance d from a base station (receiver) moves with velocity v and in the direction given by θ with respect to the transmitter-receiver axis.

The instantaneous distance from the receiver is thus described by

$$d(t) = \sqrt{\left(d + \int_0^t v_x(t) dt\right)^2 + \left(\int_0^t v_y(t) dt\right)^2} \quad (2.16)$$

The parameter $\gamma(t, \tau)$ is used in the TV lognormal model (2.7) to obtain a general spatio-temporal lognormal channel model. This is illustrated in the following example.

Example 2.2: Consider a mobile moving at sinusoidal velocity with average speed 80 Km/hr, initial distance $d=50$ meters, $\theta=135$ degrees, and $\xi(t)=0$. Figure 2.3 shows the mean reverting PL $X(t, \tau)$, $\gamma(t, \tau)$, $E[X(t, \tau)]$, velocity of the mobile v and distance $d(t)$ as a function of time. It can be seen that the mean of $X(t, \tau)$ coincides with the average PL $\gamma(t, \tau)$ and tracks the movement of the mobile. Moreover, the variation of $X(t, \tau)$ is due to uncertainties in the wireless channel such as movements of objects or obstacles between transmitter and receiver that are captured by the spatio-temporal lognormal model (2.7) and (2.15). Additional time variations of the propagating environment, while the mobile is moving, can be captured by using the TV PL coefficient $\alpha(t)$ in (2.15) in addition to the TV parameters $\beta(t, \tau)$ and $\delta(t, \tau)$, or simply by $\xi(t)$.

In Chapter 3, we propose to recursively estimate the channel parameters as well as the TV PL directly from received signal measurements, using the EM algorithm combined with the Kalman filter.

2.2.3 Spatial Correlation of the Stochastic LTF Model

Now, we want to show that the spatial correlation of the lognormal mean-reverting model of (2.7) agrees with the experimental spatial correlation [97-99]. In particular, it is reported that the spatial correlation for shadow fading in mobile communications, which compares successfully with experimental data, can be modeled using an exponentially decreasing function multiplied by the variance of the PL process as follows

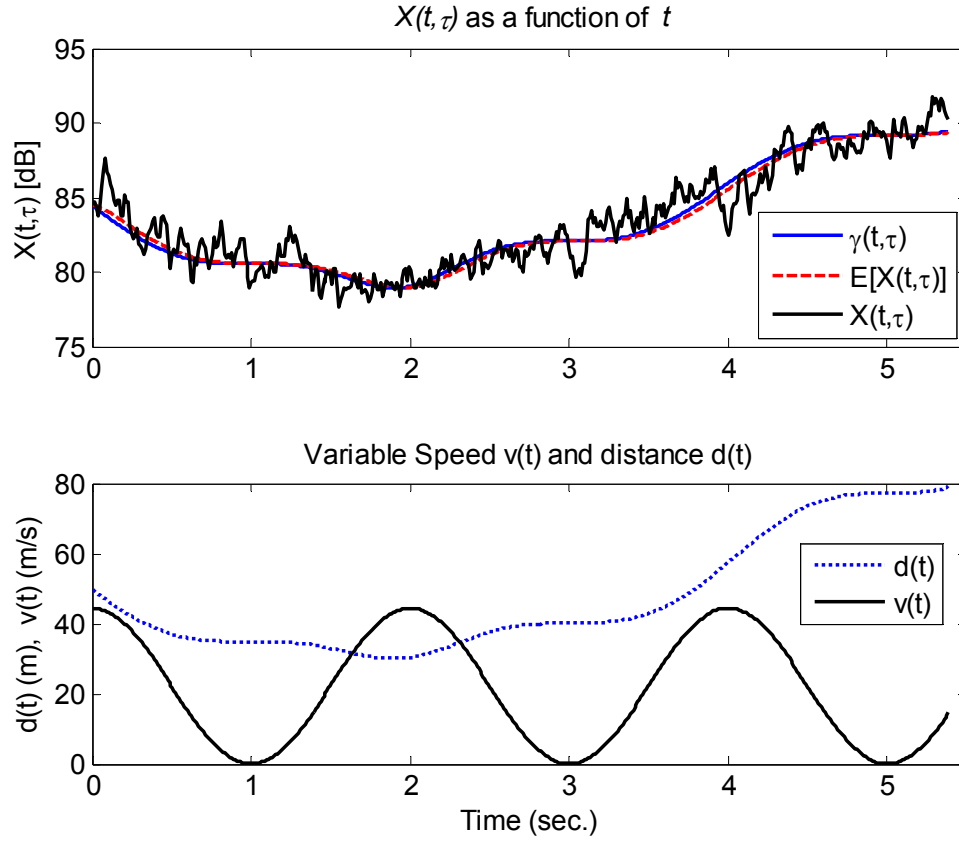


Figure 2.3: Mean-reverting power path-loss $X(t, \tau)$ for the TV LTF wireless channel model in Example 2.2. The mobile starts moving closer to the base station from point 50 meters with an angle of 135 degrees and sinusoidal speed with average 80 km/hr (22.2 m/s).

$$Cov_X(\Delta t) \triangleq \sigma_X^2 e^{-\Delta d / X_c} = \sigma_X^2 e^{-(v / X_c) \Delta t} \quad (2.17)$$

where σ_X^2 is the covariance of the PL process, Δd is the distance between two consecutive samples, v is the velocity of the mobile. X_c is the effective correlation distance which is proportional to the density of the propagating environment corresponding to the distance when the normalized correlation falls to e^{-1} [99]. Here we show that our overall spacial dynamical model captures indeed these correlation properties. Without loss of generality, consider the particular case where the parameters $\{\theta(t, \tau)\}_{t \geq 0} = \{\beta(\tau), \gamma(t, \tau), \delta(\tau)\}_{t \geq 0}$.

Let $\tilde{X}(t, \tau) \triangleq X(t, \tau) - E[X(t, \tau)]$, then we have

$$\begin{aligned} d\tilde{X}(t, \tau) &= -\beta(\tau)\tilde{X}(t, \tau)dt + \delta(\tau)dW(t), \\ \tilde{X}(t_0, \tau) &= \mathcal{N}(0; \sigma_{t_0}^2) \end{aligned} \quad (2.18)$$

The solution of (2.18) is given by [101]

$$\tilde{X}(t, \tau) = e^{-\beta(\tau)(t-t_0)} \left(\tilde{X}(t_0, \tau) + \int_{t_0}^t e^{\beta(\tau)(u-t_0)} \delta(\tau) dW(u) \right) \quad (2.19)$$

The mean of the process $\tilde{X}(t, \tau)$ is zero, and its covariance is given by [101]

$$\begin{aligned} Cov_{\tilde{X}}(t, s) &= E \left[\left(\tilde{X}(t, \tau) - E[\tilde{X}(t, \tau)] \right) \left(\tilde{X}(s, \tau) - E[\tilde{X}(s, \tau)] \right)^T \right] \\ &= e^{-\beta(\tau)(t+s)} e^{2\beta(\tau)t_0} \left[\sigma_{t_0}^2 + \frac{\delta^2(\tau)}{2\beta(\tau)} \left(e^{2\beta(\tau)(t \wedge s - t_0)} - 1 \right) \right] \end{aligned} \quad (2.20)$$

where $t \wedge s \triangleq \min(t, s)$. Letting $s = t + \Delta t$, then we have

$$Cov_{\tilde{X}}(t, t + \Delta t) = e^{-2\beta(\tau)(t-t_0) - \beta(\tau)\Delta t} \left[\sigma_{t_0}^2 + \frac{\delta^2(\tau)}{2\beta(\tau)} \left(e^{2\beta(\tau)(t-t_0)} - 1 \right) \right] \quad (2.21)$$

The covariance of the overall dynamical model indicates what proportion of the environment remains constant from one observation instant or location to the next, separated by the sampling interval. Since the mobile is in motion, it implies that this

corresponds to a spatial covariance. If we choose the variance of the initial condition such

that $\sigma_{t_0}^2 = \frac{\delta^2(\tau)}{2\beta(\tau)}$, then we get

$$Cov_{\tilde{X}}(t, t + \Delta t) = \frac{\delta^2(\tau)}{2\beta(\tau)} e^{-\beta(\tau)\Delta t} = \sigma_{t_0}^2 e^{-\beta(\tau)\Delta t} \triangleq Cov_{\tilde{X}}(\Delta t) \quad (2.22)$$

Expression (2.22) indicates that the spatial covariance of our overall dynamical model corresponds to the reported experimental spatial covariance given by (2.17). The comparison further indicates that $\beta(\tau)$ is a characteristic of both the propagating environment and the separation distance of two consecutive samples, i.e., $\beta(\tau)$ is inversely proportional to the density of the propagating environment, and directly proportional to the sample separation distance. Note that the spatial covariance is an important characteristic for our dynamical mean-reverting shadow fading model since it can be clearly used in order to identify the random parameters $\{\beta(\tau), \delta(\tau)\}$. This could be accomplished by using experimental data of $Cov_{\tilde{X}}(\Delta t)$ in order to identify $\beta(\tau)$. The latter can be used further in conjunction with $\sigma_{t_0}^2$ in order to identify $\delta(\tau)$. Therefore, the parameters $\{\beta(\tau), \delta(\tau)\}$ can be estimated on-line from experimental measurements. Finally, we note that the variance of the initial condition of the PL process, $\sigma_{t_0}^2$, should inevitably increase with distance, or equivalently $\delta(\tau)$ should increase and/or $\beta(\tau)$ decrease.

The TV LTF channel model is used to generate the link gains for the proposed PCA which introduced in Chapter 4. The TV STF channel model is discussed in the next section.

2.3 Stochastic TV STF Channel Modeling

2.3.1 The Deterministic DPSD of Wireless Channels

The traditional STF model is based on Ossanna [49] and later Clarke [50] and Aulin's [44] developments. Aulin's model is shown in Figure 2.4. This model assumes that at

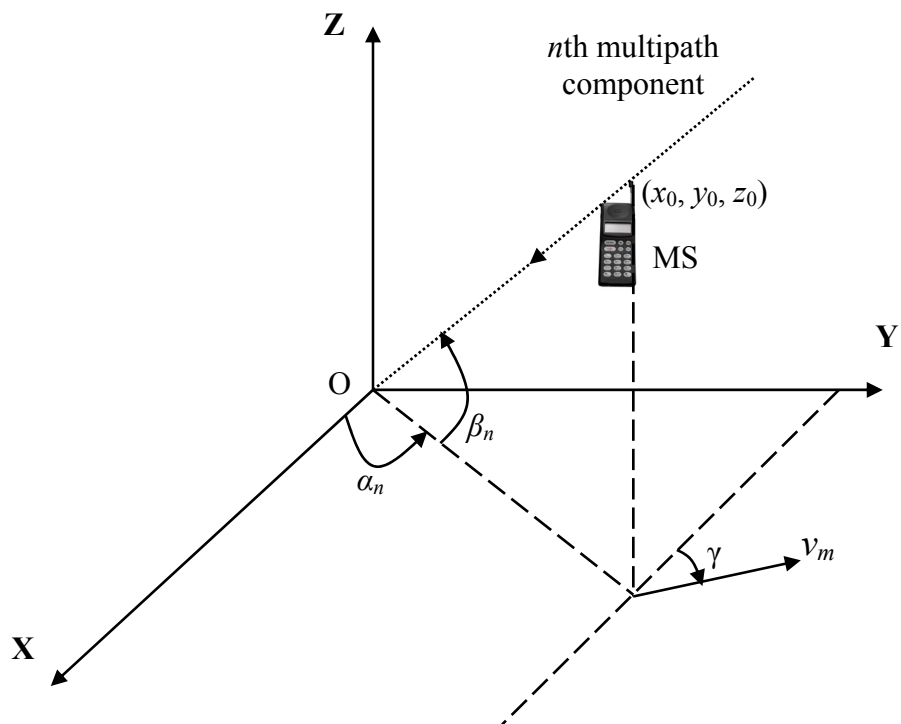


Figure 2.4: Aulin's 3D multipath channel model.

each point between a transmitter and a receiver, the total received wave consists of the superposition of N plane waves each having traveled via a different path. The n th wave is characterized by its field vector $E_n(t)$ given by [44]

$$E_n(t) = \text{Re}\{r_n(t)e^{j\Phi_n(t)}e^{j\omega_c t}\} = I_n(t)\cos\omega_c t - Q_n(t)\sin\omega_c t \quad (2.23)$$

where $\{I_n(t), Q_n(t)\}$ are the inphase and quadrature components for the n th wave, respectively, $r_n(t) = \sqrt{I_n^2(t) + Q_n^2(t)}$ is the signal envelope, $\Phi_n(t) = \tan^{-1}(Q_n(t)/I_n(t))$ is the phase and ω_c is the carrier frequency. The total field $E(t)$ can be written as

$$E(t) = \sum_{n=1}^N E_n(t) = I(t)\cos\omega_c t - Q(t)\sin\omega_c t \quad (2.24)$$

where $\{I(t), Q(t)\}$ are inphase and quadrature components of the total wave, respectively, with $I(t) = \sum_{n=1}^N I_n(t)$ and $Q(t) = \sum_{n=1}^N Q_n(t)$. An application of the central limit theorem states that for large N , the inphase and quadrature components have Gaussian distributions $\mathcal{N}(\bar{x}; \sigma^2)$ [50]. The mean is $\bar{x} = E\{I(t)\} = E\{Q(t)\}$ and the variance is $\sigma^2 = \text{Var}\{I(t)\} = \text{Var}\{Q(t)\}$. In the case where there is non-line-of-sight (NLOS), then the mean $\bar{x} = 0$ and the received signal amplitude has Rayleigh distribution. In the presence of line-of-sight (LOS) component, $\bar{x} \neq 0$ and the received signal is Ricean distributed. Also, it is assumed that $I(t)$ and $Q(t)$ are uncorrelated and thus independent since they are Gaussian distributed [44].

Dependent on mobile speed, wavelength, and angle of incidence, the Doppler frequency shifts on the multipath rays give rise to a Doppler power spectral density (DPSD). The DPSD is defined as the Fourier transform of the autocorrelation function of the channel, and represents the amount of power at various frequencies. Define $\{\alpha_n, \beta_n\}$ as the direction of the incident wave onto the receiver as illustrated in Figure 2.4. For the case of α_n is uniformly distributed and β_n is fixed, the deterministic DPSD is given by [4]

$$S(f) = \begin{cases} \frac{E_0}{4\pi} \frac{1/f_m}{\sqrt{1 - \left(\frac{f}{f_m}\right)^2}}, & |f| < f_m \\ 0, & \text{otherwise} \end{cases} \quad (2.25)$$

where f_m is the maximum Doppler frequency, and $E_0/2 = \text{Var}\{I(t)\} = \text{Var}\{Q(t)\}$. A more complex, but realistic, expression for the DPSD, which assumes β_n has probability density function $p_\beta(\beta) = \frac{\cos \beta}{2 \sin \beta_m}$ for $|\beta| \leq |\beta_m| \leq \frac{\pi}{2}$, and for small angles β_m , is given by

$$S(f) = \begin{cases} 0, & |f| > f_m \\ \frac{E_0}{4f_m \sin \beta_m}, & f_m \cos \beta_m \leq |f| \leq f_m \\ \frac{E_0}{4\pi f_m \sin \beta_m} \left[\frac{\pi}{2} - \sin^{-1} \left(\frac{2 \cos^2 \beta_m - 1 - (f/f_m)^2}{1 - (f/f_m)^2} \right) \right], & |f| < f_m \cos \beta_m \end{cases} \quad (2.26)$$

Expression (2.26) is illustrated in Figure 2.5 for different values of mobile speed. Notice that the direction of motion does not play a role because of the uniform scattering assumption, and that the DPSDs described in (2.25) and (2.26) are *band limited*.

The DPSD is the fundamental channel characteristic on which STF dynamical models are based on. The approach presented here is based on traditional system theory using the state space approach [100] while capturing the spectral characteristics of the channel. The main idea in constructing dynamical models for STF channels is to factorize the deterministic DPSD into an approximate n th order even transfer function, and then use a stochastic realization [101] to obtain a state space representation for the inphase and quadrature components.

The wireless channel is considered as a dynamical system for which the input-output map is described in (2.4). In practice, one obtains from measurements the power spectral density of the output, and with the knowledge of the power spectral density of the input the power spectral density of the transfer function (wireless channel) can be deduced as

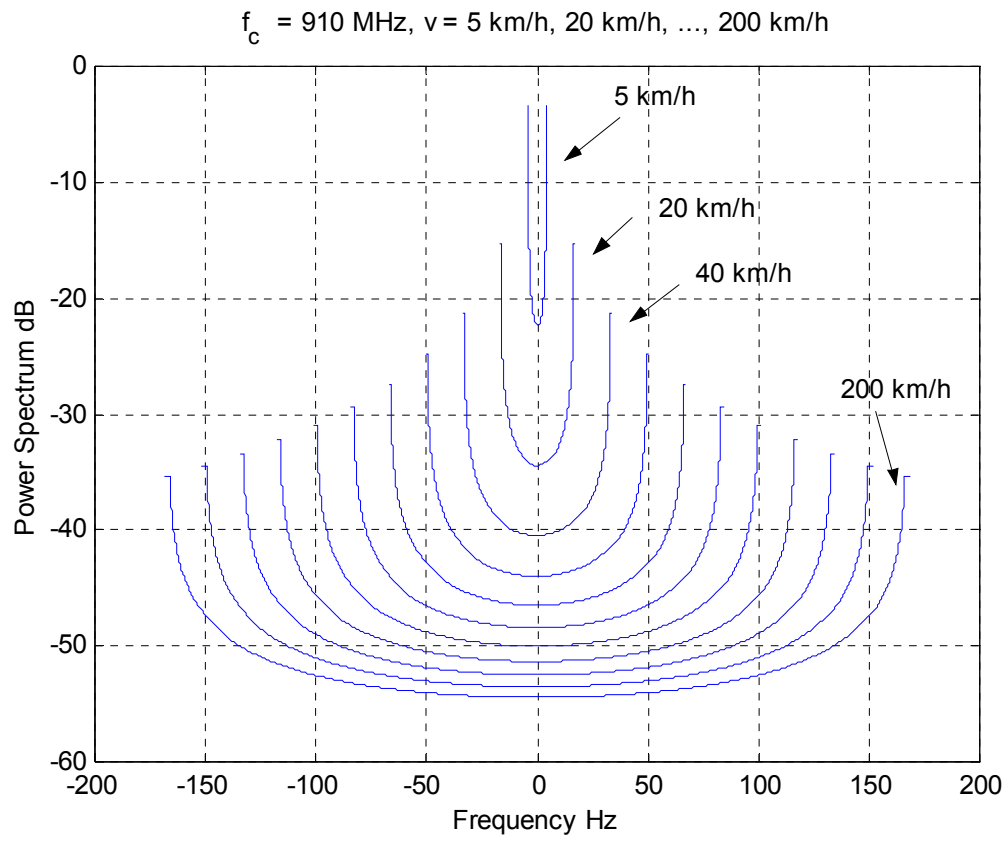


Figure 2.5: DPSD for $\beta_m = 10$ degrees and different values of mobile speed.

$$S_{yy}(f) = |H(f)|^2 S_{xx}(f) \quad (2.27)$$

where $x(t)$ is a random process with power spectral density $S_{xx}(f)$ representing the input signal to the channel, $y(t)$ is a random process with power spectral density $S_{yy}(f)$ representing the output signal of the channel, and $H(f)$ is the frequency response of the channel, which is the Fourier transform of the impulse response of the channel.

In general, in order to identify the random process associated with $S(f)$ in (2.25) or (2.26) in the form of an SDE, we need to find a transfer function, $H(f)$ whose magnitude square equals $S(f)$, i.e. $S(f) = |H(f)|^2$. This is equivalent to $S(s) = H(s)H(-s)$, where $s = j2\pi f$. That is, we need to factorize the DPSD. This is an old problem which had been studied by Paley and Wiener [51] and is reformulated here as follows:

Given a non-negative integrable function, $S(f)$, such that the Paley-Wiener condition $\int_{-\infty}^{\infty} \left[\frac{|\log S(f)|}{(1+f^2)} \right] df < \infty$ is satisfied, then there exists a causal, stable, minimum-phase, $H(f)$, such that $|H(f)|^2 = S(f)$, implying that $S(f)$ is factorizable, namely, $S(s) = H(s)H(-s)$. The factor $H(s)$ represents the frequency response of a causal, stable, and minimum-phase system, which, if driven by the process $x(t)$, the power spectral density of its output will be given by (2.27). It can be seen that the Paley-Wiener condition is not satisfied when $S(f)$ is *band limited*, which is the case of wireless links. Therefore, the deterministic DPSD has to be first approximated by a rational transfer function, say $\tilde{S}(f)$, and is discussed next.

2.3.2 Approximating the Deterministic DPSD

A number of rational approximation methods [56] can be used to approximate the deterministic DPSD, the choice of which depends on the complexity and the required

accuracy. The order of approximation dictates how close the approximate curve would be to the actual one. Higher order approximations capture higher order dynamics, and provide better approximations for the DPSD, however computations become more involved. In this section, we consider a simple approximating method which uses a 4th order stable, minimum phase, real, rational approximate transfer function. In Section 2.4, we consider the complex cepstrum approximation algorithm [54], which is based on the Gauss-Newton method for iterative search, and is more accurate but requires more computations.

In the simple approximating method, a 4th order even transfer function $\tilde{S}(s)$, is used to approximate the deterministic cellular DPSD, $S(s)$. The approximate function $\tilde{S}(s) = H(s)H(-s)$ is given by

$$\tilde{S}(s) = \frac{K^2}{s^4 + 2\omega_n^2(1 - 2\zeta^2)s^2 + \omega_n^4}, \quad H(s) = \frac{K}{s^2 + 2\zeta\omega_n s + \omega_n^2} \quad (2.28)$$

where $\tilde{S}(s)$ is the approximation of $S(s)$. Equation (2.28) has three arbitrary parameters $\{\zeta, \omega_n, K\}$, which can be adjusted such that the approximate curve coincides with the actual curve at different points. The reason for presenting 4th order approximation of the DPSD is that we can compute explicit expressions for the constants $\{\zeta, \omega_n, K\}$ as functions of specific points on the data-graphs of the DPSD. In fact, if the approximate density $\tilde{S}(f)$ coincides with the exact density $S(f)$ at $f=0$ and $f=f_{\max}$, then the arbitrary parameters $\{\zeta, \omega_n, K\}$ are computed explicitly as

$$\zeta = \sqrt{\frac{1}{2} \left(1 - \sqrt{1 - \frac{S(0)}{S(f_{\max})}} \right)}, \quad \omega_n = \frac{2\pi f_{\max}}{\sqrt{1 - 2\zeta^2}}, \quad K = \omega_n^2 \sqrt{S(0)} \quad (2.29)$$

Figure 2.6 shows the DPSD, $S(f)$, and its approximation $\tilde{S}(f)$ via a 4th order even function.

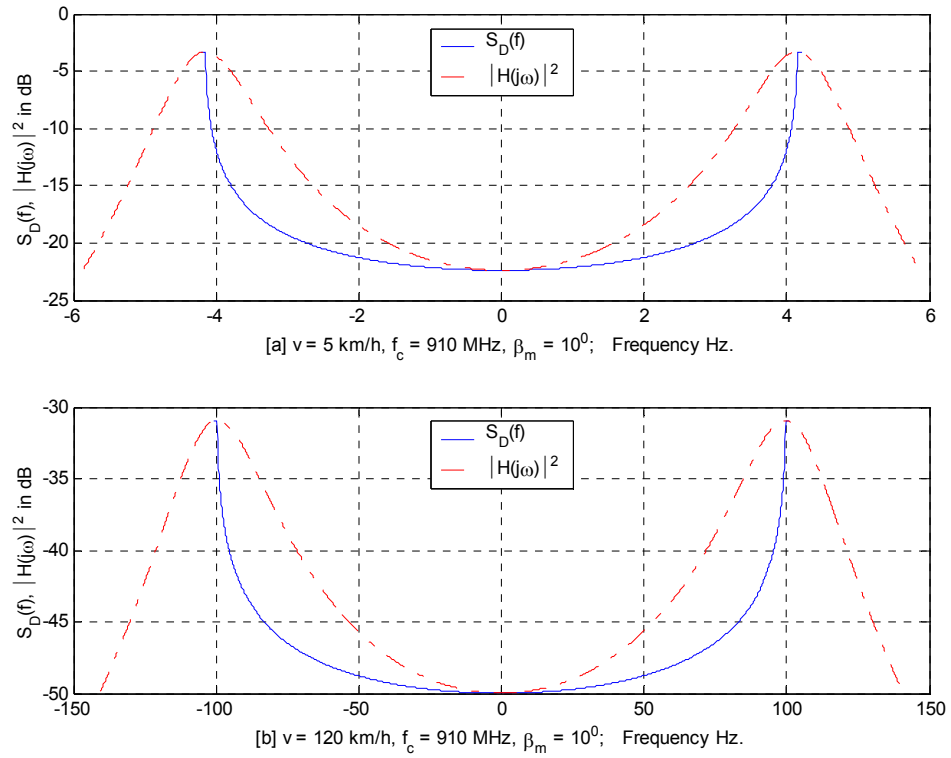


Figure 2.6: DPSD, $S_D(f)$, and its approximation $\tilde{S}(\omega) = |H(j\omega)|^2$ via a 4th order transfer function for mobile speed of (a) 5 km/hr and (b) 120 km/hr.

2.3.3 Stochastic STF Channel Models

A stochastic realization is used here to obtain a state space representation for the inphase and quadrature components [101]. The SDE, which corresponds to $H(s)$ in (2.28) is given by

$$d^2x(t) + 2\zeta\omega_n dx(t) + \omega_n^2 x(t)dt = KdW(t), \quad \dot{x}(0), x(0) \text{ are given} \quad (2.30)$$

where $\{dW(t)\}_{t \geq 0}$ is a white-noise process. Equation (2.30) can be rewritten in terms of inphase and quadrature components as

$$\begin{aligned} d^2x_I(t) + 2\zeta\omega_n dx_I(t) + \omega_n^2 x_I(t)dt &= KdW_I(t), \quad \dot{x}_I(0), x_I(0) \text{ are given} \\ d^2x_Q(t) + 2\zeta\omega_n dx_Q(t) + \omega_n^2 x_Q(t)dt &= KdW_Q(t), \quad \dot{x}_Q(0), x_Q(0) \text{ are given} \end{aligned} \quad (2.31)$$

where $\{dW_I(t)\}_{t \geq 0}$ and $\{dW_Q(t)\}_{t \geq 0}$ are two independent and identically distributed (i.i.d.) white Gaussian noises.

Several stochastic realizations [101] can be used to obtain a state-space representation for the in-phase and quadrature components of STF channel models. For example, the stochastic observable canonical form (OCF) realization [100] can be used to realize (2.31) for the inphase and quadrature components for the j th path as

$$\begin{aligned} \begin{bmatrix} dX_{I,j}^1(t) \\ dX_{I,j}^2(t) \end{bmatrix} &= \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix} \begin{bmatrix} X_{I,j}^1(t) \\ X_{I,j}^2(t) \end{bmatrix} dt + \begin{bmatrix} 0 \\ K \end{bmatrix} dW_j^I(t), \quad \begin{bmatrix} X_{I,j}^1(0) \\ X_{I,j}^2(0) \end{bmatrix}, \\ I_j(t) &= [1 \quad 0] \begin{bmatrix} X_{I,j}^1(t) \\ X_{I,j}^2(t) \end{bmatrix} + f_j^I(t), \\ \begin{bmatrix} dX_{Q,j}^1(t) \\ dX_{Q,j}^2(t) \end{bmatrix} &= \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix} \begin{bmatrix} X_{Q,j}^1(t) \\ X_{Q,j}^2(t) \end{bmatrix} dt + \begin{bmatrix} 0 \\ K \end{bmatrix} dW_j^Q(t), \quad \begin{bmatrix} X_{Q,j}^1(0) \\ X_{Q,j}^2(0) \end{bmatrix}, \\ Q_j(t) &= [1 \quad 0] \begin{bmatrix} X_{Q,j}^1(t) \\ X_{Q,j}^2(t) \end{bmatrix} + f_j^Q(t) \end{aligned} \quad (2.32)$$

where $I_j(t)$ and $Q_j(t)$ corresponds to the inphase and quadrature components of the j th path respectively, $\{W_j^I(t)\}_{t \geq 0}$ and $\{W_j^Q(t)\}_{t \geq 0}$ are independent standard Brownian motions, which correspond to the inphase and quadrature components of the j th path respectively, the parameters $\{\zeta, \omega_n, K\}$ are obtained from approximating the DPSD, $f_j^I(t)$ and $f_j^Q(t)$ are arbitrary functions representing the LOS of the inphase and quadrature components respectively, characterizing further dynamic variations in the environment.

Let us denote $\{X_I(t), X_Q(t)\}$ the state vectors for the inphase and quadrature components, respectively, and $\{I(t), Q(t)\}$ the inphase and quadrature components of the channel, then (2.32) for the j th path can be written in compact form as

$$\begin{aligned} \begin{bmatrix} dX_I(t) \\ dX_Q(t) \end{bmatrix} &= \begin{bmatrix} A_I & 0 \\ 0 & A_Q \end{bmatrix} \begin{bmatrix} X_I(t) \\ X_Q(t) \end{bmatrix} dt + \begin{bmatrix} B_I & 0 \\ 0 & B_Q \end{bmatrix} \begin{bmatrix} dW_I(t) \\ dW_Q(t) \end{bmatrix} \\ \begin{bmatrix} I(t) \\ Q(t) \end{bmatrix} &= \begin{bmatrix} C_I & 0 \\ 0 & C_Q \end{bmatrix} \begin{bmatrix} X_I(t) \\ X_Q(t) \end{bmatrix} + \begin{bmatrix} f_I(t) \\ f_Q(t) \end{bmatrix} \end{aligned} \quad (2.33)$$

where

$$A_I = A_Q = \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix}, \quad B_I = B_Q = \begin{bmatrix} 0 \\ K \end{bmatrix}, \quad C_I = C_Q = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad (2.34)$$

$\{W_I(t), W_Q(t)\}_{t \geq 0}$ are independent standard Brownian motions which are independent of the initial random variables $X_I(0)$ and $X_Q(0)$, and $\{f_I(s), f_Q(s); 0 \leq s \leq t\}$ are random processes representing the inphase and quadrature LOS components, respectively. The band-pass representation of the received signal corresponding to the j th path is given as:

$$y(t) = \left[(C_I X_I(t) + f_I(t)) \cos \omega_c t - (C_Q X_Q(t) + f_Q(t)) \sin \omega_c t \right] s_l(t - \tau_j) + v(t) \quad (2.35)$$

where $v(t)$ is the measurement noise. As the DPSD varies from one instant to the next, the channel parameters $\{\zeta, \omega_n, K\}$ also vary in time, and have to be estimated on-line from time domain measurements. Without loss of generality, we consider the case of flat fading, in which the mobile-to-mobile channel has purely multiplicative effect on the signal and the multipath components are not resolvable, and can be considered as a single path [5]. The frequency selective fading case can be handled by including multiple time-delayed echoes. In this case, the delay spread has to be estimated. A sounding device is usually dedicated to estimate the time delay of each discrete path such as Rake receiver [60]. Following the state space representation in (2.33) and the band pass representation of the received signal in (2.35), the fading channel can be represented using a general stochastic state space representation of the form

$$\begin{aligned} dX(t) &= A(t)X(t)dt + B(t)dW(t) \\ y(t) &= C(t)X(t) + D(t)v(t) \end{aligned} \quad (2.36)$$

where

$$\begin{aligned} X(t) &= [X_I(t) \quad X_Q(t)]^T, \quad A(t) = \begin{bmatrix} A_I(t) & 0 \\ 0 & A_Q(t) \end{bmatrix}, \quad B(t) = \begin{bmatrix} B_I(t) & 0 \\ 0 & B_Q(t) \end{bmatrix}, \\ C(t) &= [\cos(\omega_c t)C_I \quad -\sin(\omega_c t)C_Q], \quad D(t) = [\cos(\omega_c t) \quad -\sin(\omega_c t)] \\ v(t) &= [v_I(t) \quad v_Q(t)]^T, \quad dW(t) = [dW^I(t) \quad dW^Q(t)]^T \end{aligned} \quad (2.37)$$

In this case, $y(t)$ represents the received signal measurements, $X(t)$ is the state variable of the inphase and quadrature components, and $v(t)$ is the measurement noise.

Time domain simulation of STF channels can be performed by passing two independent white noise processes through two identical filters, $\tilde{H}(s)$, obtained from the factorization of the deterministic DPSD, one for the inphase and the other for the quadrature component [19], and realized in their state-space form as described in (2.33) and (2.34).

Example 2.3: Consider a flat fading wireless channel with the following parameters: $f_c = 900$ MHz, $v = 80$ km/h, $\beta_m = 10^\circ$, and $f_j^I(t) = f_j^Q(t) = 0$. Time domain simulation of the inphase and quadrature components, attenuation coefficient, phase angle, input signal, and received signal are shown in Figures 2.7-2.9. The inphase and quadrature components have been produced using (2.33) and (2.34), while the received signal is reproduced using (2.35). The simulation of the dynamical STF channel is performed using Simulink in Matlab [118]. In the next chapter, we propose to estimate the channel parameters as well as the inphase and quadrature components directly from received signal measurements, using the EM algorithm together with the Kalman filter.

2.3.4 Solution to the Stochastic State Space Model

The stochastic time varying state space model described in (2.36) has a solution given by [101, 102]

$$X_L(t) = \Phi_L(t, t_0) \left[X_L(t_0) + \int_{t_0}^t \Phi_L^{-1}(u, t_0) B_L(u) dW_L(u) \right] \quad (2.38)$$

where $L = I$ or Q , $\Phi_L(t, t_0)$ is the fundamental matrix, and $\dot{\Phi}_L(t, t_0) = A_L(t) \Phi_L(t, t_0)$ with initial condition $\Phi_L(t_0, t_0) = I$, where I is the identity matrix.

A simple computation shows that the mean of $X_L(t)$ is given by [101]

$$E[X_L(t)] = \Phi_L(t, t_0) E[X_L(t_0)] \quad (2.39)$$

and the covariance matrix of $X_L(t)$ is [101]

$$\Sigma_L(t) = \Phi_L(t, t_0) \left[\text{Var}[X_L(t_0)] + \int_{t_0}^t \Phi_L^{-1}(u, t_0) B_L(u) B_L^T(u) (\Phi_L^{-1}(u, t_0))^T du \right] \Phi_L^T(t, t_0) \quad (2.40)$$

A simple differentiation of expression (2.40) shows that the covariance matrix $\Sigma_L(t)$ satisfies the Riccati equation

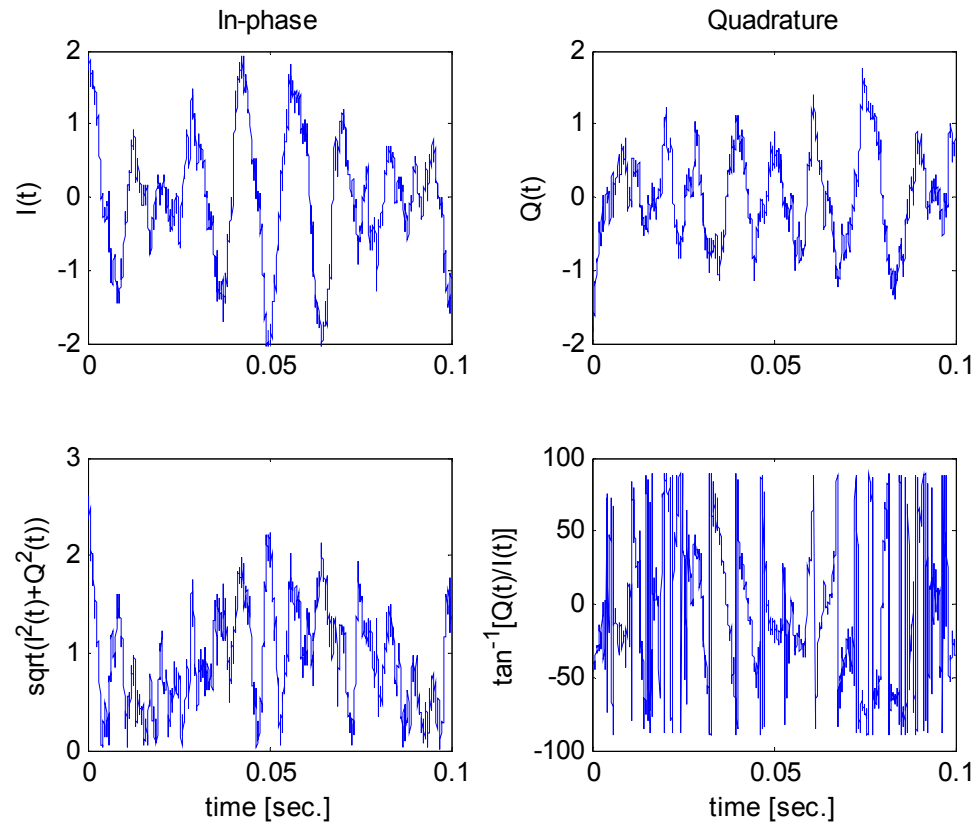


Figure 2.7: Inphase and quadrature components, attenuation coefficient, and phase angle of the STF wireless channel in Example 2.3.

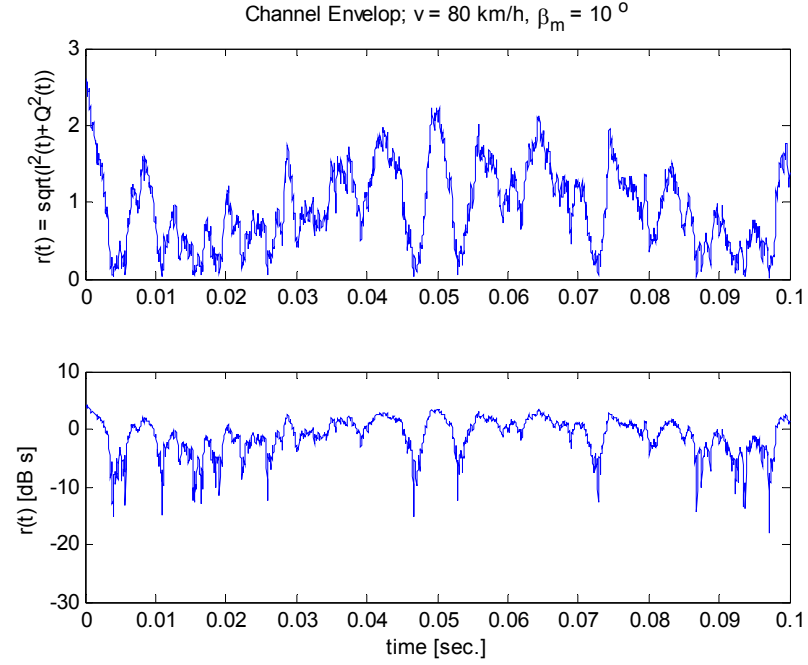


Figure 2.8: Attenuation coefficient in absolute units and in dB's for the STF wireless channel in Example 2.3.

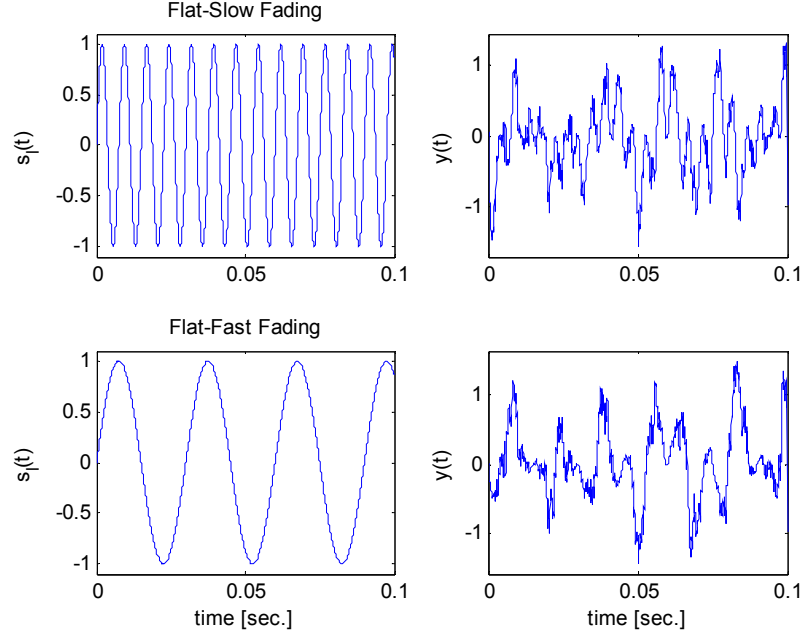


Figure 2.9: Input signal, $s(t)$, and the corresponding received signal, $y(t)$, for flat slow fading (top) and flat fast fading conditions (bottom).

$$\dot{\Sigma}_L(t) = A(t)\Sigma_L(t) + \Sigma_L(t)A^T(t) + B(t)B^T(t) \quad (2.41)$$

For the time invariant case, $A_L(t) = A_L$ and $B_L(t) = B_L$, expressions (2.38)-(2.40) simplify to

$$\begin{aligned} X_L(t) &= e^{A_L(t-t_0)} X_L(t_0) + \int_{t_0}^t e^{A_L(t-u)} B_L dW_L(u) \\ E[X_L(t)] &= e^{A_L(t-t_0)} E[X_L(t_0)] \\ \Sigma_L(t) &= e^{A_L(t-t_0)} \text{Var}[X_L(t_0)] e^{A_L^T(t-t_0)} + \int_{t_0}^t e^{A_L(t-u)} B_L B_L^T e^{A_L^T(t-u)} du \end{aligned} \quad (2.42)$$

It can be seen from (2.39) and (2.40) that the mean and variance of the inphase and quadrature components are functions of time. Note that the statistics of the inphase and quadrature components, and therefore the statistics of the STF channel, are times varying. Therefore, these stochastic state space models reflect the TV characteristics of the STF channel.

As described above, the channel parameters are obtained from approximating the deterministic DPSD. However, in reality one can not have access to the DPSD on-line and at all times during the estimation process. In the next chapter, we propose to estimate the channel parameters as well as the inphase and quadrature components directly from received signal measurements, which are usually available or easy to obtain in any wireless network. The EM algorithm and Kalman filtering are employed in the channel parameter and state estimation, respectively. This estimation algorithm is described in Chapter 3. The TV STF channel model is used to generate the link gains for the proposed PCA which is introduced in Chapter 4. Following the same procedure in developing the STF channel models, the TV stochastic ad hoc channel models are developed in the next section.

2.4 Stochastic TV Ad Hoc Channel Modeling

2.4.1 The Deterministic DPSD of Ad Hoc Channels

Dependent on mobile speed, wavelength, and angle of incidence, the Doppler frequency shifts on the multipath rays give rise to a DPSD. The cellular DPSD for a received fading carrier of frequency f_c is given by [4]

$$\frac{S(f)}{pG/\pi f_1} = \begin{cases} \frac{1}{\sqrt{1 - \left(\frac{f - f_c}{f_1}\right)^2}} & , |f - f_c| < f_1 \\ 0 & , \text{otherwise} \end{cases} \quad (2.43)$$

where f_1 is the maximum Doppler frequency of the mobile, p is the average power received by an isotropic antenna, and G is the gain of the receiving antenna. For a mobile-to-mobile (or ad hoc) link, with f_1 and f_2 as the sender and receiver's maximum Doppler frequencies, respectively, the *degree of double mobility*, denoted by α is defined by $\alpha = [\min(f_1, f_2) / \max(f_1, f_2)]$, so $0 \leq \alpha \leq 1$, where $\alpha = 1$ corresponds to a full double mobility and $\alpha = 0$ to a single mobility like the cellular link, implying that cellular channels are a special case of mobile-to-mobile channels. The corresponding deterministic mobile-to-mobile DPSD is given by [52, 53, 91, 92, 96]

$$\frac{S(f)}{(pG)^2 / \pi^2 f_m \sqrt{\alpha}} = \begin{cases} K \left(\frac{1 + \alpha}{2\sqrt{\alpha}} \sqrt{1 - \left(\frac{f - f_c}{(1 + \alpha)f_m} \right)^2} \right) & , |f - f_c| < (1 + \alpha)f_m \\ 0 & , \text{otherwise} \end{cases} \quad (2.44)$$

where $K(\cdot)$ is the complete elliptic integral of the first kind, and $f_m = \max(f_1, f_2)$. Figure 2.10 shows the deterministic mobile-to-mobile DPSDs for different values of α 's. Thus, a generalized two-dimensional (2D) DPSD has been found where the U-shaped spectrum of cellular channels is a special case.

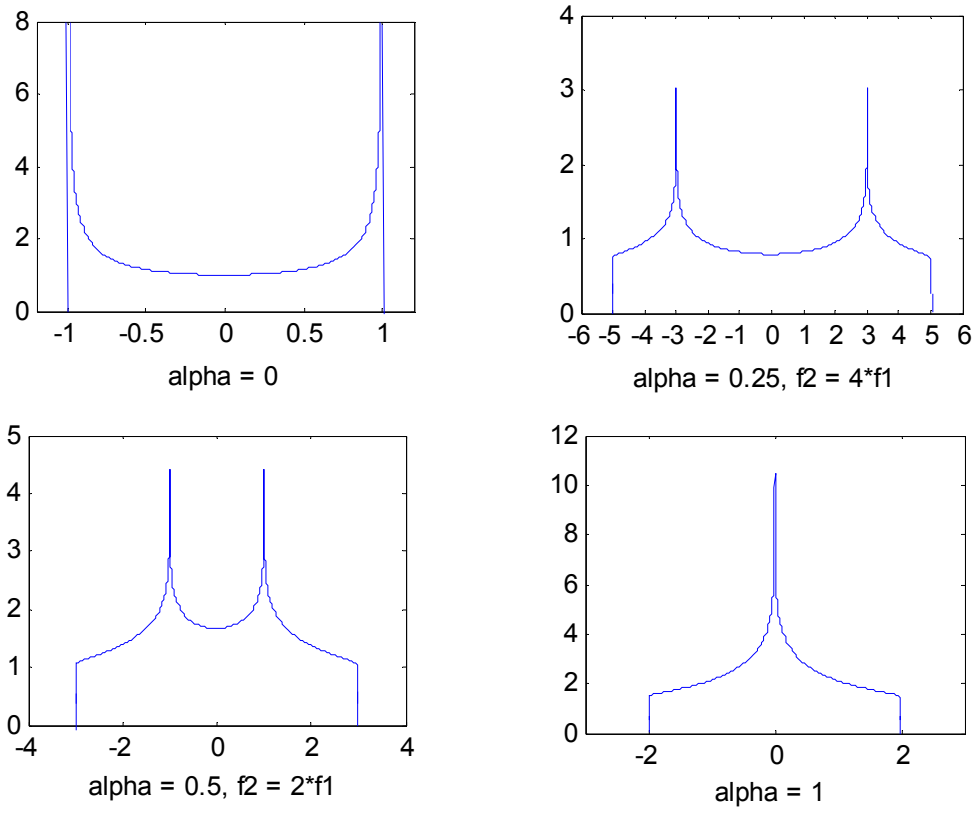


Figure 2.10: Ad hoc DPSD for different values of α 's, with parameters $f_c=0$, $f_1=1$, and $pG=\pi$.

Here, we follow the same procedure in deriving the stochastic STF channel models in Section 2.3. The deterministic ad hoc DPSD is first factorized into an approximate n th order even transfer function, and then use a stochastic realization [101] to obtain a state space representation for inphase and quadrature components. The complex cepstrum algorithm [54] is used to approximate the ad hoc DPSD. This algorithm is discussed next.

2.4.2 Approximating the Deterministic Ad Hoc DPSD

Since the ad hoc DPSD is more complicated than the cellular one, we propose to use a more complex and accurate approximating method: The complex cepstrum algorithm [54]. It uses several measured points of the DPSD instead of just three points as in the simple method (described in Section 2.3.2). It can be explained briefly as follows: On a log-log scale, the magnitude data is interpolated linearly, with a very fine discretization. Then, using the complex cepstrum algorithm [54], the phase, associated with a stable, minimum phase, real, rational transfer function with the same magnitude as the magnitude data is generated.

With the new phase data and the input magnitude data, a real rational transfer function can be found by using the Gauss-Newton method for iterative search [56], which is used to generate a stable, minimum phase, real rational transfer function, denoted by $\tilde{H}(s)$, to identify the best model from the data of $H(f)$ as

$$\min_{b,a} \sum_{k=1}^l wt(f_k) \left| H(f_k) - \tilde{H}(f_k) \right|^2 \quad (2.45)$$

where

$$\tilde{H}(s) = \frac{b_{m-1}s^{m-1} + \dots + b_1s + b_0}{s^m + a_{m-1}s^{m-1} + \dots + a_1s + a_0} \quad (2.46)$$

$b = \{b_{m-1}, \dots, b_0\}$, $a = \{a_{m-1}, \dots, a_0\}$, $wt(f)$ is the weight function, and l is the number of frequency points. Several variants have been suggested in the literature, where the

weighting function gives less attention to high frequencies [56]. This algorithm is based on Levi [55]. Figure 2.11 shows the DPSD, $S(f)$, and its approximation $\tilde{S}(f)$ via different orders using complex cepstrum algorithm. Higher order of $\tilde{S}(f)$, better approximation obtained. It can be seen that approximating by a 4th order transfer function gives very good results.

Figure 2.12(a) and 2.12(b) show the DPSD, $S(f)$, and its approximation $\tilde{S}(f)$ using the complex cepstrum and simple approximation methods, respectively, for different values of α 's via 4th order even function. It can be noticed that the former gives better approximation than the latter; since it employs all measured points of the DPSD instead of just three points in the simple method.

2.4.3 Stochastic Ad Hoc Channel Models

The same procedure as the cellular case is used to represent mobile-to-mobile channels. The stochastic OCF [100] is used to realize (2.46) for the inphase and quadrature components as

$$\begin{aligned} dX_{I,j}(t) &= A_I X_{I,j}(t)dt + B_I dW_j^I(t) \\ I_j(t) &= C_I X_{I,j}(t) + f_j^I(t) \\ dX_{Q,j}(t) &= A_Q X_{Q,j}(t)dt + B_Q dW_j^Q(t) \\ Q_j(t) &= C_Q X_{Q,j}(t) + f_j^Q(t) \end{aligned} \quad (2.47)$$

where

$$\begin{aligned} X_{I,j}(t) &= [X_{I,j}^1(t), X_{I,j}^2(t), \dots, X_{I,j}^m(t)]^T, \quad X_{Q,j}(t) = [X_{Q,j}^1(t), X_{Q,j}^2(t), \dots, X_{Q,j}^m(t)]^T \\ A_I = A_Q &= \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ -a_0 & -a_1 & -a_2 & \dots & -a_{m-1} \end{bmatrix}, \quad B_I = B_Q = \begin{bmatrix} b_{m-1} \\ \vdots \\ \vdots \\ b_1 \\ b_0 \end{bmatrix}, \quad C_I = C_Q = [1 \quad 0 \dots 0] \end{aligned} \quad (2.48)$$

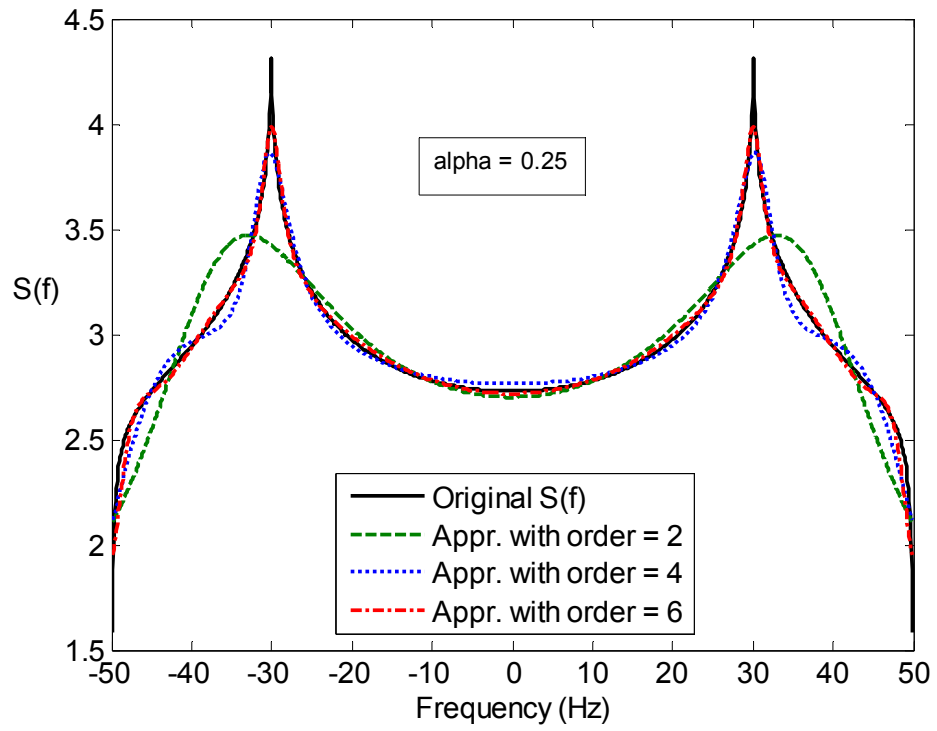
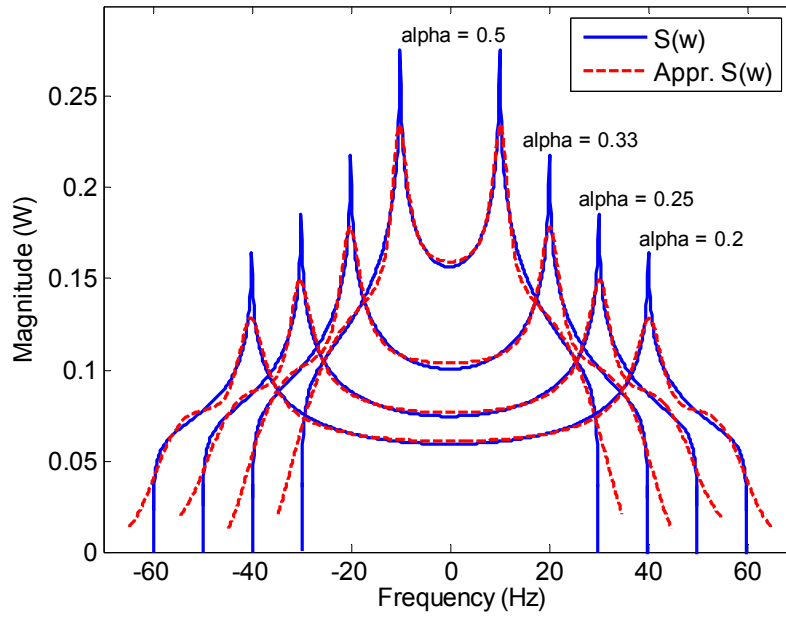
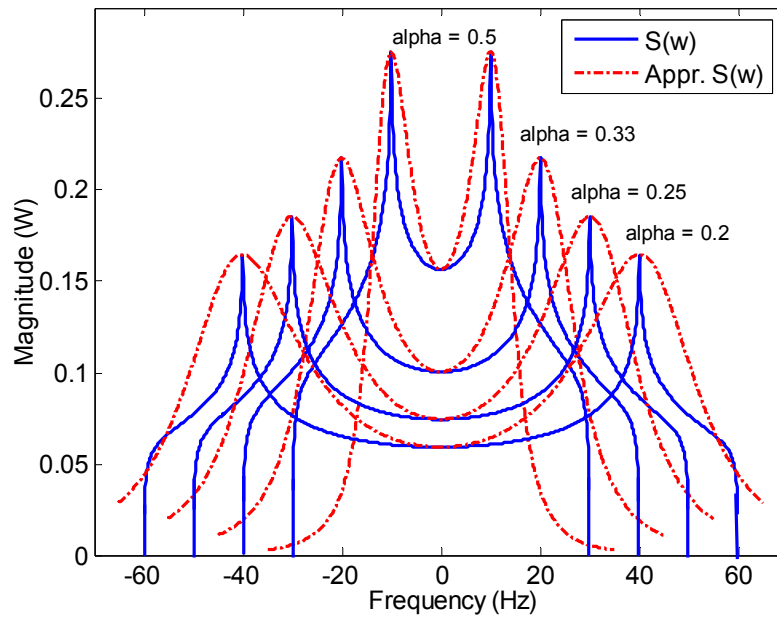


Figure 2.11: DPSD, $S(f)$, and its approximations, $\tilde{S}(f)$, using complex cepstrum algorithm for different orders of $\tilde{S}(f)$.



(a)



(b)

Figure 2.12: DPSD, $S(f)$, and its approximation, $\tilde{S}(f)$, via 4th order function for different α 's using (a) the complex cepstrum, and (b) the simple approximation methods.

$X_{I,j}(t)$ and $X_{Q,j}(t)$ are state vectors of the inphase and quadrature components of the j th path. $I_j(t)$ and $Q_j(t)$ corresponds to the inphase and quadrature components of the j th path respectively, $\{W_j^I(t)\}_{t \geq 0}$ and $\{W_j^Q(t)\}_{t \geq 0}$ are independent standard Brownian motions, which correspond to the inphase and quadrature components of the j th path respectively, the parameters $\{a_{m-1}, \dots, a_0, b_{m-1}, \dots, b_0\}$ are obtained from the approximation of the ad hoc DPSD, and $f_j^I(t)$ and $f_j^Q(t)$ are arbitrary functions representing the LOS of the inphase and quadrature components respectively, characterizing further dynamic variations in the environment. Equation (2.47) for the inphase and quadrature components of the j th path can be described as in (2.33), and the solution of the ad hoc state space model in (2.47) is similar to the one for STF model described in Section 2.3.4. The mean and variance of the ad hoc inphase and quadrature components have the same form as the ones in the STF case in (2.39) and (2.40), which show that the statistics are functions of time. The general TV state space representation for the ad hoc channel model is similar to the STF state space representation in (2.36) and (2.37).

As the DPSD varies from one instant to the next, the channel parameters $\{a_{m-1}, \dots, a_0, b_{m-1}, \dots, b_0\}$ also vary in time, and have to be estimated on-line from time domain measurements.

Example 2.4: Consider a mobile-to-mobile channel with parameters $v_1 = 36 \text{ km/hr}$ (10 m/s) and $v_2 = 24 \text{ km/hr}$ (6.6 m/s), in which $\alpha = 0.66$. Figure 2.13 shows time domain simulation of the inphase and quadrature components, and the attenuation coefficient. The inphase and quadrature components have been produced using (2.47) and (2.48), while the received signal is reproduced using (2.35). In Figure 2.13 Gauss-Newton method is used to approximate the deterministic DPSD with 4th order transfer function. The simulation is performed using Simulink in Matlab [118].

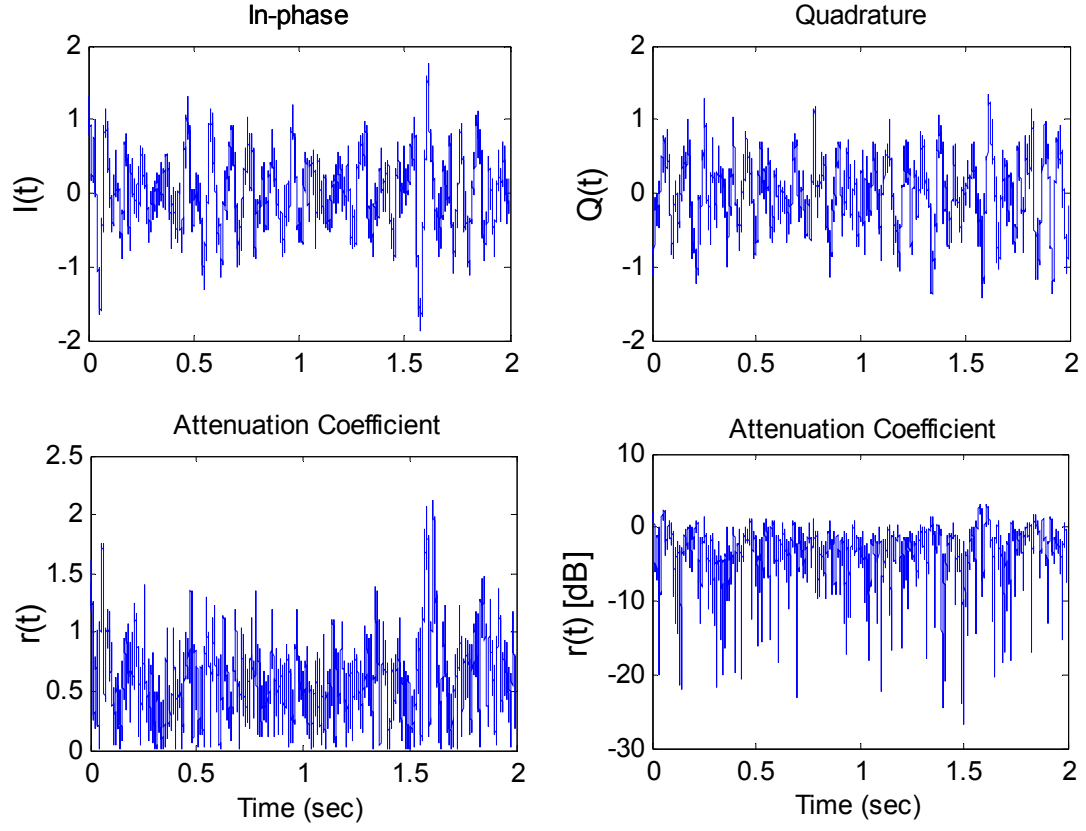


Figure 2.13: Inphase and quadrature components $\{I(t), Q(t)\}$, and the attenuation coefficient $r_n(t) = \sqrt{I_n^2(t) + Q_n^2(t)}$, for a mobile-to-mobile channel with $\alpha = 0.66$.

2.5 Link Performance for Cellular and Ad Hoc Channels

Now, we want to compare the performance of mobile-to-mobile link with a cellular link. For simplicity we will consider the case of flat fading, in which the ad hoc channel has purely multiplicative effect on the signal and the multipath components are not resolvable. Thus it can be considered as a single path [5]. We consider BPSK is the modulation technique and the carrier frequency is $f_c = 900\text{MHz}$. We test 10000 frames of $P = 100$ bits each. We assume mobile nodes are vehicles, with the constraint that the average speed over the mobile nodes is 30 km/hr. This implies $v_1 + v_2 = 60\text{ km/hr}$, thus for a mobile-to-mobile link with $\alpha = 0$ we get $v_1 = 60\text{ km/hr}$ and $v_2 = 0$. The cellular case is defined as the scenario where a link connects a mobile node with speed 30 km/hr to a permanently stationary node, which is the base station. Thus, there is only one mobile node, and the constraint is satisfied. We consider the NLOS case ($f_I = f_Q = 0$), which represents an environment with large obstructions.

The state space models developed in (2.32) and (2.47) are used for simulating the inphase and quadrature components for the cellular and ad hoc channels, respectively. The complex cepstrum approximation method is used to approximate the ad hoc DPSD with 4th order stable, minimum phase, real, and rational transfer function. The received signal is reproduced using (2.35). Figure 2.14 shows the attenuation coefficient, $r(t) = \sqrt{I^2(t) + Q^2(t)}$, for both the cellular case and the worst-case mobile-to-mobile case ($\alpha = 0$). It can be observed that a mobile-to-mobile link suffers from faster fading by noting the higher frequency components in the worst-case mobile-to-mobile link. Also it can be noticed that deep fading (envelope less than -12 dB) on the mobile-to-mobile link occurs more frequently and less bursty (48 % of the time for the mobile-to-mobile link and 32 % for the cellular link). Therefore, the increased Doppler spread due to double mobility tends to smear the errors out, causing higher frame error rates.

Consider the data rate given by $R_b = P/T_c = 5\text{ Kbps}$ which is chosen such that the coherence time T_c equals the time it takes to send exactly one frame of length P bits, a condition where variation in Doppler spread greatly impacts the frame error rate (FER).

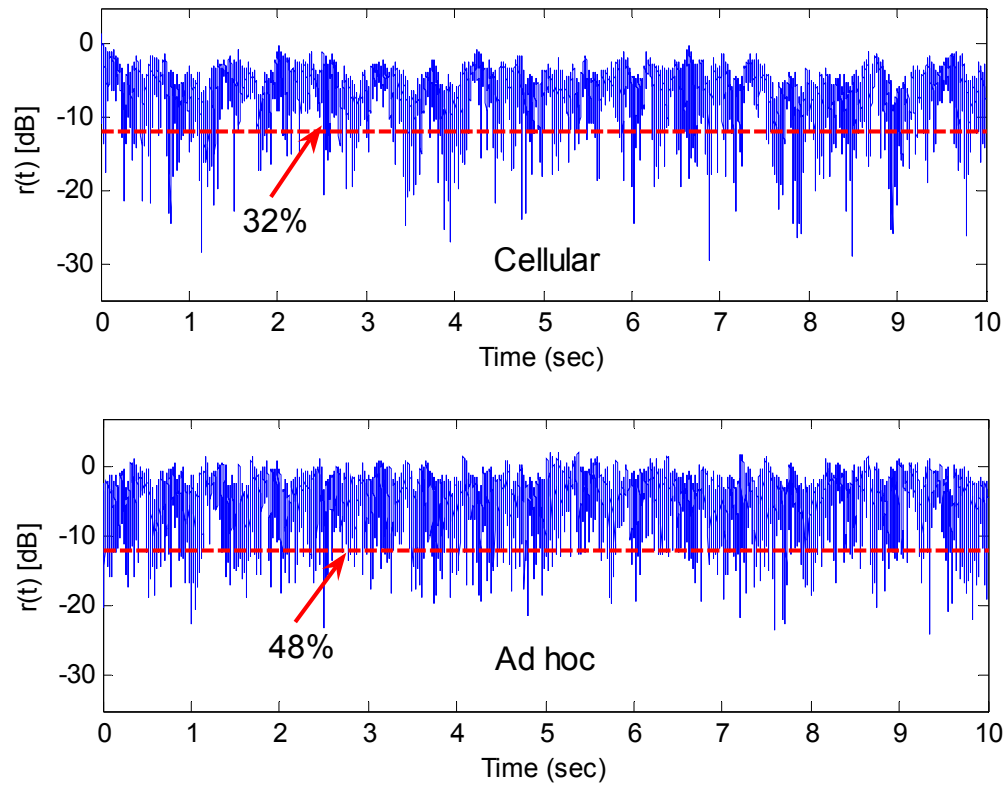


Figure 2.14: Rayleigh attenuation coefficient for cellular link and worst-case mobile-to-mobile link.

Figure 2.15 shows the link performance for 10000 frames of 100 bits each. It is clear that the mobile-to-mobile link is worse than the cellular link, but the performance gap decreases as $\alpha \rightarrow 1$. This agrees with the main conclusion of [53], that an increase in degree of double mobility mitigates fading by lowering the Doppler spread. The gain in performance is nonlinear with α , as the majority of gain is from $\alpha = 0$ to $\alpha = 0.5$. Intuitively, it makes sense that link performance improves as the degree of double mobility increases, since mobility in the network becomes distributed uniformly over the nodes in a kind of “equilibrium”.

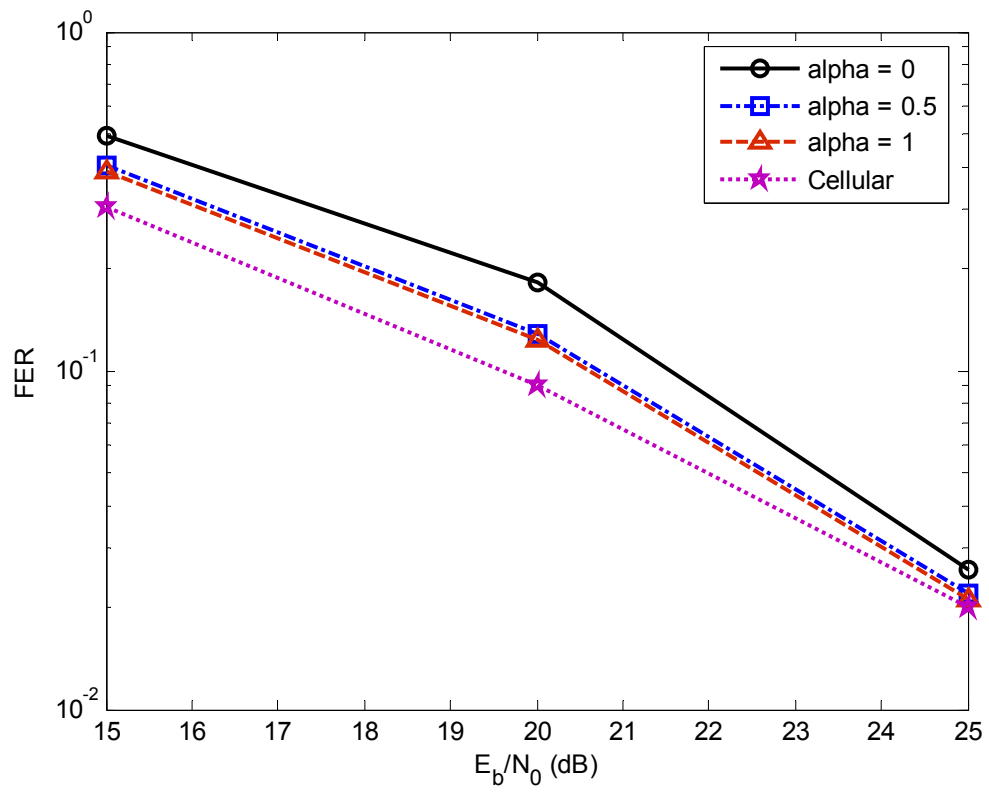


Figure 2.15: FER results for Rayleigh mobile-to-mobile link for different α 's compared with cellular link.

Chapter 3

Wireless Channel Estimation and Identification via the Expectation Maximization Algorithm and Kalman Filtering

Since the developed models are based on state space representations, we propose to estimate the channel parameters and states directly from received signal level measurements, which are usually available or easy to obtain in any wireless network. A filter-based expectation maximization (EM) algorithm [79, 80] and Kalman filter [81] are employed in the estimation process. These filters use only the first and second order statistics and are recursive and therefore can be implemented on-line. The standard EM algorithm [82] has a wide range of applications, for example, in the estimation of speech signals in acoustic environments [83], in localization of narrowband sources [84] and in speech coding [85] to cite a few. The proposed models and estimation algorithms are tested using received signal level measurement data collected from cellular and ad hoc experimental setups. Parts of the results presented here have been published in [105, 107, 110].

3.1 The EM Together with the Kalman Filter

Consider a discrete-time state space representation given by

$$\begin{aligned}x_{t+1} &= A_t x_t + B_t w_t \\ y_t &= C_t x_t + D_t v_t\end{aligned}\tag{3.1}$$

where $x_t \in \mathfrak{R}^n$ is a state vector, $y_t \in \mathfrak{R}^d$ is a measurement vector, $w_t \in \mathfrak{R}^m$ is a state noise, and $v_t \in \mathfrak{R}^d$ is a measurement noise. The noise processes w_t and v_t are assumed to be independent zero mean and unit variance Gaussian processes.

The system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ as well as the system states x_t are unknown and can be estimated through received signal measurement data, $Y_N = \{y_1, y_2, \dots, y_N\}$. The parameters are identified using a filter-based EM algorithm and the channel states are estimated using the Kalman filter. The Kalman filter is introduced next.

3.1.1 Channel State Estimation: The Kalman Filter

The Kalman filter estimates the channel states x_t for given system parameter θ_t and measurements Y_t . It is described by the following equations [81, 102]

$$\begin{aligned}\hat{x}_{t|t} &= A_t \hat{x}_{t-1|t-1} + P_{t|t} C_t^T D_t^{-2} (y_t - C_t A_t \hat{x}_{t-1|t-1}) \\ \hat{x}_{t|t-1} &= A_t \hat{x}_{t-1|t-1}, \quad \hat{x}_{0|0} = m_0\end{aligned}\tag{3.2}$$

where $t = 0, 1, 2, \dots, N$, and $P_{t|t}$ is given by

$$\begin{aligned}\bar{P}_{t|t}^{-1} &= P_{t-1|t-1}^{-1} + A_t^T B_t^{-2} A_t \\ P_{t|t}^{-1} &= C_t^T D_t^{-2} C_t + B_t^{-2} - B_t^{-2} \bar{P}_{t|t} A_t^T B_t^{-2} \\ P_{t|t-1} &= A_t P_{t-1|t-1} A_t^T + B_t^2\end{aligned}\tag{3.3}$$

where $B_t^2 = B_t B_t^T$, and $D_t^2 = D_t D_t^T$. The channel parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ are estimated using the EM algorithm which is introduced next.

3.1.2 Channel Parameter Estimation: The EM Algorithm

The filter-based EM algorithm uses a bank of Kalman filters to yield a maximum likelihood (ML) parameter estimate of the Gaussian state space model [79]. The EM algorithm is an iterative numerical algorithm for computing the ML estimate. Each iteration consists of two steps: the expectation and the maximization step [79, 80, 82]. The filtered expectation step only uses filters for the first and second order statistics. The

memory costs are modest and the filters are decoupled and hence easy to be implemented in parallel on a multi-processor system [79]. The algorithm yields parameter estimates with nondecreasing values of the likelihood function, and converges under mild assumptions [82].

Let $\theta_t = \{A_t, B_t, C_t, D_t\}$ denote the system parameters in (3.1), P_0 denotes a fixed probability measure; and $\{P_{\theta_t}; \theta_t \in \Theta\}$ denotes a family of probability measures induced by the system parameters θ_t . If the original model is a white noise sequence, then $\{P_{\theta_t}; \theta_t \in \Theta\}$ is absolutely continuous with respect to P_0 [80]. Moreover, it can be shown that under P_0 we have

$$P_0 : \begin{cases} x_{t+1} = w_t \\ y_t = v_t \end{cases} \quad (3.4)$$

The EM algorithm computes the ML estimate of the system parameters θ_t , given the data Y_t . Specifically, each iteration of the EM algorithm consists of two steps: The expectation step and the maximization step.

The expectation step evaluates the conditional expectation of the log-likelihood function given the complete data, which is described by

$$\Lambda(\theta_t, \hat{\theta}_t) = E_{\hat{\theta}_t} \left\{ \log \frac{dP_{\theta_t}}{dP_{\hat{\theta}_t}} | Y_t \right\} \quad (3.5)$$

where $\hat{\theta}_t$ denotes the estimated system parameters at time step t . The maximization step finds

$$\hat{\theta}_{t+1} \in \arg \max_{\theta_t \in \Theta} \Lambda(\theta_t, \hat{\theta}_t) \quad (3.6)$$

The expectation and maximization steps are repeated until the sequence of model parameters converge to the real parameters. The EM algorithm is described by the following equations [79, 80]

$$\begin{aligned}
\hat{A}_t &= E \left(\sum_{k=1}^t x_k x_{k-1}^T \mid Y_t \right) \times \left[E \left(\sum_{k=1}^t x_k x_k^T \mid Y_t \right) \right]^{-1} \\
\hat{B}_t^2 &= \frac{1}{t} E \left(\sum_{k=1}^t \left((x_k - A_k x_{k-1}) (x_k - A_k x_{k-1})^T \right) \mid Y_t \right) \\
&= \frac{1}{t} E \left(\sum_{k=1}^t \left((x_k x_k^T) - A_k (x_k x_{k-1}^T)^T - (x_k x_{k-1}^T) A_k^T + A_k (x_{k-1} x_{k-1}^T) A_k^T \right) \mid Y_t \right) \\
\hat{C}_t &= E \left(\sum_{k=1}^t y_k x_k^T \mid Y_t \right) \times \left[E \left(\sum_{k=1}^t x_k x_k^T \mid Y_t \right) \right]^{-1} \\
\hat{D}_t^2 &= \frac{1}{t} E \left(\sum_{k=1}^t \left((y_k - C_k x_k) (y_k - C_k x_k)^T \right) \mid Y_t \right) \\
&= \frac{1}{t} E \left(\sum_{k=1}^t \left((y_k y_k^T) - (y_k x_k^T) C_k^T - C_k (y_k x_k^T)^T + C_k (x_k x_k^T) C_k^T \right) \mid Y_t \right)
\end{aligned} \tag{3.7}$$

where $E(\cdot)$ denotes the expectation operator. The system (3.7) gives the EM parameter estimates at each iteration for the model (3.1). Furthermore, since $\Lambda(\theta_t, \hat{\theta}_t)$ is continuous in both θ_t and $\hat{\theta}_t$ the EM algorithm converges to a stationary point in the likelihood surface [79, 80, 82].

The system parameters $\{\hat{A}_t, \hat{B}_t^2, \hat{C}_t, \hat{D}_t^2\}$ can be computed from the conditional expectations as [79]

$$\begin{aligned}
L_t^{(1)} &= E \left\{ \sum_{k=1}^t x_k^T Q x_k \mid Y_t \right\}, \quad L_t^{(2)} = E \left\{ \sum_{k=1}^t x_{k-1}^T Q x_{k-1} \mid Y_t \right\}, \\
L_t^{(3)} &= E \left\{ \sum_{k=1}^t [x_k^T R x_{k-1} + x_{k-1}^T R^T x_k] \mid Y_t \right\}, \quad L_t^{(4)} = E \left\{ \sum_{k=1}^t [x_k^T S y_k + y_k^T S^T x_k] \mid Y_t \right\}
\end{aligned} \tag{3.8}$$

where Q, R and S are given by

$$Q = \left\{ \frac{e_i e_j^T + e_j e_i^T}{2} \right\}, \quad R = \left\{ \frac{e_i e_j^T}{2} \right\}, \quad S = \left\{ \frac{e_i e_l^T}{2} \right\}; \quad i, j = 1, 2, \dots, n; \quad l = 1, 2, \dots, d \tag{3.9}$$

in which e_i is the unit vector in the Euclidean space; that is $e_i = 1$ in the i th position, and

0 elsewhere. For instance, consider the case $n = d = 2$, then $E \left(\sum_{k=1}^t x_k x_{k-1}^T \mid Y_t \right)$ is

$$E\left(\sum_{k=1}^t x_k x_{k-1}^T \mid Y_t\right) = \begin{bmatrix} L_t^{(3)}(R_{11}) & L_t^{(3)}(R_{21}) \\ L_t^{(3)}(R_{12}) & L_t^{(3)}(R_{22}) \end{bmatrix} \quad (3.10)$$

where $R_{ij} = \{e_i e_j^T / 2; i, j = 1, 2\}$. The other terms in (3.7) can be computed similarly.

The conditional expectations $\{L_t^{(1)}, L_t^{(2)}, L_t^{(3)}, L_t^{(4)}\}$ are estimated from measurements Y_t as follows [79]:

1) Filter estimate of $L_t^{(1)}$:

$$\begin{aligned} L_t^{(1)} &= E\left\{\sum_{k=1}^t x_k^T Q x_k \mid Y_t\right\} = -\frac{1}{2} \text{Tr}\left(N_t^{(1)} P_{t|t}\right) - \frac{1}{2} \sum_{k=1}^t \text{Tr}\left(N_{k-1}^{(1)} \bar{P}_{k|k}\right) \\ &\quad - \frac{1}{2} \sum_{k=1}^t \left(-2x_{k|k}^T P_{k|k}^{-1} r_k^{(1)} + 2x_{k|k-1}^T P_{k|k-1}^{-1} r_{k|k-1}^{(1)} - x_{k|k}^T N_k^{(1)} x_{k|k} + x_{k|k-1}^T B_k^{-2} A_k \bar{P}_{k|k} N_{k-1}^{(1)} \bar{P}_{k|k} A_k^T B_k^{-2} x_{k|k-1}\right) \end{aligned} \quad (3.11)$$

where $\text{Tr}(\cdot)$ denotes the matrix trace. In (3.11), $r_k^{(1)}$ and $N_k^{(1)}$ satisfy the following recursions

$$\begin{cases} r_k^{(1)} = (A_k - P_{k|k} C_k^T D_k^{-2} C_k A_k) r_{k-1}^{(1)} + 2P_{k|k} Q x_{k|k-1} - P_{k|k} N_k^{(1)} P_{k|k} C_k^T D_k^{-2} (y_k - C_k x_{k|k-1}) \\ r_{k|k-1}^{(1)} = A_k r_k^{(1)} \\ r_0^{(1)} = 0_{m \times 1} \\ N_k^{(1)} = B_k^{-2} A_k \bar{P}_{k|k} N_{k-1}^{(1)} \bar{P}_{k|k} A_k^T B_k^{-2} - 2Q \\ N_0^{(1)} = 0_{m \times m} \end{cases} \quad (3.12)$$

2) Filter estimate of $L_t^{(2)}$:

$$L_t^{(2)} = E\left\{\sum_{k=1}^t x_{k-1}^T Q x_{k-1} \mid Y_t\right\} = E_\theta\{x_0^T Q x_0 \mid Y_t\} + E_\theta\left\{\sum_{k=1}^t x_k^T Q x_k \mid Y_t\right\} - E_\theta\{x_t^T Q x_t \mid Y_t\} \quad (3.13)$$

Therefore, $L_t^{(2)}$ can be obtained from $L_t^{(1)}$.

3) Filter estimate of $L_t^{(3)}$:

$$L_t^{(3)} = E \left\{ \sum_{k=1}^t \left(x_k^T R x_{k-1} + x_{k-1}^T R^T x_k \right) | Y_t \right\} = -\frac{1}{2} \text{Tr} \left(N_t^{(3)} P_{t|t} \right) - \frac{1}{2} \sum_{k=1}^t \text{Tr} \left(N_{k-1}^{(3)} \bar{P}_{k|k} \right) - \frac{1}{2} \sum_{k=1}^t \left(-2x_{k|k}^T P_{k|k}^{-1} r_k^{(3)} + 2x_{k|k-1}^T P_{k|k-1}^{-1} r_{k|k-1}^{(3)} - x_{k|k}^T N_k^{(3)} x_{k|k} + x_{k|k-1}^T B_k^{-2} A_k \bar{P}_{k|k} N_{k-1}^{(3)} \bar{P}_{k|k} A_k^T B_k^{-2} x_{k|k-1} \right) \quad (3.14)$$

In this case, $r_k^{(3)}$ and $N_k^{(3)}$ satisfy the following recursions

$$\begin{cases} r_k^{(3)} = \left(A_k - P_{k|k} C_k^T D_k^{-2} C_k A_k \right) r_{k-1}^{(3)} - P_{k|k} N_k^{(3)} P_{k|k} C_k^T D_k^{-2} \left(y_k - C_k x_{k|k-1} \right) \\ \quad + \left(2P_{k|k} R + 2P_{k|k} B_k^{-2} A_k \bar{P}_{k|k} R^T A_k \right) x_{k-1|k-1} \\ r_{k|k-1}^{(3)} = A_k r_k^{(3)} \\ r_0^{(3)} = 0_{m \times 1} \\ N_k^{(3)} = B_k^{-2} A_k \bar{P}_{k|k} N_{k-1}^{(3)} \bar{P}_{k|k} A_k^T B_k^{-2} - 2R \bar{P}_{k|k} A_k^T B_k^{-2} - 2B_k^{-2} A_k \bar{P}_{k|k} R^T \\ N_0^{(3)} = 0_{m \times m} \end{cases} \quad (3.15)$$

4) Filter estimate of $L_t^{(4)}$:

$$L_t^{(4)} = E \left\{ \sum_{k=1}^t \left(x_k^T S y_k + y_k^T S^T x_k \right) | Y_t \right\} = \sum_{k=1}^t \left(x_{k|k}^T P_{k|k}^{-1} r_k^{(4)} - x_{k|k-1}^T P_{k|k-1}^{-1} r_{k|k-1}^{(4)} \right) \quad (3.16)$$

where $r_k^{(4)}$ satisfy the following recursions

$$\begin{cases} r_k^{(4)} = \left(A_k - P_{k|k} C_k^T D_k^{-2} C_k A_k \right) r_{k-1}^{(4)} + 2P_{k|k} S y_k \\ r_{k|k-1}^{(4)} = A_k r_k^{(4)} \\ r_0^{(4)} = 0_{m \times 1} \end{cases} \quad (3.17)$$

Using the filters for $L_t^{(i)}$ ($i=1,2,3,4$) and the Kalman filter described earlier, the system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ can be estimated through the EM algorithm described in (3.7). Numerical and experimental results that show the viability of the

above algorithm in estimating the channel parameters as well as the channel states from measurements are discussed in the following sections.

3.2 LTF Channel Estimation Using the EM Together with Kalman Filtering

The general spatio-temporal lognormal model in (2.7) can be realized by stochastic state space representation of the form

$$\begin{aligned}\dot{X}(t, \tau) &= A(t, \tau)X(t, \tau) + B(t, \tau)w(t) \\ y(t) &= s(t)e^{kX(t, \tau)} + v(t)\end{aligned}\tag{3.18}$$

where $A(t, \tau) = -\beta(t, \tau)$, $B(t, \tau) = [\delta(t, \tau) \quad \beta(t, \tau)\gamma(t, \tau)]$, $w(t) = [dW(t) \quad 1]^T$, $s(t)$ is the information signal, $v(t)$ is the channel disturbance or noise at the receiver, $X(t, \tau)$ is the TV power loss (PL) in dB, and $S(t) = e^{kX(t, \tau)}$ is the TV signal attenuation coefficient, where $k = -\ln(10)/20$.

However, for simplicity we consider the discrete-time version of (3.18) given by

$$\begin{aligned}x_{t+1} &= A_t x_t + B_t w_t \\ y_t &= s_t e^{kx_t} + D_t v_t\end{aligned}\tag{3.19}$$

where $x_t \in \mathfrak{R}^n$ is a state vector, $y_t \in \mathfrak{R}^d$ is a measurement vector, $w_t \in \mathfrak{R}^m$ is a state noise, and $v_t \in \mathfrak{R}^d$ is a measurement noise. Note that the state space model is nonlinear since the output equation in (3.19) is nonlinear. We consider the general form of state space form since the estimation algorithm is derived for the general case. However, in our system model (3.18), we have $n = d = 1$ and $m = 2$. The noise processes w_t and v_t are assumed to be independent zero mean and unit variance Gaussian processes. Further, the noises are independent of the initial state x_0 , which is assumed to be Gaussian distributed.

The unknown system parameters $\theta_t = \{A_t, B_t, D_t\}$ as well as the system states x_t are estimated through a finite set of received signal measurement data, $Y_N = \{y_1, y_2, \dots, y_N\}$. The methodology proposed is recursive and based on the EM algorithm combined with the extended Kalman filter (EKF) to estimate the channel state variables. The latter is used due to the nonlinear output equation.

The EKF approach is based on linearizing the nonlinear system model (3.19) around the previous estimate. It estimates the channel states x_t for given system parameter $\theta_t = \{A_t, B_t, D_t\}$ and measurements Y_t . The EKF is similar to the Kalman filter described in (3.2) and (3.3) except we add the linearizing part to (3.2) and is described by [81]

$$\begin{aligned}\hat{x}_{t|t} &= A_t \hat{x}_{t-1|t-1} + P_{t|t} C_t^T D_t^{-2} (y_t - C_t A_t \hat{x}_{t-1|t-1}) \\ \hat{x}_{t|t-1} &= A_t \hat{x}_{t-1|t-1} \\ C_t &= s_t \frac{d(e^{kx_{t|t}})}{dx_{t|t}} \bigg|_{x_{t|t} = \hat{x}_{t-1|t-1}} = s_t k e^{kx_{t|t}} \bigg|_{x_{t|t} = \hat{x}_{t-1|t-1}}\end{aligned}\tag{3.20}$$

and (3.3) remains the same. The channel parameters $\theta_t = \{A_t, B_t, D_t\}$ are estimated based on the EM algorithm, which is described in Section 3.1.2.

Now, we consider the estimation of a LTF wireless channel from received signal measurements. In particular, the estimation includes the channel parameters, channel PL, and received signal. The measurement data are generated by the following system parameters

$$\gamma(t, \tau) = \gamma_m(\tau) \left(1 + 0.15 e^{-2t/T} \sin\left(\frac{10\pi t}{T}\right) \right), \quad \delta(t, \tau) = 5, \quad \beta(t, \tau) = 0.2,\tag{3.21}$$

where $\gamma_m(\tau)$ is the average PL at a specific location τ and is chosen to be 25, T is the observation interval and is chosen to be 0.3 millisecond, and the variances of the state and measurement noises are 10^{-2} and 10^{-6} , respectively.

Figure 3.1 shows the actual and estimated received signal using the EM algorithm together with the extended Kalman filter for 500 sampled data. From Figure 3.1, it can be noticed that the received signal have been estimated with very good accuracy. Figure 3.2 shows the received signal estimates root mean square error (RMSE) for 100 runs. It can be noticed that it takes just few iterations (less than 15) for the filter to converge, and the steady state performance of the proposed LTF channel estimation algorithm using the EM together with Kalman filtering is excellent.

3.3 STF Channel Estimation Using the EM Together with Kalman Filtering

In this section, we consider the stochastic STF state space models in (2.32) and (2.36), and use a set of measurement data provided by the Canadian communication research center (CRC) to perform the EM algorithm together with the Kalman filter in order to estimate the STF channel model parameters as well as the inphase and quadrature components respectively, which are then compared to the ones obtained from the measurement data.

However, for simplicity we consider the discrete-time version of (2.32) and (2.36) given by

$$\begin{aligned} x_{t+1} &= A_t x_t + B_t w_t \\ y_t &= C_t x_t + D_t v_t \end{aligned} \tag{3.22}$$

where $x_t \in \mathfrak{R}^n$ is a state vector, $y_t \in \mathfrak{R}^d$ is a measurement vector, $w_t \in \mathfrak{R}^m$ is a state noise, and $v_t \in \mathfrak{R}^d$ is a measurement noise. We consider the general form of state space form since the estimation algorithm is derived for the general case. However, in our system model (2.32), we have $n = m = 2$, $d = 1$ and y_t represents the inphase or quadrature components corrupted by noise. While in (2.36), we have $n = m = 4$, $d = 1$ and y_t represents the band pass received signal. The noise processes w_t and v_t are assumed to be independent zero mean and unit variance Gaussian processes. Further, the noises are independent of the initial state x_0 , which is assumed to be Gaussian distributed.

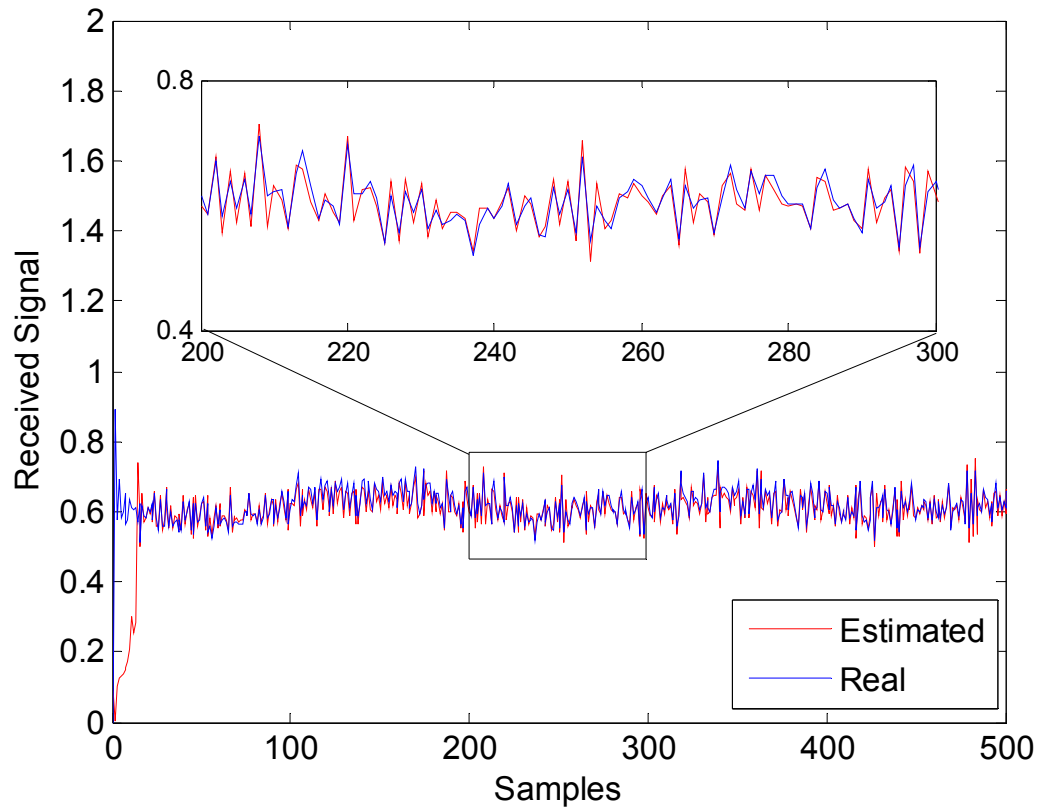


Figure 3.1: Real and estimated received signal for the LTF channel model.

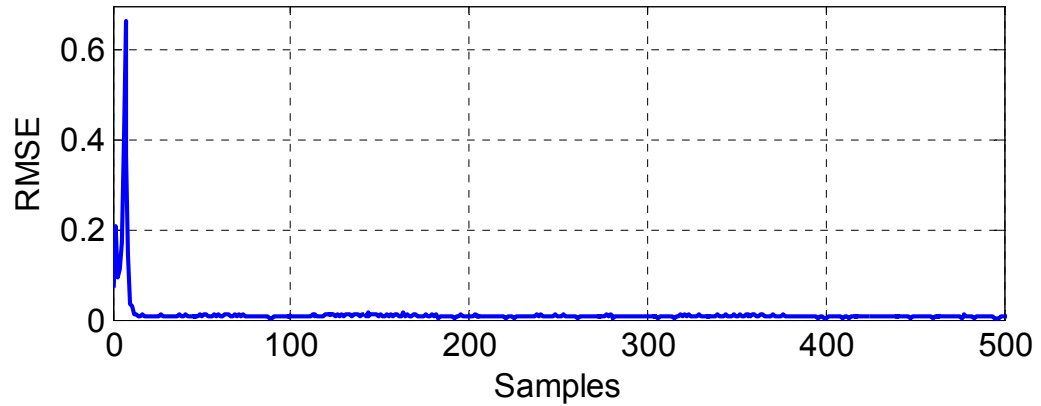


Figure 3.2: Received signal estimates RMSE for 100 runs using the EM algorithm together with the extended Kalman filter.

The unknown system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ as well as the system states x_t are estimated through a finite set of received signal measurement data, $Y_N = \{y_1, y_2, \dots, y_N\}$. For the system model in (2.32), we use measurement data for the inphase component or the quadrature component obtained separately. While for the system model in (3.36), the measurement data correspond to a linear combination of the inphase component and the quadrature component. The measurement data provided by the CRC contain 98 data files. The number of samples of the inphase and quadrature components in each data file is 766. The methodology proposed is recursive and based on the EM algorithm combined with the Kalman filter to estimate the channel state variables. A 4th order channel model as described in (2.36) is considered. Therefore, the system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ can be represented as

$$A_t = \begin{bmatrix} 0 & 1 & 0 & 0 \\ a_1 & a_2 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & a_3 & a_4 \end{bmatrix}, B_t = \begin{bmatrix} b_1 & \delta_{12} & \delta_{13} & \delta_{14} \\ b_2 & \delta_{22} & \delta_{23} & \delta_{24} \\ \delta_{31} & \delta_{32} & b_3 & \delta_{34} \\ \delta_{41} & \delta_{42} & b_4 & \delta_{44} \end{bmatrix}, \quad (3.23)$$

$$C_t = [\cos(\omega_c t) \quad 0 \quad -\sin(\omega_c t) \quad 0], D_t = [d_1 \quad d_2]$$

Note that B_t in (3.23) is different from (2.36) and (2.37), since in (2.37) $B(t)$ is block diagonal. In (3.23) we made B_t nonsingular by including some small numbers for the other entries. As previously mentioned, the estimation of a flat fading wireless channel from received signal measurement data is considered. In particular, the estimation includes the channel parameters, inphase and quadrature components, and the received signal, which are then compared to the ones obtained from measurement data. Using the measurement data, the sample paths of inphase and quadrature components are plotted together, and then compared to the ones obtained by viewing the measurements as corrupted by white noise sequences. Figure 3.3 shows the measured and estimated inphase and quadrature components as well as the received signal using the EM algorithm together with Kalman filter for 400 sampled data taken from the measurements

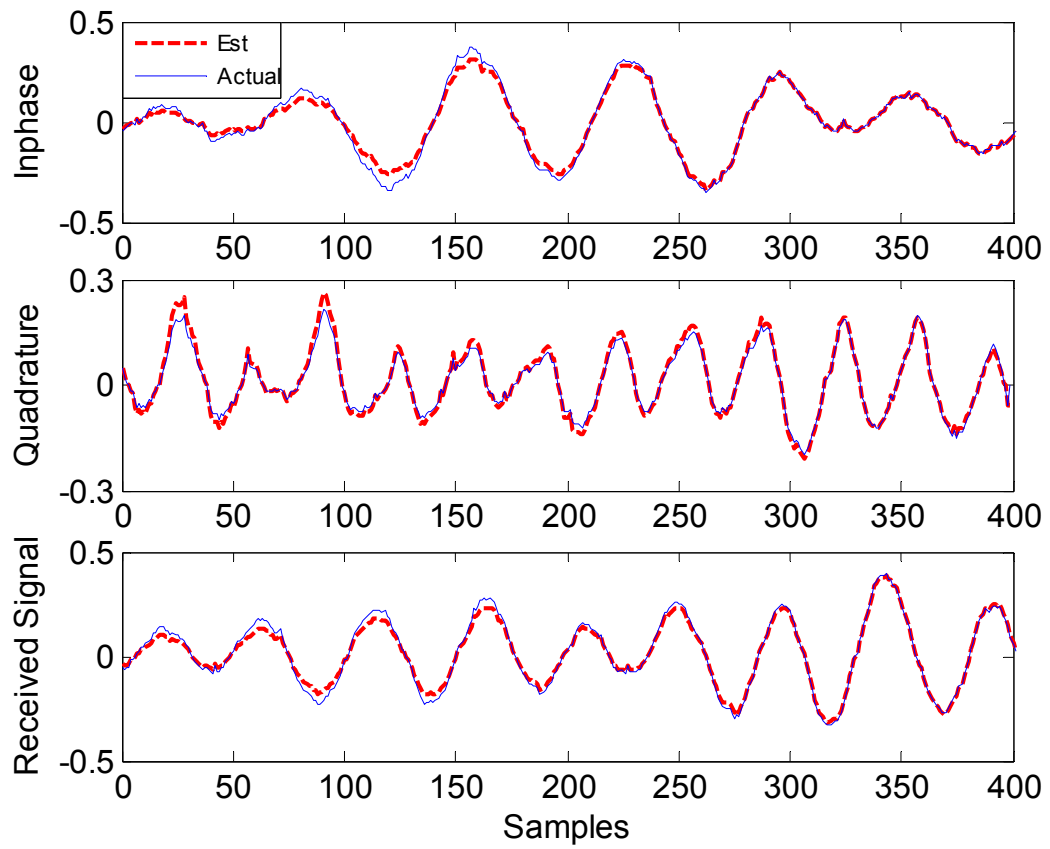


Figure 3.3: The measured and estimated inphase and quadrature components, and received signal for 4th order channel model using the EM algorithm together with Kalman filter.

of one channel chosen at random. From Figure 3.3, it can be noticed that the inphase and quadrature components of the wireless fading channel as well as the received signal have been estimated with very high accuracy. It can also be noticed that the estimation error decreases as the number of samples increases; this is because the algorithm is recursive and the channel parameters converge to the actual values as more samples are being estimated. The system parameters are estimated as

$$\begin{aligned}\hat{A} &= \begin{bmatrix} 0 & 1 & 0 & 0 \\ -0.0756 & -0.0474 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -0.6638 & 0.0717 \end{bmatrix}, \\ \hat{B}^2 &= \begin{bmatrix} 0.0484 & -0.0029 & -0.0453 & 4.0686*10^{-4} \\ -0.0029 & 0.0462 & 0.0013 & -0.0438 \\ -0.0453 & 0.0013 & 0.0573 & 0.0047 \\ 4.0686*10^{-4} & -0.0438 & 0.0047 & 0.0564 \end{bmatrix}, \\ \hat{C} &= [\cos(\omega_c t) \quad 0 \quad -\sin(\omega_c t) \quad 0], \quad \hat{D}^2 = [0.0119].\end{aligned}\tag{3.24}$$

Numerical results indicate that the measured data can be generated through a simple 4th order discrete-time stochastic differential equation.

3.4 Ad Hoc Channel Estimation Using the EM Together with Kalman Filtering

In this section, we consider the mobile-to-mobile state space model in (2.47) and (2.36), and carry out an experiment to measure the received signal power of moving sensors in a wireless sensor platform. Then the EM algorithm together with Kalman filtering is used to estimate the mobile-to-mobile channel parameters as well as the inphase and quadrature components from the measured received signal. Again, we consider (3.22) as the discrete-time version of (2.47) and (2.36). The unknown system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ as well as the system states x_t are estimated through a finite set of received signal measurement data, $Y_N = \{y_1, y_2, \dots, y_N\}$. These measurements are

collected in the extreme measurement communication center (EMC²) laboratory at Oak Ridge National Laboratory (ORNL) using two moving wireless sensor nodes.

The wireless sensors used in our experiment are Crossbow's TelosB sensor nodes. A single TelosB sensor node is shown in Figure 3.4. It has the following specifications [103]: IEEE 802.15.4 compliant, data rate is 250 kbps, carrier frequency is 2.4 GHz, and has USB interface. These sensors are implemented with a Chipcon CC2420 RF transceiver chip which provides a built-in received signal strength indicator (RSSI). This indicator is averaged over 8 symbol periods (128 micro second). The RSSI has a dynamic range of 100 dB and is accurate to +/- 6 dB.

Our experimental setup consists of two moving transceivers (sensors 1 and 2) and one passive receiver (sensor 3) connected to a workstation as shown in Figure 3.5. At each time step, sensors 1 and 2 broadcast a packet containing a source address and the RSSI of the most recently received packet from the other sensor. Sensor 3 never transmits; rather, it forwards packets from sensors 1 and 2 to a workstation for analysis. The mobile-to-mobile channel between sensor 1 and 2 is time varying since both sensors move with different (variable) velocities and directions. Indoor and outdoor environments are considered as well. In our experiment, the indoor environment is the laboratory room shown in Figure 3.6, while the outdoor environment is shown in Figure 3.7.

In the estimation and identification process, a 4th order mobile-to-mobile channel model as described in (2.47) and (2.48) is considered. Thus, the system parameters $\theta_t = \{A_t, B_t, C_t, D_t\}$ can be represented as in (3.23).

The estimation includes the channel parameters, inphase and quadrature components, and the received signal, which are then compared to the ones obtained from measurement data. It is assumed that the received signal measurement data are corrupted by white noise sequences. Figures 3.8(a) and 3.8(b) show respectively indoor and outdoor measured and estimated received signals using the EM algorithm together with Kalman filter for 500 sampled data taken from measurements between sensor 1 and 2. At a certain time instant, indoor system parameters are estimated as

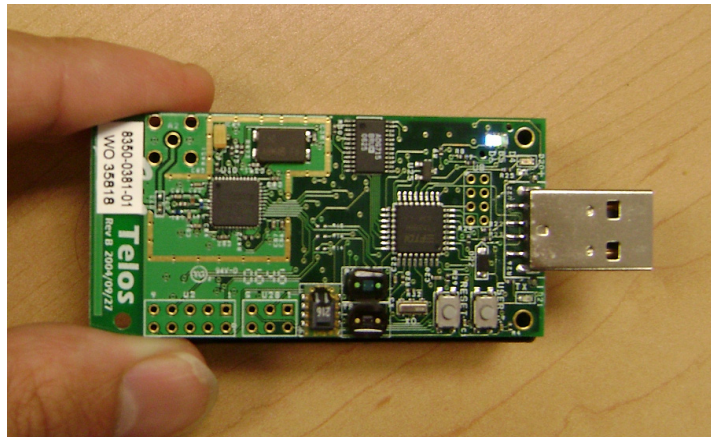


Figure 3.4: Crossbow TelosB sensor node.

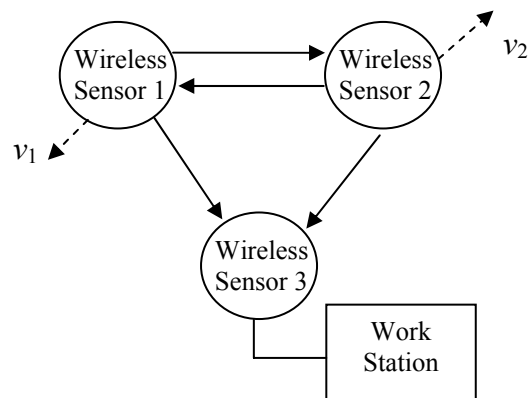


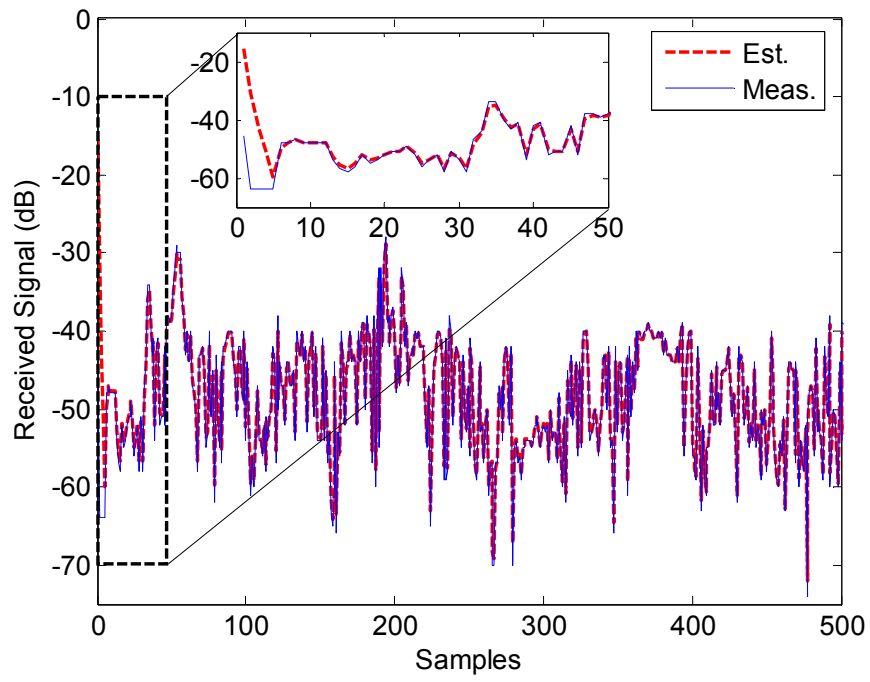
Figure 3.5: Experimental setup: Two moving transceivers (sensors 1 and 2) and one fixed receiver (sensor 3).



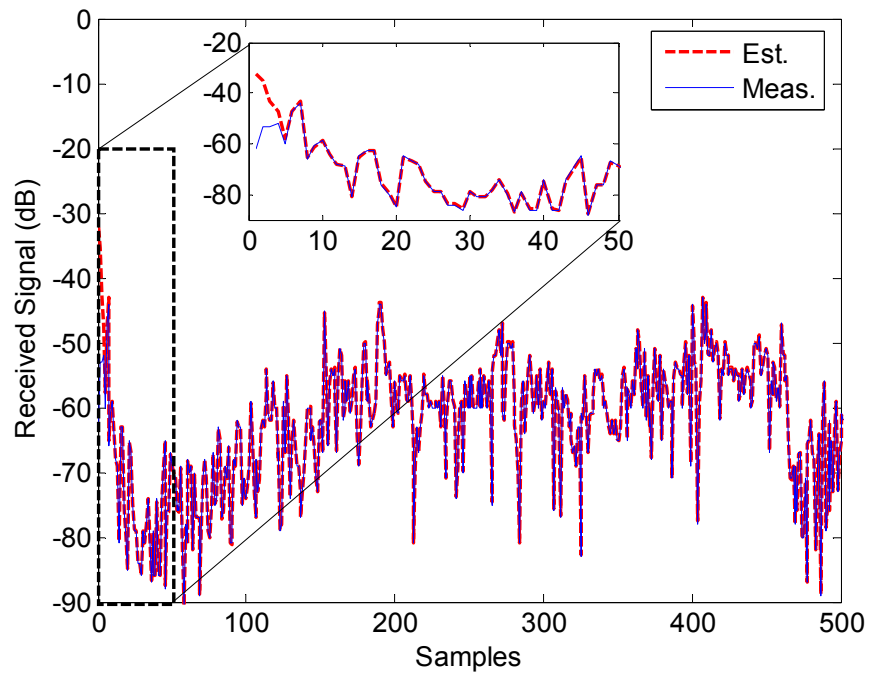
Figure 3.6: Indoor environment considered in our experiment.



Figure 3.7: Outdoor environment considered in our experiment.



(a)



(b)

Figure 3.8: Measured and estimated received signal from sensor 2 by using a 4th order ad hoc channel model for (a) indoor and (b) outdoor environments.

$$\begin{aligned}
\hat{A} &= \begin{bmatrix} 0 & 1 & 0 & 0 \\ -0.3066 & 0.0016 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -0.5940 & 0.0059 \end{bmatrix}, \\
\hat{B}^2 &= \begin{bmatrix} 0.8531 & -0.0369 & -0.0284 & 2.8531*10^{-4} \\ -0.3962 & 0.0649 & 0.0032 & -0.0193 \\ -0.0742 & 0.0074 & 0.0753 & 0.0021 \\ 3.1804*10^{-4} & -0.0532 & 0.0064 & 0.0853 \end{bmatrix}, \\
\hat{C} &= [\cos(\omega_c t) \quad 0 \quad -\sin(\omega_c t) \quad 0], \quad \hat{D}^2 = [2.0262].
\end{aligned} \tag{3.25}$$

while outdoor system parameters are estimated as

$$\begin{aligned}
\hat{A} &= \begin{bmatrix} 0 & 1 & 0 & 0 \\ -0.7151 & 0.0037 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -0.1500 & 0.0515 \end{bmatrix}, \\
\hat{B}^2 &= \begin{bmatrix} 0.5824 & -0.0735 & -0.0735 & 1.5395*10^{-4} \\ -0.7452 & 0.0846 & 0.0083 & -0.0375 \\ -0.0864 & 0.0365 & 0.0454 & 0.0264 \\ 1.8643*10^{-4} & -0.0643 & 0.0820 & 0.0753 \end{bmatrix}, \\
\hat{C} &= [\cos(\omega_c t) \quad 0 \quad -\sin(\omega_c t) \quad 0], \quad \hat{D}^2 = [1.1725].
\end{aligned} \tag{3.26}$$

From Figures 3.8(a) and 3.8(b), it can be noticed that the received signals from indoor and outdoor environments have been estimated with very high accuracy. It takes a few iterations (about 5 iterations) for the estimation algorithm to converge. The root mean square errors (RMSE) for indoor and outdoor environments are shown in Figure 3.9. It can be seen that indoor RMSE is higher than the one for outdoor because of reflections from walls and objects in indoor environment. Experimental results indicate that the measured data can be generated through a simple 4th order discrete-time stochastic differential equation with excellent accuracy, and therefore demonstrating the validity of the method.

In the next chapter, we introduce one important application, namely, stochastic PC based on the developed channel models and estimation algorithms.

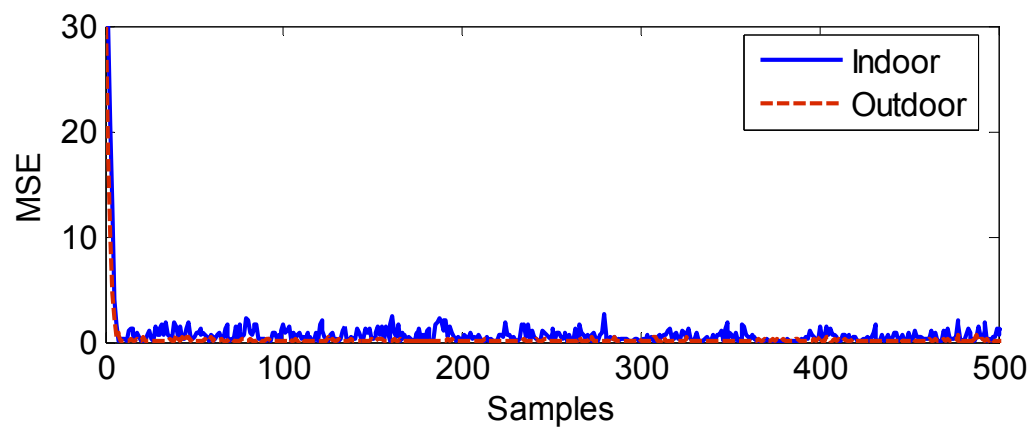


Figure 3.9: Received signal estimates RMSE for indoor and outdoor environments using the EM algorithm together with the Kalman filter.

Chapter 4

Stochastic Power Control Algorithms for Time Varying Wireless Networks

The aim of the PCAs described here is to minimize the total transmitted power of all users while maintaining acceptable QoS for each user. The measure of QoS can be defined by the SIR for each link to be larger than a target SIR. In this chapter, different PCAs are introduced based on the TV channel models derived in Chapter 2. A deterministic PCA (DPCA) is introduced first, and then a stochastic PCA (SPCA) is presented. Both centralized and distributed PCAs are considered. Parts of the results presented here have been published in [46-48, 68, 104, 106, 107].

4.1 Representation of TV Wireless Networks

Consider a cellular network with M mobiles (users) and N base stations. The LTF spatio-temporal model described in (2.7) for a cellular network can be described as

$$\begin{aligned} dX_{ij}(t, \tau) &= \beta_{ij}(t, \tau)(\gamma_{ij}(t, \tau) - X_{ij}(t, \tau))dt + \delta_{ij}(t, \tau)dW_{ij}(t), \\ X_{ij}(t_0, \tau) &= \mathcal{N}\left(\overline{PL}(d)_{ij}[dB]; (\sigma_{t_0}^2)_{ij}\right), \quad 1 \leq i, j \leq M \end{aligned} \tag{4.1}$$

where subscript ij corresponds to the channel parameters between mobile j and the base station assigned to mobile i . The signal attenuation coefficients $S_{ij}(t, \tau)$ are generated using the relation $S_{ij}(t, \tau) = e^{kX_{ij}(t, \tau)}$, where $k = -\ln(10)/20$. Moreover, correlation between channels in a multi-user/multi-antenna case can be induced by letting the

different Brownian motions W_{ij} 's to be correlated, i.e., $E[\mathbf{W}(t)\mathbf{W}^T(t)] = \mathbf{Q}(\tau) \cdot t$, where $\mathbf{W}(t) \triangleq (W_{ij}(t))$, and $\mathbf{Q}(\tau)$ is some (not necessarily diagonal) matrix that is a function of τ and dies out as τ becomes large. The TV received signal of the i th mobile at its assigned base station at time t is given by

$$y_i(t) = \sum_{j=1}^M \sqrt{p_j(t)} s_j(t) S_{ij}(t) + n_i(t) \quad (4.2)$$

where $p_j(t)$ is the transmitted power of mobile j at time t , which acts as a scaling on the information signal $s_j(t)$, and $n_i(t)$ is the channel disturbance or noise at the base station of mobile i .

Similarly, following the same procedure as the LTF network, the TV STF state space representation in (2.36) for M mobiles and N base stations cellular network is written as

$$\begin{aligned} dX_{ij}(t) &= A_{ij}(t) X_{ij}(t) dt + B_{ij}(t) dW_{ij}(t) \\ y_i(t) &= \sum_{k=1}^M \sqrt{p_k(t)} s_k(t) C(t) X_{ik}(t) + n_i(t) \end{aligned} \quad (4.3)$$

where $X_{ik}(t) \triangleq [X_{I_{ik}}(t) \ X_{Q_{ik}}(t)]^T$, the processes $X_{I_{ik}}(t)$ and $X_{Q_{ik}}(t)$ are the channel states for the inphase and quadrature components, respectively, between mobile j and the base station assigned to mobile i , $C(t) \triangleq [\cos \omega_c t \ 0 \ -\sin \omega_c t \ 0]$, and $1 \leq i, j \leq M$. The TV LTF and STF channel models in (4.1) and (4.3) are used to generate the link gains of wireless networks for the PCAs proposed next.

4.2 Centralized Deterministic PCA in TV Wireless Networks

In this section, we consider the uplink channel of a cellular network and we assume that users are already assigned to their base stations. The *centralized* PC problem for *time invariant* channels for the cellular network can be stated as follows [57]

$$\min_{(p_1 \geq 0, \dots, p_M \geq 0)} \sum_{i=1}^M p_i \quad \text{subject to} \quad \frac{p_i g_{ii}}{\sum_{j \neq i}^M p_j g_{ij} + \eta_i} \geq \varepsilon_i, \quad 1 \leq i \leq M \quad (4.4)$$

where p_i is the power of mobile i , $g_{ij} > 0$ is the time invariant channel gain between mobile j and the base station assigned to mobile i , $\varepsilon_i > 0$ is the target SIR of mobile i , and $\eta_i > 0$ is the noise power level at the base station of mobile i .

Expression (4.4) for TV LTF and STF wireless networks defined in (4.1) and (4.3) respectively, described using path-wise QoS of each user over a time interval $[0, T]$ becomes [46]

$$\begin{aligned} \min_{(p_1 \geq 0, \dots, p_M \geq 0)} & \left\{ \sum_{i=1}^M \int_0^T p_i(t) dt \right\}, \quad \text{subject to} \\ & \frac{\int_0^T p_i(t) s_i^2(t) S_{ii}^2(t) dt}{\sum_{k \neq i}^M \int_0^T p_k(t) s_k^2(t) S_{ik}^2(t) dt + \int_0^T n_i^2(t) dt} \geq \varepsilon_i, \quad \text{for LTF} \\ & \frac{\int_0^T p_i(t) s_i^2(t) [C(t) X_{ii}(t)]^2 dt}{\sum_{k \neq i}^M \int_0^T p_k(t) s_k^2(t) [C(t) X_{ik}(t)]^2 dt + \int_0^T n_i^2(t) dt} \geq \varepsilon_i, \quad \text{for STF} \end{aligned} \quad (4.5)$$

and $i=1, \dots, M$. A solution to (4.5) is presented by first introducing the communication meaning of predictable power control strategies (PPCS). In wireless cellular networks, it is practical to observe and estimate channels at base stations and then send the information back to the mobiles to adjust their power signals $\{p_i(t)\}_{i=1}^M$. Since channels experience delays, and power control is not feasible continuously in time but only at discrete-time instants, the concept of predictable strategies is introduced [57].

Consider a set of discrete-time strategies $\{p_i(t_k)\}_{i=1}^M$, $0 = t_0 < t_1 < \dots < t_k < t_{k+1} < \dots \leq T$. At time t_{k-1} , the base stations observe or estimate the channel information

$\{S_{ij}(t_{k-1}), s_i(t_{k-1})\}_{i,j=1}^M$ for LTF or $\{I_{ij}(t_{k-1}), Q_{ij}(t_{k-1}), s_i(t_{k-1})\}_{i,j=1}^M$ for STF. Using the concept of predictable strategy, the base stations determine the control strategy $\{p_i(t_k)\}_{i=1}^M$ for the next time instant t_k . The latter is communicated back to the mobiles, which hold these values during the time interval $[t_{k-1}, t_k)$. At time t_k , a new set of channel information $\{S_{ij}(t_k), s_i(t_k)\}_{i,j=1}^M$ or $\{I_{ij}(t_k), Q_{ij}(t_k), s_i(t_k)\}_{i,j=1}^M$ is observed at the base stations and the time t_{k+1} control strategies $\{p_i(t_{k+1})\}_{i=1}^M$ are computed and communicated back to the mobiles which hold them constant during the time interval $[t_k, t_{k+1})$. This procedure is described in Figure 4.1. Such decision strategies are called predictable.

Using the concept of PPCS over any time interval $[t_k, t_{k+1}]$, equation (4.5) is equivalent to

$$\begin{aligned} \min_{\mathbf{p}(t_{k+1}) > 0} \sum_{i=1}^M p_i(t_{k+1}) \quad \text{subject to} \\ \mathbf{p}(t_{k+1}) \geq \mathbf{\Gamma} \mathbf{G}_I^{-1}(t_k, t_{k+1}) \times (\mathbf{G}(t_k, t_{k+1}) \mathbf{p}(t_{k+1}) + \boldsymbol{\eta}(t_{k+1})) \end{aligned} \quad (4.6)$$

where

$$\begin{aligned} g_{ij}(t_k, t_{k+1}) &:= \int_{t_k}^{t_{k+1}} s_j^2(t) S_{ij}^2(t) dt, \quad 1 \leq i, j \leq M \quad \text{for LTF,} \\ &:= \int_{t_k}^{t_{k+1}} s_j^2(t) [C(t) X_{ij}(t)]^2 dt, \quad 1 \leq i, j \leq M \quad \text{for STF,} \\ \mathbf{p}(t_{k+1}) &:= (p_1(t_{k+1}), \dots, p_M(t_{k+1}))^T, \quad \eta_i(t_k, t_{k+1}) := \int_{t_k}^{t_{k+1}} n_i^2(t) dt, \\ \mathbf{G}_I(t_k, t_{k+1}) &:= \text{diag}(g_{11}(t_k, t_{k+1}), \dots, g_{MM}(t_k, t_{k+1})), \\ \mathbf{G}(t_k, t_{k+1}) &:= \begin{cases} 0, & \text{if } i = j \\ g_{ij}(t_k, t_{k+1}), & \text{if } i \neq j \end{cases}, \quad 1 \leq i, j \leq M, \\ \boldsymbol{\eta}(t_k, t_{k+1}) &:= (\eta_1(t_k, t_{k+1}), \dots, \eta_M(t_k, t_{k+1}))^T, \quad \mathbf{\Gamma} := \text{diag}(\varepsilon_1, \dots, \varepsilon_M), \end{aligned} \quad (4.7)$$

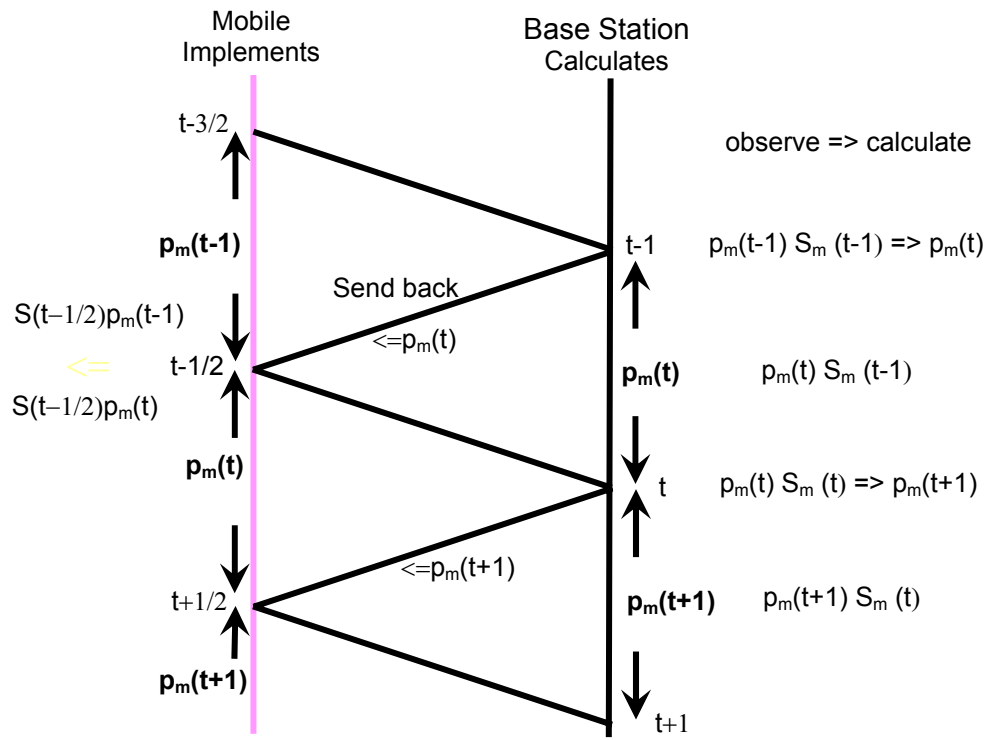


Figure 4.1: Power update and information flow for uplink power control using predictable power control strategies (PPCS).

and $\text{diag}(\cdot)$ denotes a diagonal matrix with its argument as diagonal entries, and “ T ” stands for matrix or vector transpose. The optimization in (4.7) is a linear programming problem in $M \times 1$ vector of unknowns $\mathbf{p}(t_{k+1})$. Here $[t_k, t_{k+1}]$ is a time interval such that the channel model does not change significantly, i.e., $[t_k, t_{k+1}]$ should be smaller than the coherence time of the channel.

4.3 Distributed Deterministic PCA in TV Wireless Networks

In this section, we consider an iterative distributed version of the centralized PCA in (4.6). This is convenient for on-line implementation since it helps autonomous execution at the node or link level, requiring minimal usage of network communication resources for control signaling. The iterative distributed PCA proposed in [2] and [14] can be used to find a distributed version to the centralized PCA in (4.6). The constraint in (4.6) can be written as

$$(\mathbf{I} - \mathbf{\Gamma} \mathbf{G}_I^{-1}(t_k, t_{k+1}) \mathbf{G}(t_k, t_{k+1})) \mathbf{p}(t_{k+1}) \geq \mathbf{\Gamma} \mathbf{G}_I^{-1}(t_k, t_{k+1}) \boldsymbol{\eta}(t_{k+1}) \quad (4.8)$$

Defining $\mathbf{F}(t_k, t_{k+1}) \triangleq \mathbf{\Gamma} \mathbf{G}_I^{-1}(t_k, t_{k+1}) \mathbf{G}(t_k, t_{k+1})$ and $\mathbf{u}(t_k, t_{k+1}) \triangleq \mathbf{\Gamma} \mathbf{G}_I^{-1}(t_k, t_{k+1}) \boldsymbol{\eta}(t_{k+1})$, (4.8) can be written as

$$(\mathbf{I} - \mathbf{F}(t_k, t_{k+1})) \mathbf{p}(t_{k+1}) \geq \mathbf{u}(t_k, t_{k+1}) \quad (4.9)$$

If the channel gains are time invariant, i.e., $\mathbf{F}(t_k, t_{k+1}) = \mathbf{F}$ and $\mathbf{u}(t_k, t_{k+1}) = \mathbf{u}$, then the power control problem is feasible if $\rho_F < 1$, where ρ_F is the Perron-Frobenius eigenvalue of $\mathbf{F}$ [2]. It is shown in [2] and [14] that the following iterative PCA converges to the minimal power vector when $\rho_F < 1$

$$\mathbf{p}(t_{k+1}) = \mathbf{F} \mathbf{p}(t_k) + \mathbf{u} \quad (4.10)$$

However, our channel gains are TV, thus a TV version of the deterministic PCA (DPCA)

in (4.10) can be defined as

$$\mathbf{p}(t_{k+1}) = \mathbf{F}(t_k, t_{k+1})\mathbf{p}(t_k) + \mathbf{u}(t_k, t_{k+1}) \quad (4.11)$$

Clearly, in general the power vector $\mathbf{p}(t_k)$ will not converge to some deterministic constant as in (4.10). Rather, in a TV (random) propagation environment, it is required that the power vector $\mathbf{p}(t_k)$ converges in distribution to a well defined random variable. Since $\mathbf{F}(t_k, t_{k+1})$ is a random matrix-valued process, the key convergence condition is that the Lyapunov exponent $\lambda_F < 0$ [58], where λ_F is defined as

$$\lambda_F = \lim_{k \rightarrow \infty} \frac{1}{k} \log \|\mathbf{F}(t_0, t_1)\mathbf{F}(t_1, t_2) \dots \mathbf{F}(t_k, t_{k+1})\| \quad (4.12)$$

The distributed version of (4.11) can be written as

$$p_i(t_{k+1}) = \frac{\varepsilon_i(t_k)}{R_i(t_k)} p_i(t_k), \quad i = 1, \dots, M \quad (4.13)$$

where $R_i(t_k)$ is the instantaneous SIR defined by

$$R_i(t_k) = \frac{p_i(t_k)g_{ii}(t_k, t_{k+1})}{\sum_{j \neq i}^M p_j(t_k)g_{ij}(t_k, t_{k+1}) + \eta_i(t_k, t_{k+1})}, \quad (4.14)$$

It is shown in [33] that the performance of the DPCA in (4.13) in terms of power consumption is not optimal when the channel environment is TV. Actually, the performance can be severely degraded when PCAs that are designed for deterministic channels are applied to TV channels [33]. Therefore, stochastic PCAs (SPCAs) must be used in order to ensure stable optimal power consumption. The latter is discussed in the next section.

4.4 Stochastic PCA in TV Wireless Networks

The matrix $\mathbf{F}(t_k, t_{k+1})$ in (4.9) has non-negative elements and if the SIR targets are feasible, then it has been shown in [33, 112] that the power vector which satisfies the equality of (4.9) minimizes the sum of the transmitted power, i.e., the power vector $\mathbf{p}(t_{k+1})$ that satisfies

$$(\mathbf{I} - \mathbf{F}(t_k, t_{k+1}))\mathbf{p}(t_{k+1}) - \mathbf{u}(t_k, t_{k+1}) = 0 \quad (4.15)$$

is the minimum power vector.

We first briefly introduce one basic result on stochastic approximation that will be used to solve for the optimal power vector in (4.15). Consider an unknown measurable function, $\mathbf{h}(\mathbf{x})$. A zero point of $\mathbf{h}$, $\bar{\mathbf{x}}$, is defined by $\mathbf{h}(\bar{\mathbf{x}}) = 0$, and can be calculated by various rapidly convergent methods such as Newton's method.

Assume now that the observation function is provided by $\mathbf{h}(\cdot)$ but subject to an additive measurement noise. The k th measurement is given by

$$\mathbf{y}(k) = \mathbf{h}(\mathbf{x}(k)) + \xi(k) \quad (4.16)$$

where $\mathbf{y}(k)$ is the observation at the k th time, and $\xi(k)$ is the zero mean measurement error at the k th time and may be dependent on $\mathbf{x}(k)$. In 1951, Robbins and Monro [67] suggested a method for solution of this and a more general problem, which they called the method of stochastic approximation. The purpose of using stochastic approximation is to find a zero point $\bar{\mathbf{x}}$ based on the noisy observation $\mathbf{y}(k)$. Given an arbitrary initial point $\mathbf{x}(0)$ and an arbitrary sequence of positive numbers $a(k)$ such that

$$\sum_{k=0}^{\infty} a(k) = \infty, \quad \sum_{k=0}^{\infty} a(k)^2 < \infty \quad (4.17)$$

Then, it is shown in [67] that the following approximation sequence,

$$\mathbf{x}(k+1) = \mathbf{x}(k) - a(k)\mathbf{y}(k) \quad (4.18)$$

converges to the zero point $\bar{\mathbf{x}}$ of $\mathbf{h}(\cdot)$ with probability one.

Since the link gains are random, it can be assumed that the random part in the left hand side of (4.15) can be represented as an additive zero mean random noise $\xi(k)$, therefore, applying the stochastic approximation algorithm in (4.18) to (4.15) we get

$$\mathbf{p}(t_{k+1}) = \mathbf{p}(t_k) - a(t_k) \left[(\mathbf{I} - \mathbf{F}(t_k, t_{k+1})) \mathbf{p}(t_k) - \mathbf{u}(t_k, t_{k+1}) \right] \quad (4.19)$$

which can be written as

$$\mathbf{p}(t_{k+1}) = (\mathbf{I} - a(t_k)) \mathbf{p}(t_k) + a(t_k) \left[\mathbf{F}(t_k, t_{k+1}) \mathbf{p}(t_k) + \mathbf{u}(t_k, t_{k+1}) \right] \quad (4.20)$$

Using (4.14), the distributed version of (4.20) is

$$p_i(t_{k+1}) = (1 - a(t_k)) p_i(t_k) + a(t_k) \frac{\varepsilon_i(t_k)}{R_i(t_k)} p_i(t_k) \quad (4.21)$$

If the PC problem is feasible, the distributed SPCA in (4.21) converges to the optimal power vector when the step-size sequence satisfies certain conditions. Two different types of convergence results are shown in [59] under different choices of the step-size

sequence. If the step-size sequence satisfies $\sum_{k=0}^{\infty} a(t_k) = \infty$ and $\sum_{k=0}^{\infty} a(t_k)^2 < \infty$, then the

SPCA in (4.21) converges to the optimal power vector with probability one. However, due to the requirement for the SPCA to track TV environments, the iteration step-size sequence is not allowed to decrease to zero. So we consider the case where the condition

$\sum_{k=0}^{\infty} a(t_k)^2 < \infty$ is violated. This includes the situation when the step-size sequence

decreases slowly to zero, and the situation when the step-size is fixed at a small constant.

In the first case when $a(t_k) \rightarrow 0$ slowly, the SPCA in (4.21) converges to the optimal

power vector in probability. While in the second case the power vector clusters around the optimal power [59]. In fact, the error between the power vector and the optimal value does not vanish for non-vanishing step-size sequence; this is the price paid in order to make the algorithm in (4.21) able to track TV environments.

This algorithm is fully distributed in the sense that each user iteratively updates its power level by estimating the received SIR of its own channel. It does not require any knowledge of the link gains and state information of other users. It is worth mentioning that the proposed distributed SPCA in (4.21) is different from the algorithm proposed in [33] where two parameters, namely, the received SIRs $R_i(t_k)$ and the channel gains $g_{ii}(t_k, t_{k+1})$, are required to be known, while only $R_i(t_k)$ are required in (4.21).

The selection of an appropriate $[t_k, t_{k+1}]$ will have a significant impact on the system performance. For small $[t_k, t_{k+1}]$, the power control updates will be more frequent and thus convergence will be faster. However, frequent transmission of the feedback on the downlink channel will effectively decrease the capacity of the system since more system resources will have to be used for power control. The performance of the proposed PCA is determined numerically in the next section.

4.5 Numerical Results

In this section, we consider two numerical examples to determine the performance of the proposed PCAs. Example 4.1 and Example 4.2 consider the TV LTF and STF wireless networks, respectively.

Example 4.1: The LTF cellular network has the following setup: Number of transmitters (mobiles) is $M = 24$, the information signal $s_i(t) = 1$ for $i=1, \dots, M$, initial distances of all mobiles with respect to their own base stations d_{ii} are generated as uniformly independent identically distributed (iid) random variables (RVs) in $[10 - 100]$ meters, cross initial distances of all mobiles with respect to other base stations $d_{ij}, i \neq j$, are generated as uniformly iid RVs in $[250 - 550]$ meters, the angle θ_{ij} between the direction

of motion of mobile j and the distance vector passes through base station i and mobile j are generated as uniformly iid RVs in $[0 - 180]$ degrees, the average velocities of mobiles are generated as uniformly iid RVs in $[40 - 100]$ km/hr, all mobiles move at sinusoidal variable velocities around their average velocities such that the peak velocity is two times the average speed, power path-loss exponent is 3.5, initial reference distance from each of the transmitters is 10 meters, power path-loss at the initial reference distance is 67 dB, $\delta_{ij}(t, \tau) = 1400$ and $\beta_{ij}(t, \tau) = 225000$ for the SDEs, η_i 's are iid Gaussian RVs with zero mean and variance 10^{-12} W.

The performance measure is outage probability (OP). It is defined as the probability that a randomly chosen link fails due to excessive interference [12]. Therefore, smaller OP implies larger capacity of the wireless network. A link with a received SIR R_i , less than or equal to a target SIR ε_i , is considered a communication failure. The OP $O(\varepsilon_i)$ is expressed as $O(\varepsilon_i) = \text{Prob}\{R_i \leq \varepsilon_i\}$. The OP is computed using Monte-Carlo simulations. The targets SIR, ε_i , for all users are the same, and varied from 5 dB to 35 dB with step 5 dB. For each value of ε_i the OP is computed every 15 millisecond, i.e., $[t_k, t_{k+1}] = 15$ millisecond. The simulation is performed for 5 seconds, i.e., $[0, T] = 5$ seconds.

In this example, the centralized DPCA based on PPCS in (4.6) is performed on two different TV LTF wireless networks; the stochastic TV channel models in (4.1) and the static models encountered in the literature [12]. The OP for the centralized DPCA using PPCS based on both stochastic and static TV LTF channel models are shown in Figure 4.2(a) and 4.2(b), respectively. Figure 4.2 shows how the OP changes with respect to the target SIR, ε_i , and time. As the target SIR increases the OP increases. This is obvious since we expect more users to fail as ε_i increases. The OP also changes as a function of time, since mobiles move in different directions and velocities.

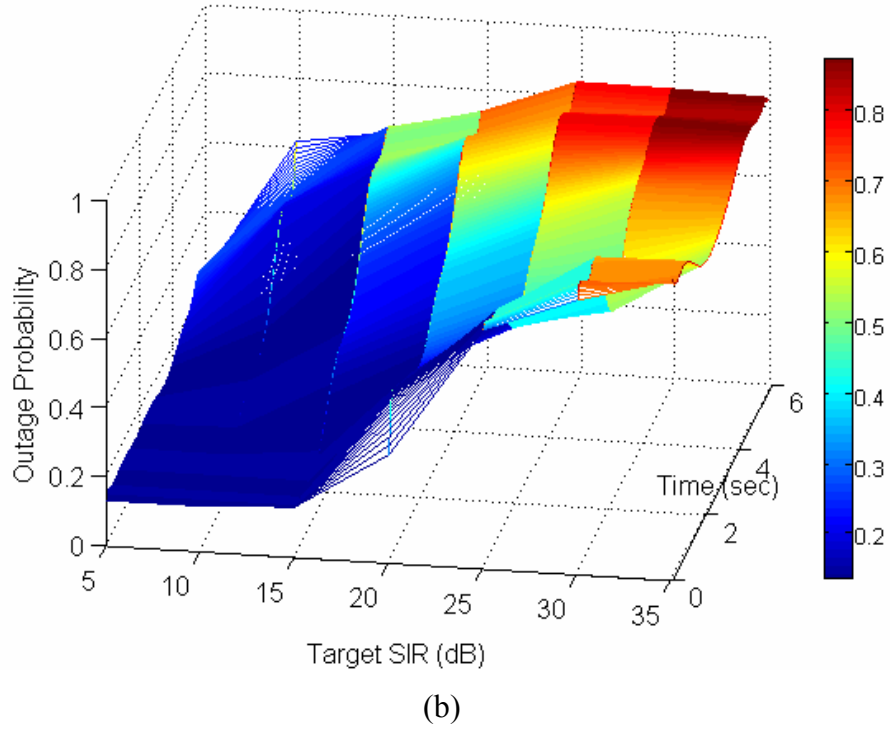
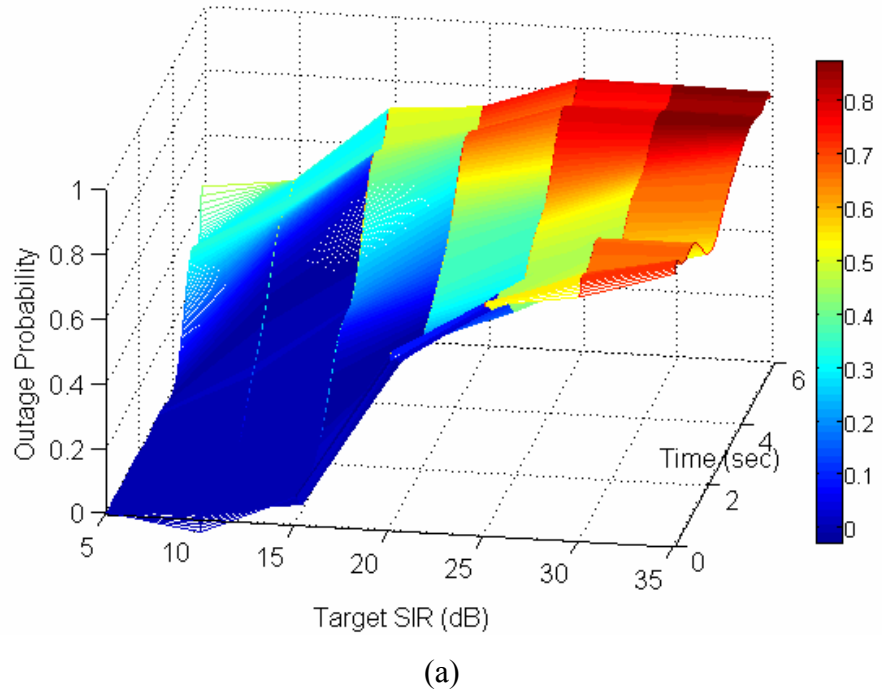


Figure 4.2: OP for the centralized DPCA using PPCS under the TV LTF models in Example 4.1 for (a) stochastic models, (b) static models.

The *average* OP versus ε_i over the whole simulation time (5 seconds) is shown in Figure 4.3, which shows that the performance of PPCS using the stochastic models is on average much better than that of static models. This is because the static models do not capture the time variations of the channels. For example, at 10 dB target SIR, the OP is reduced from 0.26 for static models to 0.18 for TV stochastic ones; this represents an improvement of over 30%. The PPCS algorithm for stochastic models outperforms the static ones by an order of magnitude. It can be seen that as ε_i increases the performance gap between the PPCS using stochastic and static models decreases. This is because the effect of ε_i (required QoS) is dominant.

Figure 4.4 shows the average OP over the whole simulation time (5 seconds) for higher noise variance ($\delta(t, \tau) = 2800$). In this case the stochastic PL $X(t, \tau)$ have higher variations or fluctuations around the average PL $\gamma(t, \tau)$, since this parameter controls the instantaneous variance of the stochastic PL. The PPCS based on static models when the actual channels have high variance gives higher OP than when the actual channels have low variance as observed in Figure 4.3 and 4.4. This is due to the fact that channels with high variance deviate significantly from the average (static) channels. For example, at 10 dB target SIR, the OP in the static case is about 0.32 while in the stochastic case, it is about 0.2, an improvement of over 37%. Therefore, the optimal transmitted power for the static models is no longer optimal when it is used for more realistic stochastic models. Hence, stochastic models provide a far more realistic and efficient optimal control.

Now, the performance of the distributed DPCA in (4.13) is compared with that of the distributed SPCA in (4.21) under stochastic TV LTF channels. With the same parameters as Example 4.1, in addition to the target SIRs $\varepsilon_i = 5$ for all users and $a_k = 0.1$, the total transmitted powers of all mobiles using the distributed DPCA in (4.13) and the SPCA in (4.21) under stochastic TV LTF channels are shown in Figure 4.5. Note that the power axis is *logarithmic*. Clearly, the distributed SPCA using stochastic approximations provides better power stability and consumption than that of the distributed DPCA described in [2, 14].

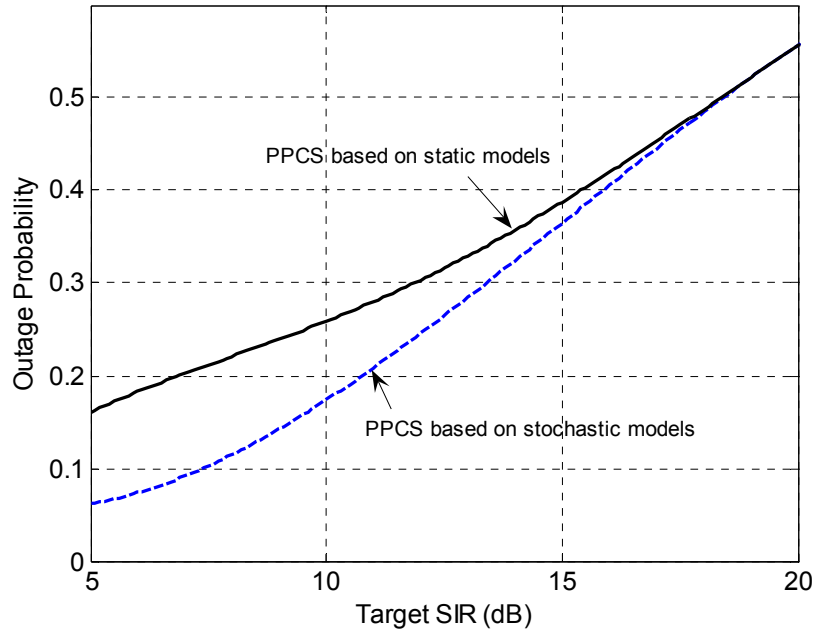


Figure 4.3: Average OP for TV LTF channel models with $\delta(t) = 1400$. Performance comparison.

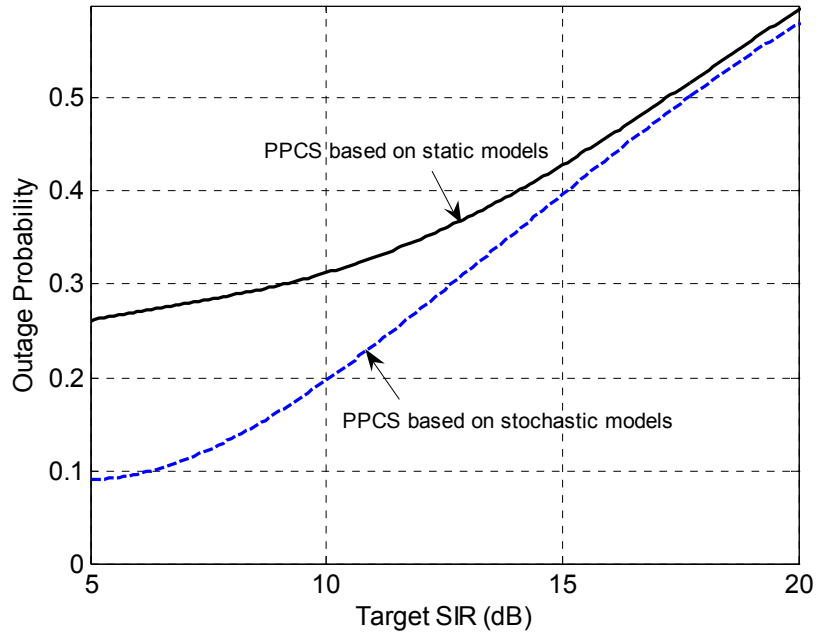


Figure 4.4: Average OP for TV LTF channel models with $\delta(t) = 2800$. Performance comparison.

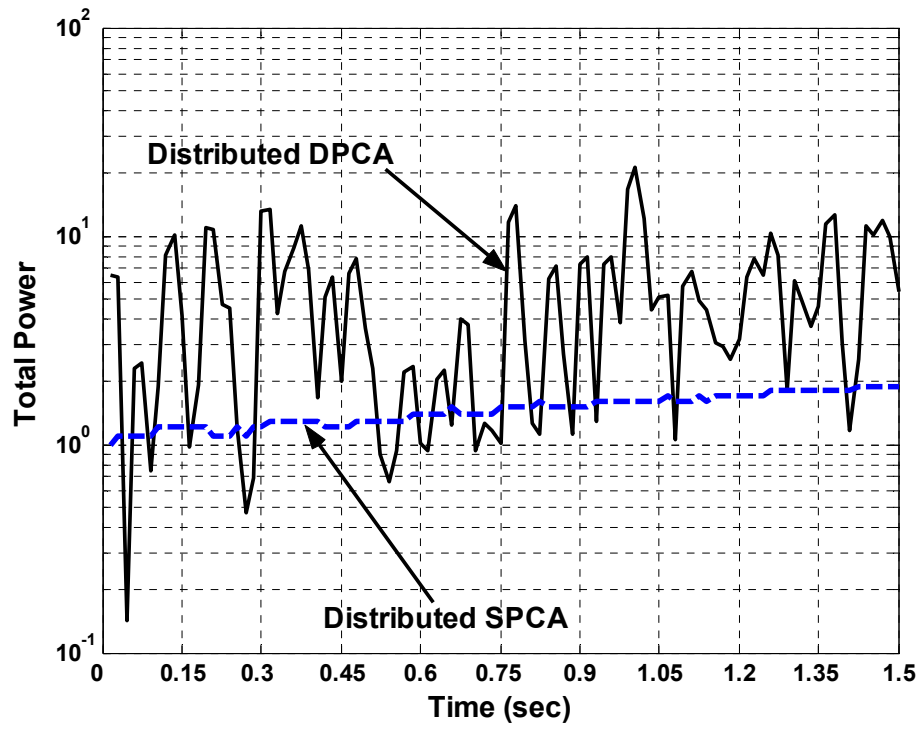
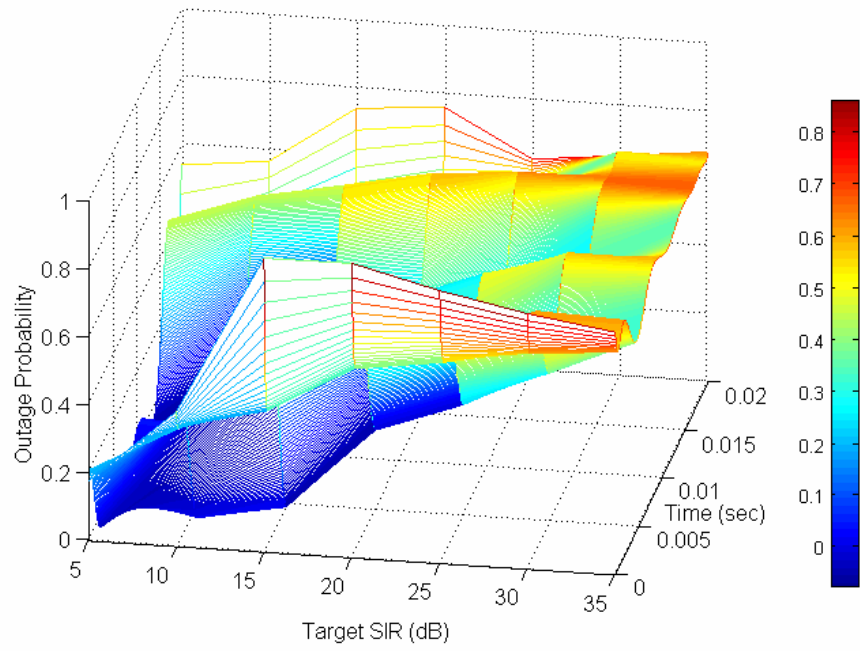


Figure 4.5: Sum of transmitted power of all mobiles for the distributed DPCA and the distributed SPCA under TV LTF channels.

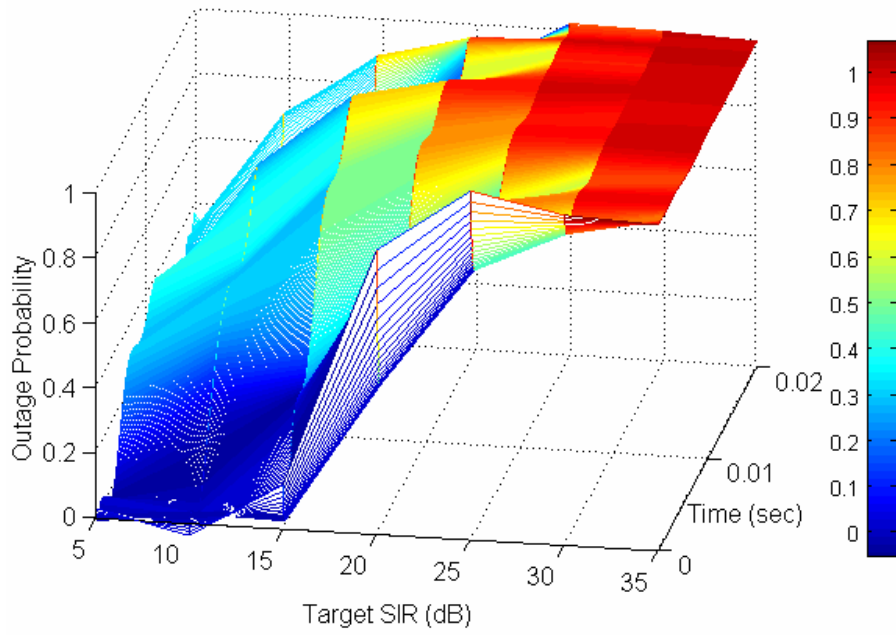
Example 4.2: In this example, the OP of the PPCS algorithm for both Rayleigh and Ricean fading channel models is computed numerically and compared with that of no power control (NPC). The STF cellular network has the following features: Number of mobiles M , target SIRs ε_i , step-size sequence $a(t_k)$, $[t_k, t_{k+1}]$, $[0, T]$, average velocities of mobiles, and η_i 's are the same as in Example 4.1, carrier frequency = 910 MHz, E_{0ii} 's are uniformly iid RVs in the range [400-600], E_{0ij} 's ($i \neq j$) are uniformly iid RVs in [25-150], angles of arrival β_{mij} 's for each link are generated as uniformly iid RVs in [0 – 16] degrees.

The OP as a function of target SIR, ε_i , and time for both PC based PPCS and NPC under a Rayleigh wireless network are shown in Figure 4.6(a) and 4.6(b), respectively. Similar remarks as in the LTF network in Example 4.1 still apply here. The average OP versus ε_i over the whole simulation time for Rayleigh and Ricean wireless networks is shown in Figure 4.7. The performance of PPCS is compared with the one for fixed transmitter power (i.e. NPC). Results show that the PPCS algorithm outperforms the reference algorithm. For example, at 15 dB target SIR, the outage probability of Rayleigh flat channel is reduced from 0.6 for NPC case to 0.3 for PPCS case, this represents an improvement of 50%. Moreover, the performance of flat Ricean fading is better than the one for flat Rayleigh fading channels. This is because the existence of LOS component in Ricean channels.

Figure 4.8 shows the total transmitted power of all mobiles using the distributed DPCA in (4.13) and the SPCA in (4.21) under stochastic TV STF wireless network described in Example 4.2. The same conclusion as LTF case, the distributed SPCA using stochastic approximations provides better power stability and consumption than that of the DPCA.



(a)



(b)

Figure 4.6: OP under the dynamical STF channel models in Example 4.2. (a) Using PPCS algorithm. (b) Using NPC.

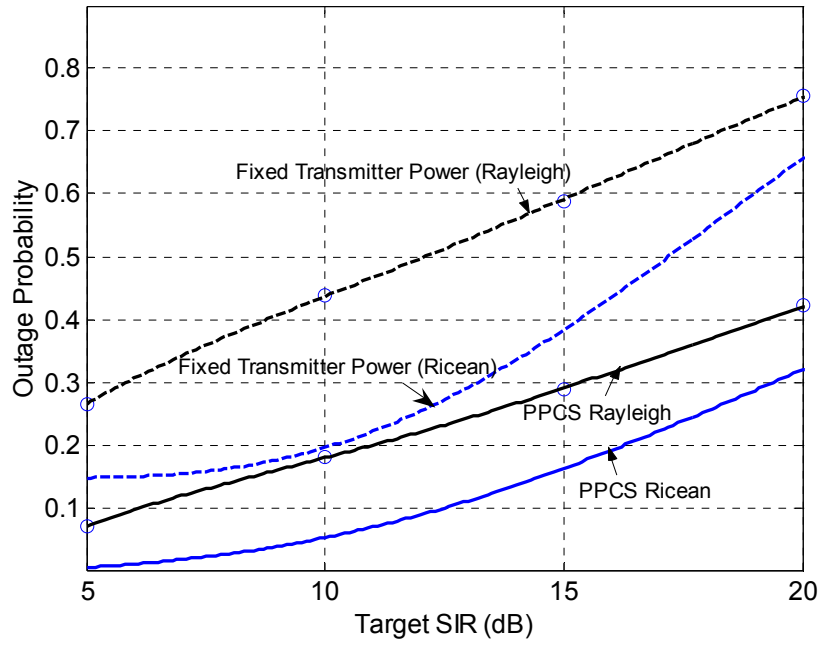


Figure 4.7: Average OP under dynamical flat Rayleigh and Ricean STF channels. Performance comparison.

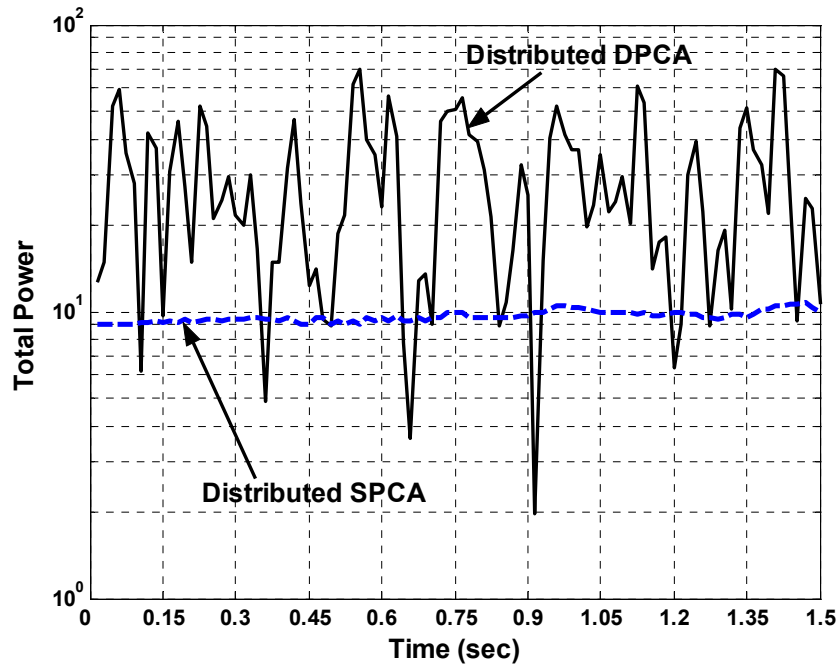


Figure 4.8: Sum of transmitted power of all mobiles for the distributed DPCA and SPCA under TV STF channels.

Chapter 5

Mobile Station Location and Velocity Estimation in Cellular Networks

In this chapter, several mobile station (MS) location and velocity estimation algorithms in cellular network based on received signal measurements are proposed. The received signal level method is first used in combination with Maximum Likelihood (ML) estimation and triangulation to obtain an estimate of the location of the mobile. Due to non-line-of-sight (NLOS) conditions and multipath propagation environments, this estimate lacks acceptable accuracy for demanding services as numerical results reveal. The 3D wave scattering multipath channel model of Aulin is employed together with recursive nonlinear Bayesian estimation algorithms to obtain improved location estimates with high accuracy. Several Bayesian estimation algorithms are considered such as the extended Kalman filter (EKF), the particle filter (PF), and the unscented particle filter (UPF). These algorithms cope with nonlinearities in order to estimate the mobile location and velocity. Since the EKF is very sensitive to the initial state, we propose to use the ML estimate as an initial state to the EKF. In contrast to the EKF tracking approach, the PF and the UPF approaches do not rely on linearized motion models, measurement relations, and Gaussian assumptions. Numerical results are presented to evaluate the performance of the proposed algorithms when measurement data do not correspond to the ones generated by the model. This shows the robustness of the algorithm based on modeling inaccuracies. Parts of the results presented here have been published in [69, 70, 108, 111].

5.1 System Mathematical Models

5.1.1 The Lognormal Propagation Channel Model

Here we consider a 2D geometry with the MS located at (x_0, y_0) and the base stations (BSs) located at $((x_{BS_1}, y_{BS_1}), (x_{BS_2}, y_{BS_2}), \dots, (x_{BS_B}, y_{BS_B}))$. The general lognormal propagation channel model is described by [19]

$$PL_b^s(d_b) = PL(d_{0_b}) + 10\varepsilon_b \log\left(\frac{d_b}{d_{0_b}}\right) + X_b^s \quad (5.1)$$

where $d_b \geq d_{0_b}$, $s \in \{1, 2, \dots, S\}$, $b \in \{1, 2, \dots, B\}$, $PL_b^s(d_b)$ is the path loss from the b th BS at distance d_b for the s th sample, d_{0_b} is the reference distance, ε_b is the path loss exponent and $X_b^s \sim \mathcal{N}(0; \sigma_b^2)$ is a Gaussian random variable (RV) represents the shadowing variance due to gross variations in the terrain profile and changes in the local topography. In cellular networks, the MS preserves and frequently updates, in idle and active mode, the received power of the strongest non-serving BSs (e.g., in GSM the 6 strongest [71]) in addition to the one of the serving cell. Exploiting these measurements from surrounding BSs lead to estimate the location of the MS. The maximum likelihood estimation (MLE) approach described in Section 5.2 that employs this channel model is used to estimate the MS location.

5.1.2 Aulin's Scattering Model

The basic 3D wireless scattering channel model described in [44], which assumes that the electric field, denoted by $E(t)$, at any receiving point (x_0, y_0, z_0) is the resultant of P plane waves as described in Figure 2.4, in which the receiver moves in the X-Y plane having velocity v_m in a direction making an angle γ with the X-axis, is given by

$$E(t) = \sum_{n=1}^P E_n(t) = \sum_{n=1}^P r_n \cos(\omega_c t + \omega_n t + \theta_n) + e(t) \quad (5.2)$$

where

$$\omega_n = \frac{2\pi v_m}{\lambda} (\cos(\gamma - \alpha_n) \cos \beta_n) \quad (5.3)$$

$$\theta_n = \frac{-2\pi}{\lambda} (x_0 \cos \alpha_n \cos \beta_n + y_0 \sin \alpha_n \cos \beta_n + z_0 \sin \beta_n) + \phi_n \quad (5.4)$$

and α_n, β_n are spatial angles of arrival, ω_n is the Doppler shift, θ_n is the phase shift, r_n is the amplitude, ϕ_n is the phase of the n th component, λ is the wavelength, $e(t)$ is a white Gaussian noise, and P is the total number of waves. It can be seen from (5.3) and (5.4) that the Doppler and phase shifts depend on the velocity and location of the receiver, respectively.

Clearly, (5.2) assumes transmission of a narrowband signal. This assumption is valid only when the signal bandwidth is smaller than the coherence bandwidth of the channel. Nevertheless, the above model is not restrictive since it can be modified to represent a wideband transmission by including multiple time-delayed echoes. In this case, the delay spread has to be estimated. A sounding device is usually dedicated to estimating the time delay of each discrete path such as Rake receiver [60].

It can be seen that the noisy instantaneous received field in (5.2)-(5.4) depends parametrically on the location and velocity of the receiver. Consequently, this expression is used to estimate the MS location and velocity by using the EKF, the PF, and/or the UPF. Next, we formulate the location estimation as a filtering problem in state-space form [61]. The general form, once discretized, is given by

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{w}_{k-1}) \\ \mathbf{z}_k &= \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k) \end{aligned} \quad (5.5)$$

where $\mathbf{f}(\cdot, \cdot)$ and $\mathbf{h}(\cdot, \cdot)$ are known vector functions, k is the estimation step, $\mathbf{z}_k$ is the output measurement at time step k , and $\mathbf{x}_k$ is the system state at time step k and must not be confused with location coordinates. Further, $\mathbf{w}_k$ and $\mathbf{v}_k$ are the discrete zero-mean, independent state and measurement noise processes, with covariance matrices $\mathbf{Q}$ and $\mathbf{R}$, respectively.

Now let $\mathbf{x}_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$ denote the state of the MS at time k , where x_k and y_k are the Cartesian coordinates of the MS, $\dot{x}_k$ and $\dot{y}_k$ are the velocities of the MS in the X and Y directions, respectively. We choose the case where the velocity of the MS is not known and is subject to unknown accelerations. The dynamics of the MS can be written as [62]

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ \dot{x}_k \\ y_k \\ \dot{y}_k \end{bmatrix} = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{w}_{k-1}) = \begin{bmatrix} 1 & \Delta_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta_k \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ \dot{x}_{k-1} \\ y_{k-1} \\ \dot{y}_{k-1} \end{bmatrix} + \begin{bmatrix} \Delta_k^2 / 2 & 0 \\ \Delta_k & 0 \\ 0 & \Delta_k^2 / 2 \\ 0 & \Delta_k \end{bmatrix} \begin{bmatrix} w_{k-1,1} \\ w_{k-1,2} \end{bmatrix} \quad (5.6)$$

where Δ_k is a (possibly non-uniform) measurement interval between time $k-1$ and k .

The measurement equation can be found from Aulin's scattering model (5.2)-(5.4), which can be written in discrete form as

$$z_k = h(\mathbf{x}_k, v_k) = \sum_{n=1}^P r_{n_k} \cos(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}) + v(t_k) \quad (5.7)$$

where

$$\omega_{n_k} = \frac{2\pi\sqrt{\dot{x}_k^2 + \dot{y}_k^2}}{\lambda} \left(\cos(\gamma_k - \alpha_{n_k}) \cos \beta_{n_k} \right) \quad (5.8)$$

$$\theta_{n_k} = \frac{-2\pi}{\lambda} \left(x_k \cos \alpha_{n_k} \cos \beta_{n_k} + y_k \sin \alpha_{n_k} \cos \beta_{n_k} + z_0 \sin \beta_{n_k} \right) + \phi_{n_k} \quad (5.9)$$

Clearly, the measurement equation $h(.,.)$ is a nonlinear function of the state-space vector, as observed in (5.7)-(5.9). If we assume approximate knowledge of the channel, which is attainable either through channel estimation at the receiver (e.g., GSM receiver), or through various estimation techniques (e.g., least-squares, ML), then this problem falls under the broad area of nonlinear parameter estimation from noisy data which can be solved using the RNBE algorithms. These algorithms will be discussed in Sections 5.3-

5.6. The MLE algorithm that employs the lognormal propagation channel model is discussed in the next section.

5.2 The MLE Approach for MS Location Estimation

In this section, The MLE method that employs the lognormal propagation channel model described in Section 5.1.1 is considered for the MS location estimation. This method exploits the received power measurements at the MS which are available from network measurement reports (NMR). Thus, we write the likelihood function and then maximize it with respect to the distances $\boldsymbol{\theta} = \mathbf{d} = (d_1, d_2, \dots, d_B)$ from each BS, where $\boldsymbol{\theta}$ is the parameter to be estimated. The ML estimator, denoted by $\hat{\boldsymbol{\theta}} = \hat{\mathbf{d}} = (\hat{d}_1, \hat{d}_2, \dots, \hat{d}_B)$, represents the most possible MS/BS distances based on the measurements available at the MS.

Consider the measurement vector for the s th sample from all BSs, denoted by $\mathbf{PL}^s(\mathbf{d}) = (PL_1^s(d_1), PL_2^s(d_2), \dots, PL_B^s(d_B))$. The distribution function for this vector is the B -variate normal distribution given by

$$p(\mathbf{PL}^s(\mathbf{d}) | \boldsymbol{\theta}) = (2\pi)^{-B/2} (\det(\boldsymbol{\Sigma}_s))^{-1/2} \cdot \exp\left(-\frac{1}{2} \left(\left(\mathbf{PL}^s(\mathbf{d}) - \overline{\mathbf{PL}}^s(\mathbf{d}) \right)^T \boldsymbol{\Sigma}_s^{-1} \left(\mathbf{PL}^s(\mathbf{d}) - \overline{\mathbf{PL}}^s(\mathbf{d}) \right) \right)\right) \quad (5.10)$$

where $\mathbf{PL}^s(\mathbf{d}) \sim \mathcal{N}_B(\overline{\mathbf{PL}}^s(\mathbf{d}); \boldsymbol{\Sigma}_s)$, $\overline{\mathbf{PL}}^s(\mathbf{d}) = (\overline{PL}_1^s(d_1), \overline{PL}_2^s(d_2), \dots, \overline{PL}_B^s(d_B))$ is the mean path loss from each BS, and $\boldsymbol{\Sigma}_s$ is the covariance matrix. Assuming the noise is independent identically distributed (iid), then the logarithm likelihood function is the log product of the sample likelihood functions given by

$$L(\boldsymbol{\theta} | \mathbf{PL}^s(\mathbf{d})) = \log \left(\frac{1}{(2\pi)^{SB/2} (\det(\boldsymbol{\Sigma}_s))^{S/2}} \right) - \sum_{s=1}^S \left(\left(\mathbf{PL}^s(\mathbf{d}) - \overline{\mathbf{PL}}^s(\mathbf{d}) \right)^T \frac{\boldsymbol{\Sigma}_s^{-1}}{2} \left(\mathbf{PL}^s(\mathbf{d}) - \overline{\mathbf{PL}}^s(\mathbf{d}) \right) \right) \quad (5.11)$$

where S is the total number of samples. Maximizing (5.11) first with respect to $\overline{\mathbf{PL}}^s(\mathbf{d})$, the score function yields

$$\hat{\overline{PL}}_b(d_b) = \frac{1}{S} \sum_{s=1}^S PL_b^s(d_b), \quad \forall b \in \{1, 2, \dots, B\} \quad (5.12)$$

Solving for $\hat{\mathbf{d}}$ using the invariance property of the MLE [72], it can be shown that

$$\hat{d}_b = 10^{\left\{ \frac{1}{10\epsilon_b} \left[\frac{1}{S} \sum_{s=1}^S PL_b^s(d_b) - PL(d_{0b}) \right] \right\}}, \quad \forall b \in \{1, 2, \dots, B\} \quad (5.13)$$

is the MLE for the distance of the b th BS from the MS. Next, we perform triangulation using the least squares error method [73] to estimate the MS location (x_0, y_0) , by solving

$$\arg \min_{x_0, y_0} \left\{ \sum_{b=1}^B (d_b - \hat{d}_b)^2 \right\} \quad (5.14)$$

The performance of this location estimation algorithm is discussed through numerical results and compared to the following algorithms in Section 5.7. The Recursive Nonlinear Bayesian Estimation is discussed next.

5.3 Recursive Nonlinear Bayesian Estimation

Consider the general discrete-time dynamical system model described in (5.5). Let the known probability density functions (PDFs) of the process noise $\mathbf{w}_k$ and the measurement noise $\mathbf{v}_k$ be $p(\mathbf{w}_k)$ and $p(\mathbf{v}_k)$, respectively. As usual, $\mathbf{w}_k$ and $\mathbf{v}_k$ are assumed to be mutually independent. The set of entire measurements from the initial time step to time step k is denoted by $\mathbf{Z}_k = \{\mathbf{z}_i\}_{i=1}^k$. The distribution of the initial condition $\mathbf{x}_0$ is assumed to be given by $p(\mathbf{x}_0 | \mathbf{Z}_0) = p(\mathbf{x}_0)$.

The recursive Bayesian filter based on Bayes rule is organized into the time-update stage and the measurement-update stage [43]. The time-update stage computes the PDF $p(\mathbf{x}_k | \mathbf{Z}_{k-1})$ via the Chapman-Kolmogorov equation as

$$p(\mathbf{x}_k | \mathbf{Z}_{k-1}) = \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{Z}_{k-1}) d\mathbf{x}_{k-1} \quad (5.15)$$

where $p(\mathbf{x}_{k-1} | \mathbf{Z}_{k-1})$ has been propagated from time step $k-1$. Note that in (5.15) the Markov property of the state model $p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{Z}_{k-1}) = p(\mathbf{x}_k | \mathbf{x}_{k-1})$ has been used. The PDF $p(\mathbf{x}_k | \mathbf{x}_{k-1})$ is determined by the system model and the known PDF $p(\mathbf{w}_{k-1})$. The measurement-update stage can be carried out by applying Bayes rule as

$$p(\mathbf{x}_k | \mathbf{Z}_k) = \frac{p(\mathbf{z}_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{Z}_{k-1})}{\int p(\mathbf{z}_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{Z}_{k-1}) d\mathbf{x}_k} \quad (5.16)$$

The PDF $p(\mathbf{z}_k | \mathbf{x}_k)$ is computed by the measurement model and the known PDF $p(\mathbf{v}_k)$.

In general, the above recursive Bayesian filter does not have a closed form solution, and therefore, has to be approximated using the EKF, the PF, and/or the UPF. In the next section, the EKF approach that employs the channel model of Aulin to estimate the MS location and velocity is discussed.

5.4 The EKF Approach for MS Location and Velocity Estimation

The EKF is based on linearizing the nonlinear system models around the previous estimate. The general algorithm for the discrete EKF can be described by the time-update equations given as [42]

$$\begin{aligned} \tilde{\mathbf{x}}_k &= \mathbf{f}(\hat{\mathbf{x}}_{k-1}, 0) \\ \tilde{\mathbf{P}}_k &= \mathbf{A}_k \hat{\mathbf{P}}_{k-1} \mathbf{A}_k^T + \mathbf{W}_k \mathbf{Q}_{k-1} \mathbf{W}_k^T \end{aligned} \quad (5.17)$$

and the measurement-update equations given as

$$\begin{aligned} \mathbf{K}_k &= \tilde{\mathbf{P}}_k \mathbf{H}_k^T \left[\mathbf{H}_k \tilde{\mathbf{P}}_k \mathbf{H}_k^T + \mathbf{V}_k \mathbf{R}_k \mathbf{V}_k^T \right]^{-1} \\ \hat{\mathbf{x}}_k &= \tilde{\mathbf{x}}_k + \mathbf{K}_k (z_k - h(\tilde{\mathbf{x}}_k, 0)) \\ \hat{\mathbf{P}}_k &= (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \tilde{\mathbf{P}}_k \end{aligned} \quad (5.18)$$

where

$$\begin{aligned}
\mathbf{A}_k &= \frac{\partial \mathbf{f}}{\partial \mathbf{x}}(\hat{\mathbf{x}}_{k-1}, 0), & \mathbf{W}_k &= \frac{\partial \mathbf{f}}{\partial \mathbf{w}}(\hat{\mathbf{x}}_{k-1}, 0) \\
\mathbf{H}_k &= \frac{\partial h}{\partial \mathbf{x}}(\hat{\mathbf{x}}_k, 0), & \mathbf{V}_k &= \frac{\partial h}{\partial \mathbf{v}}(\hat{\mathbf{x}}_k, 0)
\end{aligned} \tag{5.19}$$

$\mathbf{K}$ is the gain matrix, and $\hat{\mathbf{P}}$ is the estimation error covariance. The notation $\tilde{\mathbf{x}}_k$ denotes the a priori state estimate at time step k and $\hat{\mathbf{x}}_k$ the a posteriori state estimate given measurement z_k . $\tilde{\mathbf{P}}_k$ and $\hat{\mathbf{P}}_k$ are defined similarly. Applying equation (5.19) to our system model (5.7)-(5.9), we get

$$\begin{aligned}
\mathbf{A}_k &= \begin{bmatrix} 1 & \Delta_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta_k \\ 0 & 0 & 0 & 1 \end{bmatrix}, & \mathbf{W}_k &= \begin{bmatrix} \Delta_k^2 / 2 & 0 \\ \Delta_k & 0 \\ 0 & \Delta_k^2 / 2 \\ 0 & \Delta_k \end{bmatrix} \\
\mathbf{H}_k &= [H1_k \ H2_k \ H3_k \ H4_k], & \mathbf{V}_k &= 1
\end{aligned} \tag{5.20}$$

where

$$\begin{aligned}
H1_k &= \sum_{n=1}^P \left[r_{n_k} \sin(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}) \left(\frac{2\pi}{\lambda} \cos(\alpha_{n_k}) \cos(\beta_{n_k}) \right) \right] \\
H2_k &= \sum_{n=1}^P \left[-r_{n_k} \sin(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}) \left(\frac{2\pi t_k}{\lambda \sqrt{\dot{x}_k^2 + \dot{y}_k^2}} \cos(\beta_{n_k}) \right) \right. \\
&\quad \left. \left(\dot{x}_k \cos(\gamma_k - \alpha_{n_k}) + \dot{y}_k \sin(\gamma_k - \alpha_{n_k}) \right) \right] \\
H3_k &= \sum_{n=1}^P \left[r_{n_k} \sin(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}) \left(\frac{2\pi}{\lambda} \sin(\alpha_{n_k}) \cos(\beta_{n_k}) \right) \right] \\
H4_k &= \sum_{n=1}^P \left[-r_{n_k} \sin(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}) \left(\frac{2\pi t_k}{\lambda \sqrt{\dot{x}_k^2 + \dot{y}_k^2}} \cos(\beta_{n_k}) \right) \right. \\
&\quad \left. \left(\dot{y}_k \cos(\gamma_k - \alpha_{n_k}) - \dot{x}_k \sin(\gamma_k - \alpha_{n_k}) \right) \right]
\end{aligned} \tag{5.21}$$

and $\gamma_k = \arctan(\dot{y}_k / \dot{x}_k)$.

As in any nonlinear estimation problem, the convergence of the EKF to the true value of the location depends on the initial parameter value; therefore we first develop the MLE method to obtain an initial estimator of adequate accuracy for the EKF. This hybrid algorithm, as numerical results indicate, has improved accuracy for the final MS location estimate.

The EKF described above utilizes the first term in a Taylor expansion of the nonlinear measurement model in (5.7). It always approximates $p(\mathbf{x}_k | \mathbf{Z}_k)$ by a Gaussian distribution. However, if the true density is non-Gaussian, then a Gaussian model may not describe it precisely. In such cases PFs yield an improvement in performance in comparison to that of an EKF. The design of the PF is discussed in the next section.

5.5 The PF Approach for MS Location and Velocity Estimation

The PF is a technique for implementing a recursive Bayesian filter by Monte Carlo simulations. The key idea is to represent the required posterior density function by a set of random samples $\{\hat{\mathbf{x}}_k(j)\}_{j=1}^N$ with associated weights $\{\omega_k(j)\}_{j=1}^N$ and to compute estimates based on these samples and weights. In this case the posterior density at time k can be approximated as

$$p(\mathbf{x}_k | \mathbf{Z}_k) \approx \sum_{j=1}^N \omega_k(j) \delta(\mathbf{x}_k - \hat{\mathbf{x}}_k(j)) \quad (5.22)$$

We therefore have a discrete-weighted approximation to the true posterior $p(\mathbf{x}_k | \mathbf{Z}_k)$.

The weights are chosen using the principle of importance sampling [74]

$$\omega_k(j) \propto \frac{p(\mathbf{z}_k | \tilde{\mathbf{x}}_k(j)) p(\tilde{\mathbf{x}}_k(j) | \tilde{\mathbf{x}}_{k-1}(j))}{q(\tilde{\mathbf{x}}_k(j) | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k)} \quad (5.23)$$

where $q(\tilde{\mathbf{x}}_k(j) | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k)$ is the importance proposal distribution function that generates the samples $\{\hat{\mathbf{x}}_k(j)\}_{j=1}^N$. The choice of this distribution function is one of the

most critical design issues and determines the type of the PF. The optimal proposal distribution function that minimizes the variance of the weights conditioned on $\tilde{\mathbf{x}}_{k-1}(j)$ and $\mathbf{z}_k$ is $q(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k)_{opt} = p(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k)$ [74].

However, analytical evaluation of the optimal proposal function is not possible for many models, and thus has to be approximated using local linearization [74] or the unscented transformation [75]. In this dissertation, the unscented transformation method is considered and the resulting filter is called the unscented particle filter (UPF) that is described in Section 5.6.

Nonetheless, the most popular choice of proposal function is the transition prior $q(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k) = p(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j))$. This filter is called the generic PF and is discussed herein. Although this choice of proposal function results in higher Monte Carlo variations than the optimal, it is usually simple to implement.

The time-update stage of the generic PF [63] is performed by passing the random samples $\{\hat{\mathbf{x}}_{k-1}(j)\}_{j=1}^N$ through the system model (5.6) to obtain the time-updated samples $\{\tilde{\mathbf{x}}_k(j)\}_{j=1}^N$. Namely, the time-updated samples are obtained by

$$\tilde{\mathbf{x}}_k(j) = \mathbf{f}(\hat{\mathbf{x}}_{k-1}(j), \mathbf{w}_{k-1}(j)) \quad (5.24)$$

where $\mathbf{w}_{k-1}(j)$ is a sample drawn from the PDF $p(\mathbf{w}_{k-1})$ of the system noise. The samples $\{\tilde{\mathbf{x}}_k(j)\}_{j=1}^N$ are distributed as the time updated PDF $p(\mathbf{x}_k | \mathbf{Z}_{k-1})$.

The measurement-update stage can be described by substituting the choice of proposal distribution $q(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k) = p(\mathbf{x}_k | \tilde{\mathbf{x}}_{k-1}(j))$ into (5.23) and normalizing which yields

$$\omega_k(j) = \frac{p(\mathbf{z}_k | \tilde{\mathbf{x}}_k(j))}{\sum_{j=1}^N p(\mathbf{z}_k | \tilde{\mathbf{x}}_k(j))} \quad (5.25)$$

We define a discrete density over $\{\tilde{\mathbf{x}}_k(j)\}_{j=1}^N$ with probability mass $\omega_k(j)$ associated with each sample $\tilde{\mathbf{x}}_k(j)$. Then we get the measurement-update samples $\{\hat{\mathbf{x}}_k(j)\}_{j=1}^N$ through a resampling process, such that $\Pr\{\hat{\mathbf{x}}_k(i) = \tilde{\mathbf{x}}_k(j)\} = \omega_k(j)$ for any i . Several resampling schemes are presented in the literature such as systematic [76], stratified, and residual resampling [77]. However, the specific choice of resampling scheme does not significantly affect the performance of the PF. Therefore, systematic resampling is used in all of the experiments in Section 5.7 since it is simple to implement. It can be performed by drawing a sample u_j from the uniform distribution over $(0, 1]$. Then, the sample $\{\tilde{\mathbf{x}}_k(M)\}$ is chosen as the updated sample $\hat{\mathbf{x}}_k(j)$ if the random sample u_j satisfies the relation

$$\sum_{i=0}^{M-1} \omega_k(i) < u_j \leq \sum_{i=0}^M \omega_k(i) \quad (5.26)$$

where $\omega_k(0) = 0$. This resampling process is repeated for $j = 1, \dots, N$. Finally, the estimate of the PF at time k is chosen to be the mean of the samples $\{\hat{\mathbf{x}}_k(j)\}_{j=1}^N$.

In the next section, an approximate version of the optimal proposal distribution is considered in order to have a more accurate MS location estimate.

5.6 The UPF Approach for MS Location and Velocity Estimation

The UPF results from using a scaled unscented transformation (SUT) method [75] to approximate the optimal proposal distribution within a particle filter framework. The SUT provides more accurate approximation than linearization methods [75]. In particular, the SUT calculates the posterior covariance accurately to the 3rd order, whereas linearization methods such as the EKF rely on a first order biased approximation. The SUT method is introduced next.

5.6.1 The SUT Method

The SUT method still approximates the proposal distribution by a Gaussian distribution, but it is specified using a minimal set of deterministically chosen sample points. These sample points completely capture the true mean and covariance of the Gaussian distribution, and when propagated through the true nonlinear system, captures the posterior mean and covariance accurately to the 3rd order for any nonlinearity.

Consider the state equation described in (5.5). For simplicity, let $\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1})$, where $\mathbf{x}_{k-1}$ an n_x dimensional random vector and assume $\mathbf{x}_{k-1}$ has mean $\bar{\mathbf{x}}_{k-1}$ and covariance $\mathbf{P}_{k-1}$. Then, a set of $2n_x + 1$ weighted samples or sigma points $S_i = \{W_i, \mathcal{X}_i\}$ are deterministically chosen so that they completely capture the true mean and covariance of the prior random vector $\mathbf{x}_{k-1}$. A selection scheme that satisfies this requirement is [75]

$$\begin{aligned}
 \mathcal{X}_{k-1}^0 &= \bar{\mathbf{x}}_{k-1} \\
 \mathcal{X}_{k-1}^i &= \bar{\mathbf{x}}_{k-1} + \left(\sqrt{(n_x + \lambda) \mathbf{P}_{k-1}} \right)_i, \quad i = 1, \dots, n_x \\
 \mathcal{X}_{k-1}^i &= \bar{\mathbf{x}}_{k-1} - \left(\sqrt{(n_x + \lambda) \mathbf{P}_{k-1}} \right)_i, \quad i = n_x + 1, \dots, 2n_x \\
 W_0^{(m)} &= \lambda / (n_x + \lambda) \\
 W_0^{(c)} &= \lambda / (n_x + \lambda) + (1 - \alpha^2 + \beta) \\
 W_i^{(m)} &= W_i^{(c)} = 1 / \{2(n_x + \lambda)\}, \quad i = 1, \dots, 2n_x
 \end{aligned} \tag{5.27}$$

where $\lambda = \alpha^2(n_x + \kappa) - n_x$, α, β , and κ are scaling parameters, $\left(\sqrt{(n_x + \lambda) \mathbf{P}_{k-1}} \right)_i$ is the i th row or column of the matrix square root of $(n_x + \lambda) \mathbf{P}_{k-1}$. Each sigma point is now propagated through the nonlinear function $\mathcal{X}_k^i = \mathbf{f}(\mathcal{X}_{k-1}^i)$, $i = 0, \dots, 2n_x$. And the estimated mean and covariance of $\mathbf{x}_k$ are computed as follows

$$\begin{aligned}
 \bar{\mathbf{x}}_k &= \sum_{i=0}^{2n_x} W_i^{(m)} \mathcal{X}_k^i \\
 \mathbf{P}_k &= \sum_{i=0}^{2n_x} W_i^{(c)} \left\{ \mathcal{X}_k^i - \bar{\mathbf{x}}_k \right\} \left\{ \mathcal{X}_k^i - \bar{\mathbf{x}}_k \right\}^T
 \end{aligned} \tag{5.28}$$

These estimates of the mean and covariance are accurate to the 3rd order for any nonlinear function. In comparison, the EKF only calculates the posterior mean and covariance accurately to the first order with all higher order moments truncated.

5.6.2 The UPF Design

The UPF uses the same framework as the regular PF, except that it approximates the optimal proposal distribution by a Gaussian distribution using the SUT method. In particular, the SUT is used to generate and propagate a Gaussian proposal distribution for each particle to get

$$q(\mathbf{x}_k(j) | \tilde{\mathbf{x}}_{k-1}(j), \mathbf{z}_k)_{opt} \approx \mathcal{N}(\bar{\mathbf{x}}_k(j), \mathbf{P}_k(j)), \quad j=1, \dots, N \quad (5.29)$$

That is, at time $k-1$ the SUT is used with the new data, to compute the mean and covariance of the importance distribution for each particle. Next, the j th particle is sampled from this distribution.

In the implementation of the UPF, the augmented state vector is defined as the concatenation of the original state and noise variables as $\mathbf{x}_k^a = [\mathbf{x}_k^T \mathbf{w}_k^T \mathbf{v}_k^T]^T$. Then the SUT sigma point selection scheme is applied to this new augmented state vector to calculate the corresponding sigma matrix, $\boldsymbol{\Sigma}_k^a$. The complete UPF is described as follows [75]:

- a) Initialization ($k=0$): Draw the particles $\{\mathbf{x}_0(j)\}_{j=1}^N$ from the prior $p(\mathbf{x}_0)$ and set

$$\begin{aligned} \bar{\mathbf{x}}_0(j) &= E[\mathbf{x}_0(j)] \\ \mathbf{P}_0(j) &= E[(\mathbf{x}_0(j) - \bar{\mathbf{x}}_0(j))(\mathbf{x}_0(j) - \bar{\mathbf{x}}_0(j))^T] \\ \bar{\mathbf{x}}_0^a(j) &= E[\mathbf{x}_0^a(j)] = [\bar{\mathbf{x}}_0(j)^T \quad 0 \quad 0]^T \\ \mathbf{P}_0^a(j) &= E[(\mathbf{x}_0^a(j) - \bar{\mathbf{x}}_0^a(j))(\mathbf{x}_0^a(j) - \bar{\mathbf{x}}_0^a(j))^T] = \begin{bmatrix} \mathbf{P}_0(j) & 0 & 0 \\ 0 & \mathbf{Q} & 0 \\ 0 & 0 & \mathbf{R} \end{bmatrix} \end{aligned} \quad (5.30)$$

where $E[\cdot]$ is the expectation operator.

b) Now for $k=1,2,\dots$, the importance sampling step is performed by the following steps:

- Calculating sigma points

$$\boldsymbol{\mathcal{X}}_{k-1}^a(j) = \left[\bar{\mathbf{x}}_{k-1}^a(j) \bar{\mathbf{x}}_{k-1}^a(j) \pm \sqrt{(n_a + \lambda) \mathbf{P}_{k-1}^a(j)} \right] \quad (5.31)$$

- Performing the time-update stage as

$$\begin{aligned} \tilde{\boldsymbol{\mathcal{X}}}_k^x(j) &= \mathbf{f}(\boldsymbol{\mathcal{X}}_{k-1}^x(j), \boldsymbol{\mathcal{X}}_{k-1}^w(j)), \quad \bar{\mathbf{x}}_k(j) = \sum_{i=0}^{2n_a} W_i^{(m)} \tilde{\boldsymbol{\mathcal{X}}}_{i,k}^x(j) \\ \tilde{\mathbf{P}}_k(j) &= \sum_{i=0}^{2n_a} W_i^{(c)} \{ \tilde{\boldsymbol{\mathcal{X}}}_{i,k}^x(j) - \bar{\mathbf{x}}_k(j) \} \{ \tilde{\boldsymbol{\mathcal{X}}}_{i,k}^x(j) - \bar{\mathbf{x}}_k(j) \}^T \\ \boldsymbol{\mathcal{Z}}_k(j) &= \mathbf{h}(\tilde{\boldsymbol{\mathcal{X}}}_k^x(j), \boldsymbol{\mathcal{X}}_{k-1}^v(j)), \quad \bar{\mathbf{z}}_k(j) = \sum_{i=0}^{2n_a} W_i^{(m)} \boldsymbol{\mathcal{Z}}_{i,k}(j) \end{aligned} \quad (5.32)$$

- Performing the measurement-update stage as

$$\begin{aligned} \mathbf{P}_{\mathbf{z}_k \mathbf{z}_k} &= \sum_{i=0}^{2n_a} W_i^{(c)} \{ \boldsymbol{\mathcal{Z}}_{i,k}(j) - \bar{\mathbf{z}}_k(j) \} \{ \boldsymbol{\mathcal{Z}}_{i,k}(j) - \bar{\mathbf{z}}_k(j) \}^T \\ \mathbf{P}_{\mathbf{x}_k \mathbf{z}_k} &= \sum_{i=0}^{2n_a} W_i^{(c)} \{ \tilde{\boldsymbol{\mathcal{X}}}_{i,k}^x(j) - \bar{\mathbf{x}}_k(j) \} \{ \boldsymbol{\mathcal{Z}}_{i,k}(j) - \bar{\mathbf{z}}_k(j) \}^T \\ \mathbf{K}_k &= \mathbf{P}_{\mathbf{x}_k \mathbf{z}_k} \mathbf{P}_{\mathbf{z}_k \mathbf{z}_k}^{-1}, \quad \bar{\mathbf{x}}_k(j) = \bar{\mathbf{x}}_k(j) + \mathbf{K}_k (z_k - \bar{\mathbf{z}}_k(j)) \\ \hat{\mathbf{P}}_k(j) &= \tilde{\mathbf{P}}_k(j) - \mathbf{K}_k \mathbf{P}_{\mathbf{z}_k \mathbf{z}_k} \mathbf{K}_k^T \end{aligned} \quad (5.33)$$

and then sampling $\hat{\mathbf{x}}_k(j)$ from $q(\mathbf{x}_k(j) | \mathbf{x}_{k-1}(j), z_k) = \mathcal{N}(\bar{\mathbf{x}}_k(j), \hat{\mathbf{P}}_k(j))$.

- Evaluating the importance weights as

$$\omega_k(j) \propto \frac{p(z_k | \hat{\mathbf{x}}_k(j)) p(\hat{\mathbf{x}}_k(j) | \mathbf{x}_{k-1}(j))}{q(\hat{\mathbf{x}}_k(j) | \mathbf{x}_{k-1}(j), z_k)} \quad (5.34)$$

and then normalizing the importance weights for $j=1,\dots,N$.

- c) Finally, a resampling process such as systematic resampling is performed to obtain N random particles $(\hat{\mathbf{x}}_k(j), \hat{\mathbf{p}}_k(j))$, and the output is generated in the same manner as for the generic PF.

In the next section, numerical examples are presented to illustrate the accuracy of the proposed algorithms.

5.7 Numerical Results

In this numerical example, the performance of the proposed MS location and velocity estimation algorithms is determined. We consider first the ML estimate of the MS location in which we employ a typical, yet realistic, wireless communication simulation setup as follows:

- The service area consists of a 19-cell cluster.
- The BSs are placed over a uniform hexagonal pattern of cells which are centrally equipped with omni-directional antennas.
- MSs are placed randomly in the central cell.
- The number of arranged users is 1000.
- Path-loss exponent ε_b is 3.5.
- Path-loss variance σ_b^2 is 8 dB.
- Reference distance d_{0_b} is 200 m for all b .
- Cell radii is 5000 m.
- Number of samples S is 10.
- Number of BSs for triangulation is 5.
- Radio-frequency is 900 MHz.
- Performed 100 Monte Carlo simulations.

Next, we consider the simulation setup for the EKF, the PF, and the UPF approaches that employ Aulin's channel model for MS location and velocity estimation. The

simulation setup for the MLE approach remains the same, only now we are trying to locate a single MS. The multipath channel has the following features:

- The envelope of the received signal for all paths, r_n 's, are generated as Rayleigh iid RVs with parameter 0.5.
- a_n, β_n , and ϕ_n are generated as uniform iid RVs in $[0, 2\pi]$, $[0, 0.2\pi]$, and $[0, 2\pi]$, respectively.
- The total number of paths P is 6 (represents urban environment).

The filters have the following parameters:

- Number of time steps (measurements) is 50 with $\Delta_k = 0.1$ seconds.
- Process noise covariance $\mathbf{Q}$ and measurement noise variance $\mathbf{R}$ are $I_{2 \times 2}$ and 0.01, respectively, where $I_{2 \times 2}$ is the two-dimensional identity matrix.
- The initial PDF of the MS position is assumed to be uniform over the entire cell size which represents the worst-case as far as choosing an initial PDF is considered.
- The initial PDF of the MS velocity is Gaussian distributed with mean 65 meters/sec and variance 10.
- Number of particles is 500.
- The SUT parameters are set to $\alpha = 1$, $\beta = 0$, and $\kappa = 0$.
- The mean estimate of all particles is used as the final estimate.

The position (or velocity) root mean square error (RMSE) is used as a performance measure and is defined as

$$\text{RMSE}(k) = \sqrt{\frac{1}{MC} \sum_{i=1}^{MC} (\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}})^T (\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}})} \quad (5.35)$$

where MC is the number of Monte Carlo simulations performed, and $\hat{\mathbf{x}}_k^i$ is the filter position estimate $(x, y)^T$ (or velocity estimate $(\dot{x}, \dot{y})^T$), at time k in Monte Carlo run i .

The overall RMSE is defined as

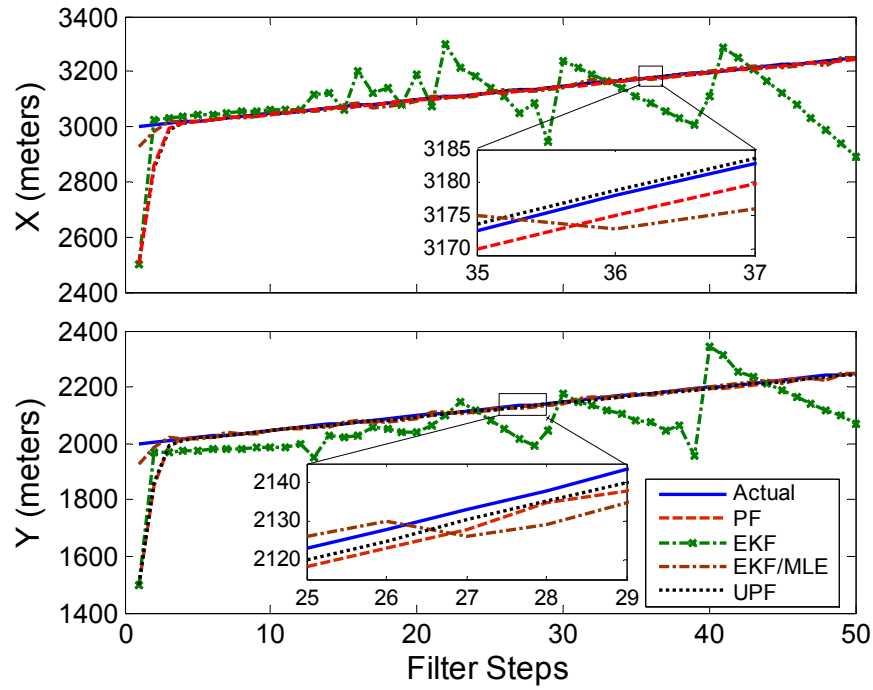
$$\text{RMSE} = \sqrt{\frac{1}{L} \sum_{k=1}^L \frac{1}{MC} \sum_{i=1}^{MC} (\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}})^T (\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}})} \quad (5.36)$$

where L is the total number of simulation time steps after the convergence of the filter.

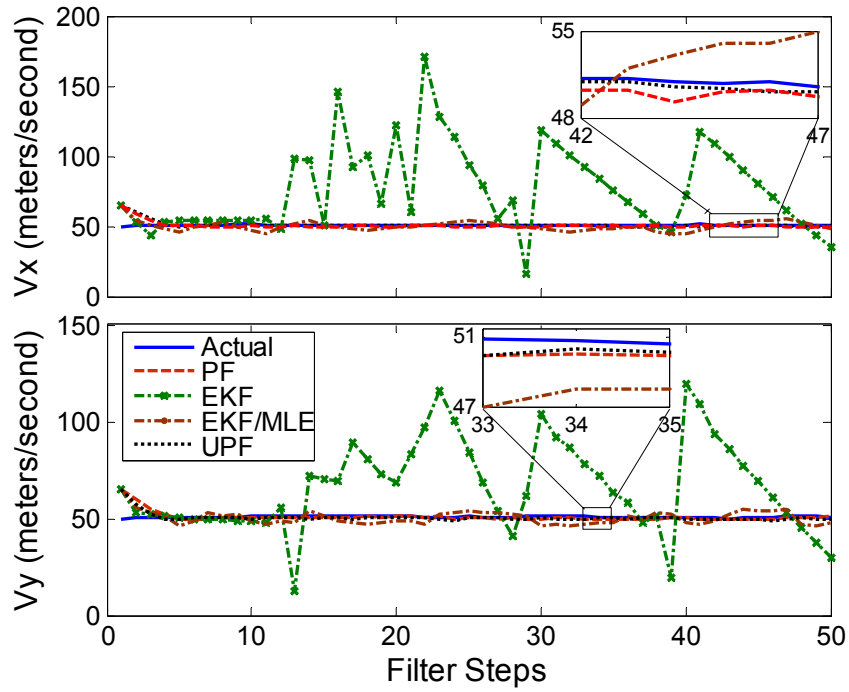
Figure 5.1(a) and 5.1(b) show one realization illustrating the convergence of the proposed algorithms to the real position and velocity of a moving MS, respectively. Figure 5.2 shows the position and velocity RMSE for each time according to (5.35), and the overall position and velocity RMSE for the convergent runs using (5.36) are shown in Table 5.1.

From Figure 5.2 and Table 5.1, it can be noticed that the accuracy of the MLE approach is satisfactory. However, in realistic NLOS and multipath conditions this method does not perform well. Nevertheless, it can be used as an initial condition for the EKF to find a more accurate estimator. It has been also observed that the accuracy increases as the number of samples, S , increases and σ_b^2 , ε_b decrease, as expected. For more accurate estimates, Aulin's channel model is employed together with the EKF, PF, and UPF.

We observe in Figure 5.1 that the EKF/MLE, PF, and UPF estimators converge to the actual location and velocity within a few iterations (less than 5). However, the EKF position and velocity estimates oscillate with large deviation around the actual position and velocity. This is because the EKF truncates higher order series expansion terms and is sensitive to the initial state. However, the latter can be improved by using the ML estimate as an initial estimate for the EKF. Since it takes less than 5 iterations for the filters to converge near the actual value as shown in Figure 5.1, the RMSE (k) in (5.35) is calculated starting from the iteration $k = 5$. Only convergent runs are used in the RMSE calculations. Figure 5.2 shows that the performance of the PF and the UPF approaches are about the same and superior to other approaches. The superior performance of the UPF is clearly evident. Table 5.1 shows the number of runs that diverged and the performance for each approach. The latter shows the appropriateness of choosing the PF and the UPF for this kind of problems. We have observed that using fewer particles does



(a)



(b)

Figure 5.1: (a) Location and (b) velocity estimates of a moving MS generated by the different filters.

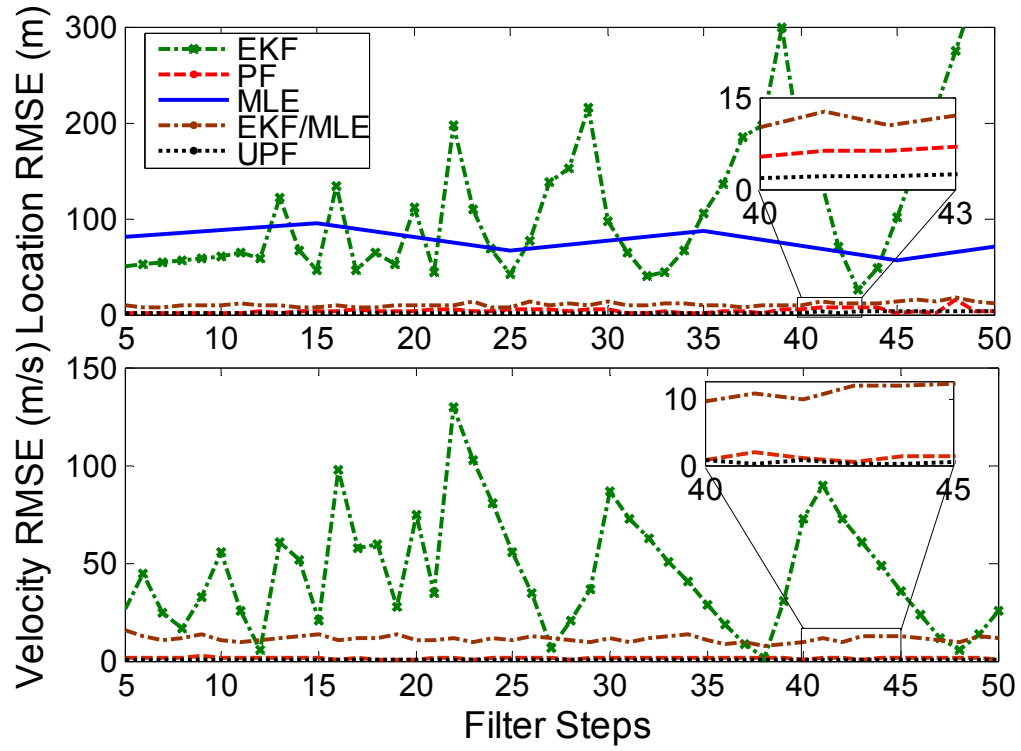


Figure 5.2: Location and velocity estimates RMSE (k) generated by the different algorithms.

Table 5.1: Performance comparison for MS location and velocity estimation algorithms using the MLE, EKF, EKF/MLE, PF, and the UPF approaches.

	MLE	EKF	EKF/ MLE	PF	UPF
Diverged Runs	—	39	6	2	2
Position RMSE (m)	73.46	142.38	11.23	4.31	3.81
Velocity RMSE (m/sec)	—	51.36	16.52	1.01	0.96

not affect significantly the UPF, while the performance of the PF deteriorates. The high accuracy is due to the appropriateness of Aulin's channel model and the efficiency of the particle filtering in this particular application.

Figure 5.3 shows how robust the particle filtering approach is if we assume that we only know the channel parameters $\{r_n, \alpha_n, \beta_n\}$ within certain tolerances. Specifically,

$$\begin{aligned} r_n &= r_{n_0} (1 + \delta r_{n_0}), \quad |\delta r_{n_0}| \leq 5\%, 10\%, 20\% \text{ and } 30\% \\ \alpha_n &= \alpha_{n_0} (1 + \delta \alpha_{n_0}), \quad |\delta \alpha_{n_0}| \leq 5\%, 10\%, 20\% \text{ and } 30\% \\ \beta_n &= \beta_{n_0} (1 + \delta \beta_{n_0}), \quad |\delta \beta_{n_0}| \leq 5\%, 10\%, 20\% \text{ and } 30\% \end{aligned} \quad (5.37)$$

where r_{n_0} , α_{n_0} and β_{n_0} are the nominal (actual) values of the channel parameters. Figure 5.3 is generated by assuming that the real channel has parameters r_{n_0} , α_{n_0} and β_{n_0} , while in the estimation stage the channel model parameters used are uniformly distributed about their nominal values as in the uncertainty model (5.37), and varying the uncertainty percentage from 5% to 30%. It can be noticed that the location and velocity RMSE still converge even if the channel parameters have errors. The higher the error is, the longer time it takes for the filter to converge. It can also be seen that the final RMSE increases for higher errors in channel parameters as expected.

The high accuracy, consistency and performance of the proposed UPF approach, makes it suitable to be used in any location and velocity estimation applications, particularly those which require high accuracy such as emergency services.

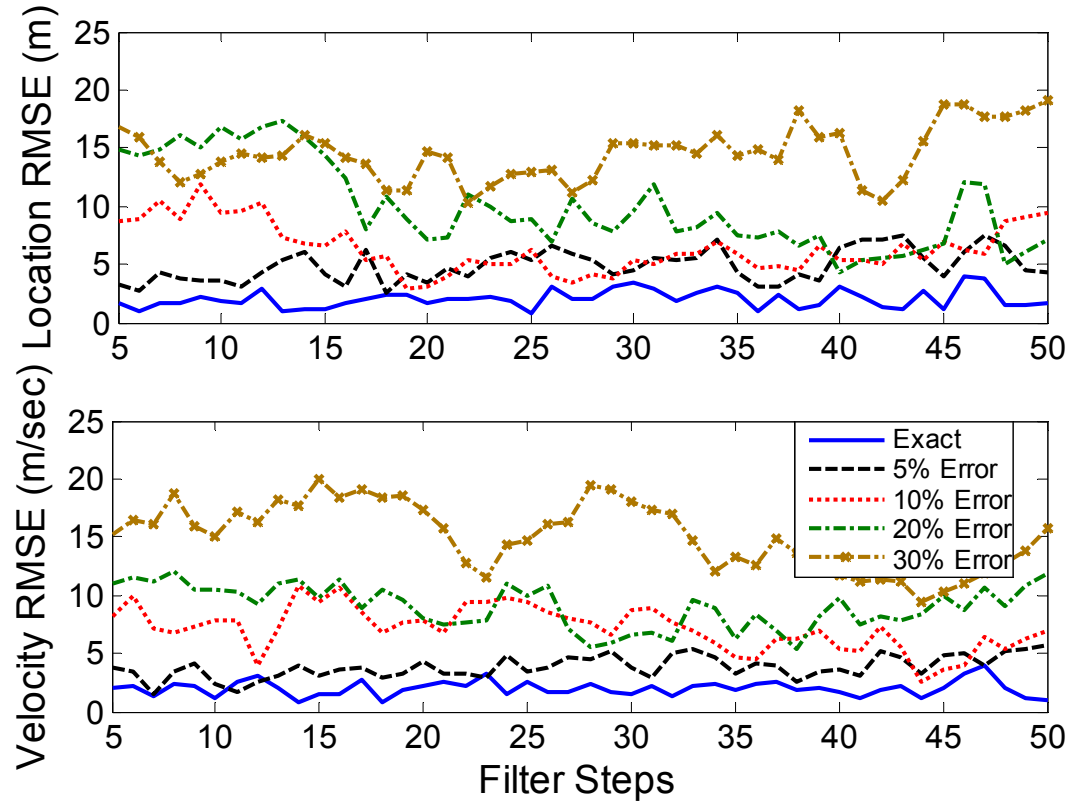


Figure 5.3: The UPF location and velocity estimates RMSE (k) for imperfect knowledge of channel parameters.

Chapter 6

Conclusions and Future Work

In this dissertation, TV LTF, STF, and ad hoc wireless channel models, which capture both the space and time variations of TV wireless channels, are developed. The dynamics of the TV wireless channels are described by SDEs and represented in stochastic state space form, which essentially capture the spatio-temporal variations of wireless communication links. The SDE models proposed allow viewing the wireless channel as a dynamical system, which shows how the channel evolves in time and space. They take into account the statistical time variations in wireless channels and are more realistic than the standard static ones usually encountered in the literature. Inphase and quadrature components of the channel and their statistics are derived from the proposed model. The proposed models are useful in capturing nodes mobility and environmental changes in mobile wireless networks. The state space models have been used to verify the effect of fading on a transmitted signal in wireless fading networks. In addition, they allow well-developed tools of estimation and identification to be applied to this class of problems [64-66].

The channel model parameters as well as the inphase and quadrature components are estimated recursively with high accuracy from received signal measurements. The proposed algorithm consists of filtering based on the Kalman filter to remove noise from data, and identification based on the filter-based EM algorithm to determine the parameters of the model which best describe the measurements. Experimental results indicate that the measured data can be generated through a simple 4th order discrete-time stochastic differential equation for STF or ad hoc links (1st order for LTF link) with excellent accuracy, and therefore demonstrating the validity of the method. The proposed

models are important in the development of a practical channel simulator that replicates wireless channel characteristics, and produces outputs that vary in a similar manner to the variations encountered in a real-world channel environment. Future work includes adjusting the proposed models in order to be able to capture other wireless environments such as indoor and ultra-wideband (UWB). This requires modifying the SDE models to be able to generate different probability distributions such as Nakagami, Weibull, etc., for the various environments. Moreover, generalization of our stochastic models to multiple-input multiple-output (MIMO) wireless communication systems, which correspond to multiple transmitting and receiving antennas, is an emanating area for future work.

An optimal DPCA based on the developed channel models is proposed. The optimal DPCA is shown to reduce to a linear programming problem if predictable power control strategies (PPCS) are used. In addition, an iterative distributed SPCA is used to solve for the optimization problem using stochastic approximations. The latter solely requires each mobile to know its received signal to interference ratio unlike common SPCAs found in the literature. Numerical results show that there are potentially large gains to be achieved by using TV stochastic models, and the distributed SPCA provides better power stability and consumption than the distributed DPCA.

Future work includes developing PCAs without assuming predictable power control strategies are applicable. In this case, two formulations in terms of convex optimization using linear programming techniques and stochastic control with integral or exponential-of-integral constraints can be introduced. The first problem is formulated in terms of convex optimization and linear programming as follows

$$\min_{(p_1 \geq 0, \dots, p_M \geq 0)} \left\{ \sum_{i=1}^M \int_{t_k}^{t_{k+1}} p_i(t) dt \right\}, \text{ subject to} \quad (6.1)$$

$$\sum_{j \neq i}^M \int_{t_k}^{t_{k+1}} p_j(t) s_j^2(t) S_{ij}^2(t) dt - \frac{1}{\mathcal{E}_i} \int_{t_k}^{t_{k+1}} p_i(t) s_i^2(t) S_{ii}^2(t) dt + \int_{t_k}^{t_{k+1}} n_i^2(t) dt \leq 0$$

where $i=1, \dots, M$. The variables in (6.1) are defined in Sections 4.1 and 4.2. According to this formulation using predictable strategies this is a convex optimization problem. In

addition, any interval $[0, T]$ can be considered as $0=t_0 < t_1 < t_2 \dots < t_k < t_{k+1} < \dots \leq T$, and by approximating the integrals by Riemann sums as close as desired, it can be shown that (6.1) reduces to a linear programming problem again. The second problem is formulated in terms of stochastic control with integral or exponential-of-integral constraints as

$$\min_{(p_1 \geq 0, \dots, p_M \geq 0)} \left\{ \sum_{i=1}^M E \int_0^T p_i(t) dt \right\}, \text{ subject to} \quad (6.2)$$

$$J_{0,T}^i(p) \triangleq E \left\{ \sum_{j \neq i}^M \int_0^T p_j(t) s_j^2(t) S_{ij}^2(t) dt - \frac{1}{\varepsilon_i} \int_0^T p_i(t) s_i^2(t) S_{ii}^2(t) dt + \int_0^T n_i^2(t) dt \right\} \leq 0$$

If there exists a set of $\{\varepsilon_i\}_{i=1}^M$ such that the QoS are feasible, by employing Lagrange multipliers λ_i for each $J_{0,T}^i(p)$ we can introduce

$$L^\lambda(p^*, \lambda) = \min_{(p_1 \geq 0, \dots, p_M \geq 0)} \left\{ \sum_{i=1}^M E \left[\int_0^T p_i(t) dt + \lambda_i \left[\sum_{j \neq i}^M \int_0^T p_j(t) s_j^2(t) S_{ij}^2(t) dt - \frac{1}{\varepsilon_i} \int_0^T p_i(t) s_i^2(t) S_{ii}^2(t) dt + \int_0^T n_i^2(t) dt \right] \right] \right\} \quad (6.3)$$

and then solving the problem $l(\lambda^*, p^*) = \sup_{\lambda \geq 0} L^\lambda(p^*, \lambda)$. Similarly, the QoS can be considered as point-wise constraints and pursue the problem

$$\min_{(p_1 \geq 0, \dots, p_M \geq 0)} \left\{ \sum_{i=1}^M E \int_0^T p_i(t) dt \right\}, \text{ subject to} \quad (6.4)$$

$$\sum_{j \neq i}^M p_j(t) s_j^2(t) S_{ij}^2(t) - \frac{1}{\varepsilon_i} p_i(t) s_i^2(t) S_{ii}^2(t) + n_i^2(t) \leq 0, \quad t \in [0, T]$$

Optimizations (6.2) and (6.4) are convex optimization problems, since their objective functions and constraints are convex.

An alternative stochastic power control formulation can be stated in terms of outage probability (OP). The stochastic PC problem that meets outage constraints can be formulated as

$$\min_{(p_1 \geq 0, \dots, p_M \geq 0)} \left\{ \sum_{i=1}^M \int_0^T p_i(t) dt \right\}, \text{ subject to} \quad (6.5)$$

$$\Pr \left\{ \left(\sum_{j \neq i}^M \int_0^T p_j(t) s_j^2(t) S_{ij}^2(t) dt - \frac{1}{\epsilon_i} \int_0^T p_i(t) s_i^2(t) S_{ii}^2(t) dt + \int_0^T n_i^2(t) dt \right) \geq 0 \right\} \leq O_i$$

where $t \in [0, T]$, O_i is the target OP of user i , and $i=1, \dots, M$. The probabilities in the constraint of (6.5) are very difficult to compute. Therefore, approximation using Chernoff bounds [113] can be used to evaluate the probability of failure to achieve a desired QoS requirement.

New estimation algorithms are proposed to track the position and velocity of a MS in a cellular network. They are based on Aulin's scattering model combined with the EKF, PF, and UPF estimation algorithms. Since the instantaneous electric field is a nonlinear function of the MS location and velocity, the EKF, PF, and UPF are appropriate for the estimation process. They take into account multipath propagation environment and NLOS conditions, which are usually encountered in wireless fading channels. Numerical results for typical simulations including the presence of parameters uncertainty show that they are highly accurate and consistent. The performance of the PF and the UPF estimation methods are superior to the EKF. This is due to the sensitivity of the EKF to the initial condition and Gaussian assumptions. An alternative is to use the ML estimate that employs the lognormal channel model, as the initial EKF state. The use of nonlinear models and/or non-Gaussian noise is the main explanation for the improvement in accuracy of the PF and the UPF over linear algorithms such as the EKF. These methods also excel in using inherent features of the cellular system, i.e., they support existing network infrastructure and channel signalling. The assumptions are knowledge of the channel and access to the instantaneous received field, which are obtained through channel sounding samples from the receiver circuitry. Future work will focus on

generating efficient channel estimation algorithms, to remove the assumption on partial knowledge of the channel. Work on building a pilot application to test the performance of the PF and/or the UPF in realistic conditions is on-going together with the incorporation of channel model parameters estimation algorithms.

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Vita

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