Cross-Layer Protocol Design and Performance Study for
Wideband Wireless Networks

by

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B.Sc., Xian Jiaotong University, China, 2000
M.Sc., Xian Jiaotong University, China, 2003

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University of Victoria

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ABSTRACT

This thesis presents a cross-layer design and optimization for emerging wideband wireless networks supporting multimedia applications, considering the interactions of the wireless channel characteristics, the physical and link layer protocols, and the user-perceived Quality-of-Service (QoS). As wireless channels are error-prone and broadcast in nature, both the error control mechanisms and the Media Access Control (MAC) protocols are critical for resource utilization and QoS provisioning. How to analyze, design and optimize the high-rate wireless networks by considering the characteristics of the propagation channels and wideband communication technologies is an open, challenging issue.

In this thesis, we consider two important wideband wireless systems, the Ultra-Wideband (UWB) and the Orthogonal Frequency-Division Multiplexing (OFDM) systems. First, we propose the packet-level channel models based on Finite State Markov Chains (FSMCs) for the two systems, which present the statistical properties of the propagation channels and the transmission systems. Second, by incorporating the proposed packet-level channel models, we develop analytical
frameworks for quantifying the performance of the high-rate wireless networks, combining the channel fading, physical- and link-layer error-control mechanisms and MAC protocols. Third, to mitigate the impact of channel fading and impairments, a cross-layer joint error-control mechanism is proposed. In addition, we also investigate the impact of channel fading on the video streaming applications, and propose a simple admission control algorithm to ensure QoS.

As considering the physical-layer characteristics is critical for ensuring QoS and efficiency of resource utilization, the packet-level channel models, cross-layer analytical frameworks, networking protocols and simulation methodologies proposed in this dissertation are essential for future proliferation of high-rate wireless networks.
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<td>AFD</td>
<td>Average Fade Duration</td>
</tr>
<tr>
<td>AMC</td>
<td>Adaptive Modulation And Coding</td>
</tr>
<tr>
<td>AOA</td>
<td>Angle-of-Arrival</td>
</tr>
<tr>
<td>APSD</td>
<td>Angular Power Spectral Density</td>
</tr>
<tr>
<td>ARQ</td>
<td>Automatic Repeat Request</td>
</tr>
<tr>
<td>BER</td>
<td>Bit-Error-Rate</td>
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<td>BSE</td>
<td>Body Shadowing Effect</td>
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<tr>
<td>CIR</td>
<td>Channel Impulse Response</td>
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<td>CNR</td>
<td>Carrier-to-Noise Ratio</td>
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<tr>
<td>CSI</td>
<td>Channel State Information</td>
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<tr>
<td>CTA</td>
<td>Channel Time Allocation</td>
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<tr>
<td>CP</td>
<td>Cyclic Prefix</td>
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<tr>
<td>Dly-ACK</td>
<td>Delayed Acknowledgment</td>
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<tr>
<td>DRP</td>
<td>Distributed Reservation Protocol</td>
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<tr>
<td>DS-UWB</td>
<td>Direct-Sequence UWB</td>
</tr>
<tr>
<td>DTP</td>
<td>Data Transfer Period</td>
</tr>
<tr>
<td>DVB</td>
<td>Digital Video Broadcasting</td>
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<tr>
<td>EPM</td>
<td>Equal Probability Method</td>
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<tr>
<td>ESMM</td>
<td>Exponential Stay Mobility Model</td>
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<tr>
<td>FER</td>
<td>Frame-Error-Rate</td>
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<tr>
<td>FSMC</td>
<td>Finite State Markov Chain</td>
</tr>
<tr>
<td>GoP</td>
<td>Group of Picture</td>
</tr>
<tr>
<td>HD</td>
<td>High Definition</td>
</tr>
<tr>
<td>IE</td>
<td>Information Element</td>
</tr>
<tr>
<td>IPTV</td>
<td>Internet Protocol Television</td>
</tr>
<tr>
<td>ISI</td>
<td>Inter-symbol Interference</td>
</tr>
<tr>
<td>LCR</td>
<td>Level Crossing Rate</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<td>--------------</td>
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<tr>
<td>LLC</td>
<td>Logic Link Control</td>
</tr>
<tr>
<td>MAC</td>
<td>Media Access Control</td>
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<tr>
<td>MAS</td>
<td>media access slots</td>
</tr>
<tr>
<td>MB-OFDM</td>
<td>Multiband-OFDM</td>
</tr>
<tr>
<td>MBWA</td>
<td>Mobile Broadband Wireless Access</td>
</tr>
<tr>
<td>MIFS</td>
<td>Minimum Interframe Spacing</td>
</tr>
<tr>
<td>MIMO</td>
<td>Multiple Output Multiple Input</td>
</tr>
<tr>
<td>mmWave</td>
<td>millimeter-wave</td>
</tr>
<tr>
<td>MSDU</td>
<td>MAC Service Data Unit</td>
</tr>
<tr>
<td>OFDM</td>
<td>Orthogonal Frequency-Division Multiplexing</td>
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<tr>
<td>PDP</td>
<td>Power Delay Profile</td>
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<td>PDR</td>
<td>Packet Drop Rate</td>
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<tr>
<td>PHY</td>
<td>physical</td>
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<tr>
<td>PLCP</td>
<td>Physical Layer Convergence Protocol</td>
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<td>PLR</td>
<td>packet loss rate</td>
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<tr>
<td>QoS</td>
<td>Quality-of-Service</td>
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<tr>
<td>RB</td>
<td>reservation block</td>
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<tr>
<td>RS</td>
<td>reservation slot</td>
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<td>RWMM</td>
<td>Random Waypoint Mobility Model</td>
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<tr>
<td>Rx</td>
<td>Receiver</td>
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<tr>
<td>SER</td>
<td>Symbol Error Rate</td>
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<tr>
<td>SIFS</td>
<td>Short Interframe Spacing</td>
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<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
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<tr>
<td>TDMA</td>
<td>Time Division Multiplexing Access</td>
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<tr>
<td>TM</td>
<td>Transmission Modes</td>
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<tr>
<td>Tx</td>
<td>Transmitter</td>
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<tr>
<td>UWB</td>
<td>Ultra-Wideband</td>
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<tr>
<td>UWSN</td>
<td>Underwater Sensor Network</td>
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<tr>
<td>VNET</td>
<td>Vehicular Network</td>
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<tr>
<td>WPAN</td>
<td>Wireless Personal Area Network</td>
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<tr>
<td>WLAN</td>
<td>Wireless Local Area Networks</td>
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Ruonan Zhang, Victoria, BC, Canada
DEDICATION

To my dearest wife, parents and daughter
Chapter 1

Introduction

1.1 Background and Objectives

Heterogenous communication networks enable people to communicate with each other, interact with information-processing devices, and receive a wide range of mobile services anywhere, anytime. Wireless networking is an important part of this versatile communication platform. To support multimedia services with satisfactory Quality-of-Service (QoS) is an important task for emerging wireless networks, such as video streaming distribution in residential premise or to the handheld electronic devices.

However, different from the wireline communications, the wireless systems experience error-prone unstable channels, which are affected by interference and have limited bandwidth. In addition, portable devices may have limited power supply. To provide satisfactory QoS at lower cost with better resource utilization in wireless networks is a critical, challenging task. The work reported in this dissertation is intended to develop new networking technologies for the emerging high-rate, QoS-aware wireless networks, in particular, by considering the unique characteristics of the wideband wireless channels and transmission technologies.

In this dissertation, we focus on two important high-rate wireless systems, the Ultra-Wideband (UWB) and the Orthogonal Frequency-Division Multiplexing (OFDM) systems. Our analytical frameworks and networking protocols proposed can be extended to other networks.

UWB is an appealing technology for short-range wireless communications [3] due to its high data rate (> 100 Mbps) and low transmission power (≤ −41.25 dBm/MHz). Wireless Personal Area Network (WPAN) based on UWB has been proposed to sup-
port multimedia service such as Internet Protocol Television (IPTV) in office or re-
residential buildings. The IEEE 802.15.3a standard [4] proposed by the IEEE 802.15.3
task group and the ECMA-368 [2] standard by WiMedia Alliance have defined the
enhanced Media Access Control (MAC) and error-control policies to improve QoS
provisioning for UWB-based WPANs, which have gained wide attention from both
the academia and industry. To support future killer applications and ensure their
QoS, how to quantify the system performance, design the network protocols, and fine
tune the system parameters, considering the distinct characteristics of UWB trans-
misions, is a critical, open issue.

On the other hand, for the wireless networks with wider coverage and even in
mobile environments, OFDM is a promising technology. It has been widely deployed,
such as in IEEE 802.11a/g/n Wireless Local Area Networks (WLAN), IEEE 802.16
(WiMAX) and Mobile Broadband Wireless Access (MBWA) systems, etc. However,
the wireless channels undergo time-vary and frequency-selective fading for OFDM
communications, which leads to serious reduction on the Carrier-to-Noise Ratio (CNR)
and consequently the degradation in link layer performance. Similar to the indoor
WPAN, it is also important to study and improve the OFDM-based networks in the
mobile propagation environments.

The wideband wireless channels and communication systems are much more com-
complicated than the wired or narrow-band wireless counterparts. Therefore, the objec-
tive of this thesis is to first model these emerging high-rate wireless systems at packet
level and then, based on these proposed packet-level channel models, to design and
quantify the performance of upper-layer network protocols, in order to improve the
efficiency, reliability and capacity of these wideband wireless networks.

1.2 Research Approach

Our cross-layer design approach is in conformance with the Internet layered architec-
ture, as shown in Fig. 1.1. The arrows indicate the interaction between the physical
(PHY) layer and the upper layers that we investigate.

1.2.1 Physical Layer: Packet-level Channel Model

The variations of wireless channels are caused by the motion of the wireless devices
and/or of the surrounding physical environment, or by the change of interference
Figure 1.1: TCP/IP reference model and cross-layer design problems
levels. Such fading causes the fluctuation of the transmission performance, such as bursts of packet errors. However, the physical models for the propagation channels and the transmission systems are typically too complex to be incorporated in the network protocol analysis and simulation tools. For example, the signal simulation of transmitting every packet of a video stream over the wireless channel comes at a high computation cost and a very long execution time.

As shown in Fig. 1.1, the wireless propagation channel, transmission system (de/coding, de/modulation and detection) and other technologies (such as adaptive modulation and coding, diversity, relay and cooperative communications, etc.) are encapsulated and modeled by the packet-level channel model.

The packet-level channel models should incorporate the characteristics of the realistic propagation environments and the salient features of the communication systems. They directly present the packet error stochastic process, such as the statistics of the Packet Error Rate (PER) of the real systems. The performance of upper-layer protocols (like link throughput, delay) in realistic propagation environments can be mathematically analyzed by combining the packet-level channel models with the traffic and upper-layer protocol models. In addition, since the packet transmission error sequence can be generated by the packet-level channel models with proper statistics and very low computational complexity, they provide fast simulation method for network research.

Therefore, the first topic in this dissertation is to develop the packet-level channel models for the wideband wireless systems, such as for the UWB and OFDM communication systems, which are key enabling tools for the study on upper-layer protocols and network performance.

1.2.2 Link Layer: Error-control and MAC

As shown in Fig. 1.1, the link layer consists of two sublayers, the Logic Link Control (LLC) and MAC. As wireless channels are error-prone and broadcast in nature, both the error-control mechanisms and the MAC protocols are critical for resource utilization and QoS provisioning.

To provide reliable data delivery and enhance the bandwidth efficiency, various error-control mechanisms are adopted in practical wireless systems, such as the Adaptive Modulation and Coding (AMC) in the PHY layer and the packet fragmentation and Automatic Repeat Request (ARQ) in the link layer. Error-control is particu-
larly important for the high data rate, marginal links (links with small SNR budget) in wideband wireless networks. On the other hand, the MAC protocol coordinates the network nodes to share the medium, and the network QoS also depends on the efficiency and fairness of the MAC protocols. To ensure QoS support, we need to quantify the packet loss and delay, considering the transmission technologies in the PHY layer, the channel access scheduling in the MAC sublayer and the retransmission/reordering by ARQ and fragmentation in the LLC sublayer. Interaction between these functionalities, the fading channel, and bursty traffic further complicates the network performance study and protocol optimization.

Therefore, the second research topic in this dissertation is, based on the proposed packet-level channel models, to analyze and improve the networking technologies in order to mitigate the channel fading and enhance QoS support.

1.2.3 Application: IPTV

As shown in Fig. 1.1, our third research topic is to investigate the impact of the wireless channel on the multimedia service support. As mentioned in Section 1.1, one of the key applications of high-speed wireless networks is the multimedia streaming, such as IPTV in-home distribution. With the state-of-the-art source coding at high compression ratio, the average data rates for video streams are decreasing, but the burstiness becomes even higher. In addition, the video quality is more sensitive to the packet loss and delay. A critical and challenging issue is how to ensure the stringent QoS requirement of video streaming transferred by the wireless networks over time-varying, error-prone channels.

Thus, the third topic in the dissertation is to use the proposed packet-level channel models to analyze the impact of channel fading on the video quality. Our objective is to estimate the delay and Packet Loss Rate (PLR) in order to obtain the admission region so that the QoS of the admitted video streams can be guaranteed.

1.3 Contributions

The primary contribution of this dissertation is to model, analyze and improve the emerging wideband wireless networks, particularly with the consideration of the channel characteristics. The work reported in this dissertation bridges the gap between the PHY-layer communication technologies and the upper-layer network protocols,
so we can analyze and optimize them jointly. The main contributions in the three research topics stated in the previous section are listed as follows.

### 1.3.1 Packet-level Channel Model for Wideband Systems

The packet-level models for narrow-band wireless systems using Finite State Markov Chains (FSMCs) have been proposed in [5, 6] for Rayleigh fading channels and in [7] for Nakagami-\(m\) fading channels. These models are attractive and have been widely used because they provide good approximation to the statistics of the real time-varying channel, and simplify considerably the mathematical analysis and the simulation of wireless networks. However, no such model is available for the wideband wireless systems, such as for UWB and OFDM, which makes the study and optimization of the network protocols using the wideband communications difficult and hampers the research in this promising area. Our contributions in this area are to develop the packet-level channel models for three different wideband wireless systems.

1. **Indoor UWB systems.**

Because WPANs are typically deployed in residential or office buildings, the Body Shadowing Effect (BSE) of a randomly moving person is the main factor to cause considerable fluctuation of the received Signal-to-Noise Ratio (SNR) and noticeable QoS degradation. In our work, we first derive the Angular Power Spectrum Density (APSD) (i.e., the angular distribution of the received signal power) of indoor UWB channel analytically. Then, based on the APSD, we propose an analytical approach to estimate the BSE (i.e., signal power attenuation). We also conduct practical measurements to validate the analytical results of the BSE. A packet-level channel model based on a FSMC is built for the time-varying shadowing channel with people random movement.

2. **Multi-carrier communication systems in mobile environments.**

For a multi-carrier wideband communication systems in mobile propagation environments, the channel experiences time-varying (e.g., Nakagami-\(m\) fading), frequency-selective fading. As one of the wideband communication technologies, multi-carrier modulation divides the whole bandwidth into multiple subchannels. With the bandwidth much smaller than the channel coherence bandwidth, each subchannel has flat fading. In our work, we first introduce a propagation model for multipath Nakagami-\(m\) fading channels and derive the Level Crossing
Rate (LCR) of the received SNR in the frequency domain. Then, we propose a novel FSMC to present the variation of the subchannels over the whole bandwidth based on the derived LCR. By combining the time- and frequency-domain FSMCs, a complete model for the multi-carrier system is developed.

3. **OFDM systems in mobile environments.**

   Because OFDM is a special multi-carrier communication technology (e.g., the subchannels are overlapped, the de/modulation are implemented by DFT/IDFT, etc.) and widely adopted, we propose a novel packet-level model for OFDM systems by considering its unique characteristics. We derive the statistics of the frequency response (i.e., the amplitude distribution and LCR) of the frequency-selective, Nakagami-\(m\) fading channels. Then, a two-dimensional FSMC for OFDM systems is built to represent the status of all the subchannels and the Bit Error Rate (BER) of the OFDM transmission.

### 1.3.2 Joint Error-control for Wireless Networks over Fading Channels

As mentioned in Section 1.2.2, we consider the error-control mechanisms of AMC in the PHY layer and the ARQ and fragmentation in the link layer. Some recent works have focused on the cross-layer design combining AMC and ARQ and studied the queueing behavior over flat-fading channels (e.g., [8, 9, 10]). There are several limits on these works. First, the MAC protocol is not considered and it is assumed that the node has full channel access. Second, by assuming a separate feedback channel, the channel state information (CSI) to do transmission mode (TM) selection is always available and accurate.

However, the nodes in practical wireless networks usually have to share the channel using MAC protocols. The channel access opportunities are usually obtained after a relatively long waiting or competing time, which introduces significant delay in both queueing and delivery of a packet. Furthermore, the transmitter has to use the CSI acquired from current frame exchange to decide the TM for the next transmission opportunity, which may not be accurate due to channel variations and the relatively long access interval. Therefore, the effectiveness of AMC may be degraded. In addition, the packet fragmentation, which is especially important for high-rate wireless networks with small SNR budget, has not been studied yet. How to optimize
the error-control mechanisms in both layers jointly for high-rate wireless networks, considering the MAC protocols and fading channel, is an important and challenging issue. Our contributions related to this topic are as follows.

1. By considering the arbitrary reservation-based MAC (the reserved time slots of one user can be arbitrarily distributed in one scheduling cycle), we propose a general 3-dimensional Markov model to quantify the sender’s queueing behavior, which incorporates the error-control mechanisms, channel access scheduling and the packet-level channel model.

2. We derive the statistics to deliver a fragmented packet over the fading channel using Delayed-Acknowledgment (Dly-ACK) ARQ scheme, and obtain the average service time.

3. A cross-layer optimization problem for joint AMC and fragmentation is formulated, and a feasible, sub-optimal joint-adaptation strategy is proposed.

1.3.3 Admission Control for IPTV Streaming over Fading Channels

Video performance and admission regions in wired and wireless networks have been heavily investigated in the literature (e.g., [11, 12, 13, 14, 15, 16]). The traditional approach is based on the fluid-flow models of the video sources, to derive the queueing delay and buffer overflow probability. To study the video performance over high-rate wireless networks, for example, the UWB-based WPANs, we can apply the existing approach by combining the fluid-flow source model and the proposed packet-level channel models. But high computation complexity will be requested to solve a set of big transition matrices for both the time-varying video source and channel. Therefore, this approach may not be feasible in real-time implementation for on-line control functions, such as admission control.

Our contribution related to this topic is, by considering the characteristics of the video source and UWB shadowing channel, to propose a simple and yet accurate algorithm to estimate the upper-bound of the Packet Loss Rate (PLR) for multiplexed IPTV steam over indoor WPANs. Then, since the delay is bounded by the pre-determined buffer size, the developed algorithm can be used as a feasible admission control for IPTV in-home distribution.
1.4 Dissertation Outline

The rest of this dissertation is organized as follows.

Chapter 2 presents the packet-level channel model for indoor UWB systems. First, we derive the APSD of the UWB signal based on the standard 3a channel model [17], and the analytical APSD is compared with the measurement results. Second, the BSE in terms of total power attenuation is estimated using the APSD and the channel reciprocity property. Third, in order to evaluate the system performance with BSE, a numerical method to estimate the PER for given received SNR is presented. Fourth, the FSMC based packet-level channel model is proposed. The channel states are defined according to the received SNR, and the state transition probabilities are obtained based on two mobility models for indoor people movement. Finally, the analytical results of BSE are validated by our practical measurements and, as an example, the numerical results of the channel model with particular system configurations (e.g., transceiver distance, average people moving speed, etc.) are presented.

Chapter 3 focuses on the packet-level channel model for the multi-carrier wideband communication systems in mobile environments. First of all, we define a waveform propagation model for the multipath Nakagami-$m$ fading channel. Then, the LCR of signal amplitude in the frequency domain is introduced and derived based on the propagation model. A first-order FSMC is proposed using the derived LCR which generates the states of one subchannel (SNR interval) according to the state of the neighboring subchannel. Finally, a complete packet-level channel model is built which combines the time-domain packet-level channel model for Nakagami-$m$ fading and the proposed frequency-domain channel model together. The simulation results of the subchannels generated by the proposed model are given to verify that the correlation between the subchannels and the Nakagami-$m$ distribution of each subchannel are maintained.

Chapter 4 presents the packet-level channel models for OFDM systems in mobile environments. We first briefly describe the OFDM system model and the frequency response of the frequency-selective Nakagami-$m$ fading channel. Second, the statistics of the amplitude of the frequency response are derived, including the distribution and LCR. Third, we develop a packet-level channel model based on a two-dimensional FSMC. We define a methodology to map the received SNR of the subchannels into a finite number of states which result in different BER. Channel coding and interleaving are also considered in evaluating PER. Second, the state transition probabilities are
Chapter 1. Introduction

derived using the obtained frequency response LCR. Simulation results are given and have verified that the statistics of the BER presented by our model are consistent with those of waveform simulations.

Chapter 5 presents the performance analysis and optimization of the joint error-control and MAC over fading channels. We first briefly overview the error-control mechanisms (including AMC of Multiband-OFDM technology, ARQ and fragmentation) and reservation-based MAC defined in ECMA-368 standard [2]. Second, the general queueing model to quantify the queueing delay and Packet Drop Rate (PDR) (due to buffer overflow) is developed, which incorporates the packet-level channel model, error-control mechanisms and MAC protocol. Third, the transmission process of a fragmented packet over error-prone channel is studied and the average delivery delay is derived. Fourth, we evaluate the throughput by combining AMC and fragmentation, and a cross-layer optimization problem is formulated. Then, we propose a joint-adaptation mechanism which is simple to implement and has near-optimal performance. Finally, the simulation results validate the analytical models and compare the performance of the three different error-control mechanisms.

Chapter 6 presents the analysis of the impact of fading channel on the application-layer QoS metrics for multimedia services. We first overview the standard H.264 coded video streams and the IPTV indoor distribution in the context of IEEE 802.15.3 WPAN [4]. Based on the fluid-flow model for video source and the packet-level model for UWB shadowing channel, we derive the upper-bound of the Packet Loss Rate (PLR) with given buffer size and delay bound for multiplexed IPTV streams. The admission region can be obtained according to the PLR to ensure the QoS (i.e., the PLR should be below certain threshold). Finally, the simulation results provided illustrate that the PLR upper-bound is tight when the load of the network is close to the admission region and thus can be used to do admission control due to its low computational complexity.

Chapter 7 concludes this dissertation and suggests the future research directions.

1.5 Bibliographic Notes

Most of the works reported in this dissertation have appeared in research papers. The works in Chapter 2 and Appendix A have been published in [18, 19, 20]. The work in Chapter 3 has been published in [21], and those in Chapter 4 and Appendix B have
appeared in [22]. The work in Chapter 5 has appeared in [23, 24, 25]. The work in Chapter 6 has been published in [26].
Chapter 2

A Packet-Level Model for Indoor UWB Channels

2.1 Motivation and Contributions

As described in Chapter 1, wireless UWB technologies are well suited for WPANs in office or residential buildings to support multimedia services. Because the transmission power has been strictly regulated by the FCC emission mask [27], the range and robustness of UWB communications depend on efficient energy collection from the significant paths. However, in such intensive multipath propagation environments, people moving in the proximity of the transceivers may frequently penetrate and obstruct the significant paths, like the Line-of-Sight (LOS). Signal propagation measurements of a fixed UWB link in [28, 29, 30, 31, 32] have revealed that the BSE can induce the received signal power attenuation by up to 8 dB if both transceivers employ omni antennas, or up to 15 dB with directional antennas. Therefore, although the UWB transceivers in an indoor environment are typically stationary (e.g., home gateway router, TV set, computers, etc.) the random motion of people can cause significant fluctuations of the received SNR and even totally interrupt the data transfer, which should be considered properly in designing UWB systems and network protocols. For example, the channel estimation techniques depend on the temporal correlations of the Channel Impulse Response (CIR). The channel fading can increase considerably the packet loss rate, queuing/transmission delay and delay jitter, which eventually affect the user’s perceived QoS.

Although the physical properties of BSE have been studied extensively at the
signal level, they have not been investigated or modeled theoretically. It is important to build a simple, packet-level channel model which can capture the temporal variation of UWB channels caused by the stochastic BSE process. The main contributions of this chapter are:

1. Based on the standard 3a channel model [17], We derive the Angular Power Spectral Density (APSD) of the indoor UWB CIR in closed-form.

2. We develop an analytical model to estimate the BSE using the derived APSD and the channel reciprocity property, and validate the model by measurements.

3. Based on two different two-dimensional random walk mobility models, we build a packet-level channel model using FSMCs for the time-varying shadowed channel.

2.2 Related Work

In the literature, the impact of moving people on a fixed UWB link has been measured extensively. Reference [28] and [29] illustrated the received power attenuation by one or several people in a corridor or a square conference room, respectively. In [30] and [31], the BSE was measured when a person moved along a line perpendicular to the LOS and fully or partially blocked the LOS. In [32], Ghaddar et al. conducted the continuous wave measurements with the presence of an obstacle (a person or a metallic cylinder) moving parallel to or perpendicularly crossing the LOS.

These measurements have revealed the following key observations: 1) the shadowing effect (power attenuation) depends on the position of the obstacle, especially its angular location and distance from the antennas, 2) if the person is moving outside the proximity of UWB transceivers (i.e., not obstructing the significant paths), the CIR and the received power do not have substantial variation, and 3) a human body may be approximated by a conducting circular cylinder, due to the strong correlation between the shadowing effects of a human body and those of a conducting cylinder.
2.3 The Angular Power Spectral Density of UWB Signals

Shadowing on a UWB channel occurs when a certain range of Angle-of-Arrival (AOA) of the signal is obstructed by an obstacle. Thus, the remaining received power or the BSE (in terms of power attenuation) can be estimated based on the angular distribution of the incident power and the AOAs which are blocked. The APSD refers to the power density received at a certain azimuth $\theta$, which presents the distribution of power versus the AOA. In [33] and [34], the measurements of the spatial propagation of indoor UWB channels have shown that the AOAs of the incident rays\(^1\) are also clustered (like the time-of-arrival characteristics) and the arrivals of rays within a cluster have a Laplacian distribution. However, analytical study of the UWB channel APSD and the BSE has not been reported in the literature. In this section, we derive the APSD in closed-form based on the standard 3a model and develop a simple modified Laplacian distribution to approximate the APSD. Our analytical results will be compared with the measurements in [33] and [34].

2.3.1 3a UWB Channel Model

The CIR defined in the 3a model [17] is a stochastic process, composed of a series of delayed and attenuated multipath components:

$$h(t) = X \sum_{l=0}^{\infty} \sum_{k=1}^{\infty} a_{k,l} \delta(t - T_l - t_{k,l}),$$

(2.1)

where $a_{k,l}$ denotes the gain of the $k$-th ray in the $l$-th cluster, $T_l$ is the delay of the $l$-th cluster, $t_{k,l}$ is the delay of the $k$-th ray in the $l$-th cluster relative to the cluster arrival time. $X$ represents the log-normal attenuation with zero mean and variance of $\sigma^2_X$. The structure of the CIR is shown in Fig. 2.1.

The cluster arrivals and the ray arrivals within each cluster are modeled as Poisson processes with rate of $\Lambda$ and $\lambda (\lambda > \Lambda)$, respectively. The delay of the first cluster is set as $T_0 = 0$. Because the time intervals between the cluster arrivals, $T_i - T_{i-1}$, are exponentially distributed, the cluster arrival time $T_i = \sum_{i=1}^{I}(T_i - T_{i-1})$ has the distribution of $\text{Gamma}(l, \Lambda), l = 1, 2, \cdots$. Similarly, the ray arrival time within a

\(^1\)A ray refers to a single propagation path and corresponds to a multipath component in the continuous-time CIR in the 3a model.
Figure 2.1: Multipath profile model of indoor UWB channels.
cluster \( t_{k,l} = \sum_{i=1}^{k}(t_{i,l} - t_{i-1,l}) \) has the distribution of \( \text{Gamma}(k, \lambda), k = 1, 2, \ldots \). The total delay of the \( k \)-th ray in the \( l \)-th cluster is \( \tau_{k,l} = T_l + t_{k,l} \).

The multipath gain coefficients \( a_{k,l} \) are modeled as: 
\[
20\log_{10}(|a_{k,l}|) \sim N(\mu_{k,l}, \sigma_1^2 + \sigma_2^2).
\]
The average power delay profile, \( E[|a_{k,l}|^2] \), exhibits double exponential decay
\[
\Omega_{k,l} = E[|a_{k,l}|^2] = \Omega_0 e^{-T_l/\Gamma} e^{-t_{k,l}/\gamma},
\]
where \( \Omega_0 \) is the mean energy of the first path of the first cluster. The total energy of the multipath components is normalized such that \( \sum_{l=0}^{\infty} \sum_{k=1}^{\infty} |a_{k,l}|^2 = 1 \).

The constant parameters (\( \Lambda, \lambda, \Gamma, \gamma, \sigma_1, \sigma_2, \text{ and } \sigma_X \)) are defined in the 3a standard [17] for four propagation scenarios (CM1 \( \sim \) CM4). CM1 are used throughout this work because it is the scenario with the LOS existing between the UWB transceivers.

Notice that \( X \) in (2.1) gives a log-normal distributed power attenuation to each CIR realization to evaluate the performance of alternative UWB PHY systems. However, such definition does not present the realistic shadowing process in indoor environments, especially the BSE. Our work provides a suitable way to determine the shadowing term \( X \) instead of using an independent log-normal distributed random variable and reveals not only the distribution of the power attenuation but also the higher-order statistics of the channel variation (e.g., the time-correlation property).

### 2.3.2 AoA Distribution and Power Density of the Rays

The AoA of each ray in the CIR is a random variable, depending on the propagation environments and the movement of scatters. The measurements in [33] and [34] have both demonstrated that the arrival azimuths of the rays are clustered and the strongest cluster is almost always concentrated in the LOS direction while the other clusters are uniformly distributed over \( [-\pi, \pi] \). The rays of the strongest angular cluster, which arrive at the receiver within a limited angular range in the LOS direction, have small excess delay (the delay with respect to the LOS) and large energy magnitude due to relatively short propagation paths and less reflections. On the other hand, the rays of the other small angular clusters are uniformly distributed over \( [-\pi, \pi] \). Their large AoA is related to more reflections and scattering, resulting in large excess delay and small energy magnitude. Therefore, the AoA of a ray can be modeled as being uniformly distributed over a certain angular spread which depends on the excess delay [35]. The probability density function (PDF) of the incident angle
with respect to the LOS, $\theta$, is

$$
  f_\theta(x|\tau) = \begin{cases}
    \frac{\tau_m}{2\pi} \text{rect} \left( \frac{\tau_m}{2\pi} x \right), & 0 < \tau \leq \tau_m, -\pi \leq x < \pi \\
    \frac{1}{2\pi}, & \tau > \tau_m, -\pi \leq x < \pi
  \end{cases}
$$

(2.3)

where $\tau$ is the total delay of the ray and $\text{rect}(\cdot)$ is the rectangular function. The parameter $\tau_m$ should be chosen such that the variance of the APSD is consistent with realistic measurements. From (2.3), the angular spread of the $k$-th ray in the $l$-th cluster is $[-\phi_{k,l}/2, \phi_{k,l}/2]$, where

$$
  \phi_{k,l} = \begin{cases}
    \frac{t_{k,0} 2\pi}{\tau_m}, & l = 0, 0 \leq t_{k,0} \leq \tau_m \\
    \frac{2\pi}{\tau_m}, & l = 0, t_{k,0} > \tau_m \\
    \frac{2\pi}{\tau_m}, & l \geq 1.
  \end{cases}
$$

(2.4)

Consequently, the angular power density of the ray can be obtained as $P_{k,l} = |a_{k,l}|^2/\phi_{k,l}$. Because $|a_{k,l}|^2$ is a random variable with the mean dependent on its total delay given by (2.2), the average received power density conditioned on $\tau_{k,l}$ can be obtained from (2.2) and (2.4) as

$$
  \overline{P_{k,l}} = \mathbb{E}[P_{k,l}|\tau_{k,l}] = \begin{cases}
    \mathbb{E}[|a_{k,0}|^2 \tau_m] = \frac{\tau_m \Omega_0}{2\pi} \frac{1}{t_{k,0}} e^{-\frac{t_{k,0}}{\tau}}, & l = 0, 0 < t_{k,0} \leq \tau_m \\
    \mathbb{E}[|a_{k,0}|^2] = \frac{\Omega_0}{2\pi} e^{-\frac{t_{k,0}}{\tau}}, & l = 0, t_{k,0} > \tau_m \\
    \mathbb{E}[|a_{k,l}|^2] = \frac{\Omega_0}{2\pi} e^{\frac{\tau}{\tau_m}} e^{-\frac{t_{k,l}}{\tau}}, & l \geq 1.
  \end{cases}
$$

(2.5)

Note that because the AOA of the LOS component has no excess delay ($t_{1,0} = 0$) and no angular spread ($\phi_{1,0} = 0$), its energy should be directly added (using a Delta function) to the power density at azimuth of $0^\circ$.

### 2.3.3 The APSD of UWB CIR

APSD is the composite angular power distribution, i.e., the total energy incident at a certain azimuth $\theta$. Since the UWB CIR is composed of a series of delayed and attenuated rays as described in (2.1), the APSD at $\theta$ consists of the energy contribution from all rays whose AOA spread is larger than or equal to $2\theta$ (i.e. $\theta \in [-\phi_{k,l}/2, \phi_{k,l}/2]$). The APSD of a CIR realization given the cluster delay and ray
delay can be expressed as

\[ P(\theta) = \sum_{\substack{\phi_{k,0} \geq 2|\theta|, t_{k,0} \leq \tau_m \atop A}} T_{k,0} + \sum_{\substack{t_{k,0} \geq \tau_m \atop B}} T_{k,0} + \sum_{l \geq 1} P_{k,l}, \tag{2.6} \]

where the summation A is the angular power density of the rays in the first cluster whose delay is less than \( \tau_m \) but angular spread is larger than \( 2\theta \). Summations B and C represent the power contribution from the other rays in the first cluster and the rays in the other clusters, respectively, whose angular spread covers all angles as shown in (2.4).

From (2.4), the boundaries of the summation A can be transformed as \( \frac{|\theta|}{\pi} \tau_m \leq t_{k,0} \leq \tau_m \). Because \( t_{k,0} \) has the distribution of Gamma\((k, \lambda)\) as described in Section 2.3.1, we use the expected value of \( E[t_{k,0}] = k/\lambda \) as the approximation of \( t_{k,0} \). Then the boundaries of the summation can be obtained as \( k_0 \leq k \leq \lfloor \tau_m \lambda \rfloor \), where \( k_0 = \max\{\lceil \frac{\tau_m \lambda}{\pi} |\theta| \rceil, 2\}, \) because, as mentioned earlier, \( k = 1 \) corresponds to the LOS component and it is excluded from the summation. \( \lceil \cdot \rceil \) and \( \lfloor \cdot \rfloor \) are the ceiling and floor functions because \( k \) is an integer. From (2.5) and (2.6), the average APSD (excluding the LOS component) with respect to the delay terms can be obtained by (see Appendix A.1 for derivation)

\[ \bar{P}(\theta) = \frac{\Omega_0}{2\pi} \tau_m \lambda \sum_{k_0} \frac{\rho^{k-1}}{k-1} A + \frac{\Omega_0}{2\pi} \frac{\rho^{\tau_m \lambda}}{1 - \rho} B + \frac{\Omega_0}{2\pi} (\Gamma \Lambda)(\gamma \lambda) C, \tag{2.7} \]

where \( \rho = \frac{\lambda \gamma}{1 + \lambda \gamma} \). The parameters \( \lambda, \Lambda, \gamma, \Gamma \) are given in the 3a standard [17] or can be measured for a specific indoor environment. \( \Omega_0 \) should be chosen such that the total power contained in the multipath components is normalized to one. Because \( h(t) \) is a stochastic process, \( \Omega_0 \) is calculated by considering the average total power of the CIR, as (see Appendix A.2 for the derivation)

\[ \Omega_0 = \frac{1}{\gamma \lambda (1 + \Gamma \Lambda)}. \tag{2.8} \]

From (2.2), \( \Omega_0 \) is the energy of the first ray in the first cluster (LOS component) and hence should be added to the power density at \( 0^\circ \). From (2.7) and (2.8), the
average APSD is

\[
\overline{P(\theta)} = \begin{cases} 
\overline{P(0)} + \frac{1}{(\gamma\lambda)(1+\Gamma\Lambda)}, & \theta = 0 \\
\overline{P(\theta)}, & 0 < |\theta| \leq \pi.
\end{cases}
\] (2.9)

### 2.3.4 Comparison with Simulation and Measurements

Totally 40 CIR realizations are generated with the 3a CM1 model and the APSD of each CIR is calculated. \( \tau_m = 14 \) nsec is chosen such that the standard deviation of the angular distribution is 31°, which is the average value of the measurements in [33, 34]. The averaged APSD is shown in Fig. 2.2. Using the parameters for CM1 [17] (\( \lambda = 2.5/\text{nsec}, \Lambda = 0.0233/\text{nsec}, \gamma = 4.3 \) and \( \Gamma = 7.1 \)), the analytical result of APSD from (2.9) is also shown in the figure. It can be seen that the analytical estimation is quite accurate.

The measurements in [33] and [34] found that the distribution of the relative arrival angles of the signal energy in one cluster was best fit to the Laplacian density of

\[
p(\theta) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{\sqrt{2}}{\sigma} |\theta|},
\]

where the standard deviation \( \sigma \) varies from 25° to 37° with various environments. Because the shape of the APSD is determined by the energy distribution of the strongest angular cluster (in the LOS direction), it should be similar to a Laplacian distribution, while there is a power floor over all angles contributed from the other clusters (uniformly distributed from \(-\pi\) to \(\pi\)). This power floor is expected because when we use omni-directional antennas in the closed spaces like the indoor environments, we should be able to received some energy over all the angles. In (2.7), terms \( \bar{B} \) and \( \bar{C} \) represent the energy contributed to all angles. Based on [33, 34], we use the modified Laplacian distribution of

\[
p'(\theta) = \frac{1}{D} \left[ \frac{1}{\sqrt{2\pi} \sigma} \exp(-\frac{\sqrt{2}}{\sigma} |\theta|) + \bar{B} + \bar{C} \right]
\]

to represent the measurement results. \( D \) is used to normalize \( p'(\theta) \) such that \( \int_{-\pi}^{\pi} p'(\theta) d\theta = 1 \). We get

\[
p'(\theta) = ae^{-\frac{\sqrt{2}}{\sigma} |\theta|} + b,
\] (2.10)

where \( a = \frac{1}{1+2\pi(B+C)} \frac{1}{\sqrt{2\pi}} \) and \( b = \frac{\bar{B}+\bar{C}}{1+2\pi(B+C)} \).

The modified Laplacian distribution with \( \sigma = 31\)° is also shown in Fig. 2.2. Constants \( \bar{B} \) and \( \bar{C} \) are calculated from (2.7) with the parameters from the 3a CM1 model as mentioned earlier. Fig. 2.2 illustrates that the analytical result is close to the Laplacian distribution, which shows a good match of the analytical approximation to the realistic measurements.
Figure 2.2: Comparison of analytical, simulation and measurement results of APSD
2.4 Body Shadowing Effect on UWB Channels

We investigate the shadowing process of a UWB channel: a single scatterer, normally a person, is moving around in the area between UWB transceivers and thus obstructing some significant paths. The body is modeled as a cylinder with radius \( r = 30 \text{ cm} \) and obstructs a certain angular range of AOA, over which the transmitted power cannot reach the receiver, as shown in Fig. 2.3.

Let the Receiver (Rx) be located at the origin, the Transmitter (Tx) at the point of \((D,0)\) and the moving person at \((x,y)\), as shown in Fig. 2.3. From the Rx’s point of view, the angular range being obstructed can be obtained by \(\theta_1 - \theta_2\) where \(\theta_1 = \arctan(y/x) + \arcsin(r/\sqrt{x^2 + y^2})\) and \(\theta_2 = \arctan(y/x) - \arcsin(r/\sqrt{x^2 + y^2})\). The remaining power of the CIR can be estimated using the APSD given in (2.9) or the modified Laplacian distribution in (2.10) for a simpler approximation. If the latter is used, the remaining received power can be obtained as

\[
E_r(\theta_1, \theta_2) = 1 - \int_{\theta_2}^{\theta_1} p'(\theta) d\theta = \begin{cases} 
1 - \frac{ab}{\sqrt{2}} (e^{-\frac{\sqrt{2}}{a} \theta_2} - e^{-\frac{\sqrt{2}}{a} \theta_1}) - b(\theta_1 - \theta_2), & \theta_2 \geq 0 \\
1 - \frac{ab}{\sqrt{2}} (2 - e^{-\frac{\sqrt{2}}{a} \theta_1} - e^{-\frac{\sqrt{2}}{a} \theta_2}) - b(\theta_1 - \theta_2), & \theta_1 \geq 0, \theta_2 < 0 \\
1 - \frac{ab}{\sqrt{2}} (e^{-\frac{\sqrt{2}}{a} \theta_1} - e^{-\frac{\sqrt{2}}{a} \theta_2}) - b(\theta_1 - \theta_2), & \theta_1 < 0,
\end{cases}
\]

(2.11)

where the total energy of the CIR is normalized to 1. Given the person’s position
\( (x, y) \), the total power attenuation (dB), which is the BSE on the Rx antenna, is

\[
\chi_r(x, y) = 10 \log_{10} [E_r(\theta_1, \theta_2)].
\]

(2.12)

Next, we use the channel reciprocity property to evaluate the BSE on the Tx antenna. The reciprocity principle refers to that if the link between the transceivers is reversed (from Rx to Tx) and operates on the same frequency band, the CIR of the reversed channel between the two antennas should be the same as the original link. This is because the electromagnetic waves traveling in both directions will undergo the same physical perturbations (i.e., reflection, refraction, diffraction, etc.).

Reciprocity for UWB channels was first investigated by Qiu et al. in [36, 37] with a baseband UWB pulse channel sounder. Since practical UWB devices are bandpass systems meeting the FCC 3.1 \( \sim \) 10.6 GHz spectrum mask, He [38, 39] examined the reciprocity in both baseband and RF bandpass channels. When the carrier frequency is shifted from 4 to 8 GHz and the distance is increased from 2 to 8 m, the correlation coefficients between the CIRs of the forward and reverse links are always close to or larger than 95%. The results demonstrate that the reciprocity does exist in the baseband and passband, LOS and NLOS indoor UWB channels, and it appears to be distance independent and frequency independent.

Based on the reciprocity of UWB channels, we have the following two propositions:

**Proposition 1:** When the person is standing at symmetric positions with respective to the Tx and Rx, the BSEs on the received power are the same.

To compare the BSE for the obstructing positions symmetric with respective to the perpendicular line crossing the mid-point of LOS, i.e., at \((x, y)\) and \((D - x, y)\), we can suppose that the person does not move but we switch the Tx and Rx. Then, according to the channel reciprocity theorem, the CIR and the total received power will be the same. Therefore, obstructing position being close to the Rx or the Tx is equivalent. Further, we can get the second proposition.

**Proposition 2:** From the view point of the Rx, the angular distribution of the transmitted signal power from the Tx, which can be captured by the Rx, also has the same APSD as in (2.9).

Throughout our work we use omni-directional antennas that have circular transmission patterns. However, it can be expected that the power transmitted along the LOS path has higher percentage to be received due to less path loss. Since we are studying the BSE on a given link, we only consider the power that is captured by
the receiver, which should have the highest density along the LOS path and decrease gradually on other directions if no shadowing exits. Again, based on the channel reciprocity property, we can obtain Proposition 2. Also, this proposition results in a symmetric BSE, which is consistent with Proposition 1.

To estimate the shadowing effect on the Tx antenna, as shown in Fig. 2.3, the angular range being blocked is \( \theta_3 - \theta_4 \), where \( \theta_3 \) and \( \theta_4 \) can be obtained by similar geometric calculations. According to Proposition 2, the remaining, un-obstructed transmission power can be obtained as \( E_t(\theta_3, \theta_4) \) from (2.11). Finally, by superimposing the shadowing effect on both antennas, we can get

\[
\chi(x, y) \text{ (dB)} = 10 \log_{10} \left[ E_r(\theta_1, \theta_2) \right] + 10 \log_{10} \left[ E_t(\theta_3, \theta_4) \right]. \tag{2.13}
\]

To visualize the BSE caused by a person, we assume that the distance between the UWB transceivers is \( D = 4.5 \) m as an example. The contours of the BSE (power attenuation in dB) when the person stands at different positions between them, calculated from (2.13), are plotted in Fig. 2.4. The \( x \)-axis and \( y \)-axis represent the obstructing position.

### 2.5 FER Estimation with the Body Shadowing Effect

The performance of the Multiband (MB)-OFDM UWB system [1] is investigated in this section, but the approach can be readily extended to other UWB PHY alternatives like Direct-Sequence (DS)-UWB. Due to the frequency-selective fading, the instantaneous received bit-energy and SNR of different subcarriers in MB-OFDM systems are random. The average received SNR, \( E_b/N_0 \), is defined as the ensemble average of the SNR of all subcarriers, which is determined by the transmitted power, path loss, implementation loss, antenna gain and shadowing.

#### 2.5.1 Large-scale Fading

When the distance between the UWB transceivers is \( D \) and there is no shadowing, the average SNR (averaged over the small-scale fading) is given by the link budget as [17, 1]

\[
\gamma(D) \text{ (dB)} = P_T - L(D) - N - N_F - I + X, \tag{2.14}
\]
Figure 2.4: The contours of the BSE with a person moving on the 2-dimensional plane ($D = 4.5$ m).
where $P_T, L(D), N, N_F$ and $I$ are the transmission power, path loss, thermal noise per bit, system noise figure and implementation loss, respectively, in dB. Their definitions and values can be found in [1]. $X$ is the total channel gain depending on different propagation environment, as defined in the $3a$ model in Section 2.3.1.

The BSE imposes attenuation on the total received power which can be regarded as large-scale fading of the indoor UWB channels (similar to the shadowing effect for narrow-band channels). So BSE causes the variation of the local mean around the pathloss. The average received SNR when a person is standing at $(x, y)$ can be obtained by

$$
\gamma'(D, x, y) \text{ (dB)} = \gamma(D) + \chi(x, y),
$$

where $\chi(x, y)$ is from (2.13).

### 2.5.2 Frame-error-rate Estimation

Because of the frequency-selective fading, the instantaneous SNR and Bit-Error-Rate (BER) of different subcarriers are random. The presence and movement of the obstacle can also cause the variation of the multipath profile. However, as shown in the system proposal [1], the Frame-Error-Rate (FER) of MB-OFDM on the random realizations of the CIRs are consistent and the performance variation is primarily due to the large-scale fading (the shadowing). This is because the MB-OFDM system has been designed to be robust against multipath, frequency-selective fading by utilizing the interleaving, channel coding, and frequency/time diversity schemes. Since the FER is mainly determined by the path loss and shadowing, we estimate the FER and define the channel states based on the average SNR.

Here, we use the simulation results of the 90th percentile FER performance provided in the MB-OFDM proposal [1] and adopt the numerical method in [40] to obtain the closed-form approximation. The FER (with payload length of 1024 bytes) [1] of 110 Mbps MB-OFDM links over $3a$ CM1 channels is plotted in Fig. 2.5. The observation suggests that we can split the FER curve into three segments, and each segment is fitted with an exponential curve (straight lines on the semi-log graph). Thus, the FER, $\varepsilon$, can be expressed as

$$
\varepsilon(\gamma') = 10^{a_i \gamma' + b_i},
$$

where $\gamma'$ is the average received SNR. The coefficients, $a_i$ and $b_i$, for each segment are obtained separately using linear regression and are listed in Table 2.1. As shown
in Fig. 2.5, the fitted curve is very close to the actual FER values.

The link budget analysis above (the available received average SNR with path loss, noise, implementation loss, shadowing, etc.) reveals the following observations. If the UWB transceivers are close enough or use low data rate Transmission Modes (TMs), the UWB system may have sufficient link margin to compensate for the additional channel loss caused by BSE. However, if the distance is large or high data rate TMs are used, there is no sufficient link margin and the link performance will degrade significantly with body shadowing.

### 2.6 FSMC for UWB Channels with Body Shadowing

In this section, we consider that a person randomly enters, moves around and exits the region between the UWB transceivers. Because the FER is dominated by the large-scale fading, we build a channel model based on the temporal fluctuation of the average SNR which is affected by the stochastic BSE. Then, the average FER and throughput of each channel state is calculated according to the obstructing zone.

#### 2.6.1 Markov Model Design

The average received SNR varies within a range when the person moves between the UWB transceivers due to the BSE. For example, when the distance between the transceivers is 7 m and a person stands at different positions, the contours of the average received SNR calculated from (2.15) are shown in Fig. 2.11 in Section 2.7.3.

The SNR values on the $N$ contour lines are denoted as $\Gamma_n, n = 1, 2, \ldots, N$ and $\Gamma_{n+1} < \Gamma_n$. These contour lines divide the whole region into $N + 1$ zones. The zone between the two boundary contours of $\Gamma_n$ and $\Gamma_{n+1}$, denoted as $Z_n$, corresponds to the SNR interval of $[\Gamma_{n+1}, \Gamma_n)$ which is defined as the $n$th channel state $S_n, n = 1, 2, \ldots, N - 1$. The zone encompassed by the $N$th contour line is $Z_N$, corresponding to the state $S_N$. $S_N$ has the severest shadowing effect with the SNR interval of $[\Gamma_{N+1}, \Gamma_N)$ where $\Gamma_{N+1}$ is the minimum received SNR. In addition, we define state $S_0$ corresponding to the zone outside the most exterior contour line, $Z_0$, which has the SNR interval $[\Gamma_1, \Gamma_0)$ where $\Gamma_0 = \gamma(D)$ is determined from (2.14). State $S_0$ represents when there is no person standing in the vicinity of the system.
Figure 2.5: FER of MB-OFDM systems in the CM1 channel environment (data rate: 110 Mbps; payload size: 1024 bytes) (− ⋄ −: simulation results [1]; − −: linear regression approximation)

Table 2.1: Coefficients and splitting points of FER fitting curves

<table>
<thead>
<tr>
<th>Segments</th>
<th>SNR range (dB)</th>
<th>$a_i$</th>
<th>$b_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0 ∼ 3.56</td>
<td>-0.0378</td>
<td>0.1041</td>
</tr>
<tr>
<td>2</td>
<td>3.56 ∼ 4.15</td>
<td>-0.4657</td>
<td>1.6294</td>
</tr>
<tr>
<td>3</td>
<td>4.15 ∼ 5.84</td>
<td>-0.9769</td>
<td>3.7547</td>
</tr>
</tbody>
</table>
The average FER of channel state $S_n$ can be obtained as

\[
\varepsilon_n = \begin{cases} 
\varepsilon \left[ \gamma(D) \right], & n = 0 \\
\frac{1}{A_n} \int_{(x,y) \in Z_n} \varepsilon \left[ \gamma'(D, x, y) \right] \, dx \, dy, & n = 1, 2, \ldots, N 
\end{cases}
\] (2.17)

where the FER $\varepsilon(\cdot)$ is given by (2.16), the SNR $\gamma(D)$ and $\gamma'(D, x, y)$ are given by (2.14) and (2.15), respectively, and $A_n$ is the area of the zone $Z_n$. Furthermore, the average throughput of state $S_n$ can be approximated as

\[
\bar{H}_n = (1 - \varepsilon_n)H, \quad n = 0, 1, \ldots, N
\] (2.18)

where $H$ (Mbps) is the link throughput without frame transmission error given in the MB-OFDM proposal [1].

Because the channel states correspond to the spatial zones and the person can only walk into adjacent zones from the current one, the shadowing process is a birth-death process with state transitions only to adjacent states. Thus, we construct a packet-level channel model using a continuous-time first-order FSMC for the shadowed UWB channels, as shown in Fig. 2.6.

### 2.6.2 State Transitions based on ESMM

The transition rates between the states are determined by the area of the zones and the person’s mobility. Since people typically move in unpredictable ways, stochastic mobility models have to be used to mimic the random walk in practice, such as those in [41, 42] for different specific scenarios. In this section, we use a simple model, named Exponential Stay Mobility Model (ESMM), which assumes that the duration for the person to stay inside a zone is exponentially distributed and the average duration is proportional to the area of the zone. Using ESMM, we can obtain the closed-form transition rates. A more complicated mobility model is considered in the
Chapter 2. A Packet-Level Model for Indoor UWB Channels

First, the contour line of $\Gamma_1$ is the boundary of the shadowing region. An arriving person (entering the boundary) results in the onset of shadowing and the state transition from $S_0$ to $S_1$. We assume that the people arrival is a Poisson process with the arrival rate $\lambda_P$, which increases with higher density and activity of the people inside the home or office. When the person moves out of the boundary, he (or another person) may re-enter the region later.

Second, the duration of the person staying inside one zone is a random variable. According to the ESMM, the average duration of state $S_n$ is $\bar{t}_n = A_n T$, where $T$ is the average duration for which the person stays in a unit area. $T$ is inversely proportional to the average movement speed. The departure rate from state $S_n$ is $v_n = 1/\bar{t}_n = 1/(A_n T)$. Suppose that the probability of moving to the inner zone (from $S_n$ to $S_{n+1}$) is $\alpha$, $0 < \alpha < 1$. Thus, the transition rates to the adjacent inner zone are

$$\lambda_n = \begin{cases} 
\lambda_P, & n = 0 \\
\alpha v_n = \frac{\alpha}{A_n T}, & n = 1, 2, \ldots, N - 1 
\end{cases} \quad (2.19)$$

and the transition rates to the adjacent exterior zone (from $S_n$ to $S_{n-1}$) are

$$\mu_n = \begin{cases} 
(1 - \alpha)v_n = \frac{1 - \alpha}{A_n T}, & n = 1, 2, \ldots, N - 1 \\
v_n = \frac{1}{A_n T}, & n = N. 
\end{cases} \quad (2.20)$$

### 2.6.3 State Transitions based on RWMM

In this subsection, we use the Random Waypoint Mobility Model (RWMM) [42] to describe the motion of a person inside the room, where a UWB transmission is ongoing in the air. The RWMM has been widely used in the simulation studies of ad hoc network protocols. More importantly, it appears to create realistic mobility patterns for the way people move in indoor environments [43, 42]. Therefore, we can use the RWMM to obtain the time-varying channel conditions due to the BSE.

With the RWMM model, an moving object (MO) begins by staying at one location for a certain period of time (a pause time). Once this time expires, the MO picks a random destination uniformly in the simulation area and travels toward the newly chosen destination at a speed that is uniformly distributed between $[v_{min}, v_{max}]$. Upon arrival, the MO pauses for a random time period which is chosen uniformly from a time interval $[T_{min}, T_{max}]$. After the pause time, the MO repeats the same process again. Since there is no expression for the duration the person stays in a
particular zone, the traces of the person’s position and the channel states can be obtained by simulations.

### 2.6.4 Steady-state Probabilities

Denot $\pi_n$ the steady-state probability of the channel state $S_n$. For ESMM, given the detailed equilibrium equations and the condition $\sum_{n=0}^{N} \pi_n = 1$, $\pi_n$ can be derived as

$$
\pi_n = \begin{cases} 
1 + \lambda_0 \sum_{i=1}^{N} \frac{1}{\mu_i} \left( \frac{\alpha}{1-\alpha} \right)^{i-1} & , \quad n = 0 \\
\frac{\lambda_0}{\mu_n} \left( \frac{\alpha}{1-\alpha} \right)^{n-1} p_0 & , \quad n = 1, 2, \cdots, N 
\end{cases}
$$

(2.21)

where $\lambda_0$ and $\mu_i$ are given in (2.19) and (2.20). For RWMM, the steady-state probabilities can be obtained by simulations.

### 2.7 Channel Measurement and Modeling Results

#### 2.7.1 BSE Measurement Setting

Time-domain measurement has been performed to verify the proposed BSE model. We use the pulser-based measurement setup as described below and capture the CIR waveform with a person standing between the transceivers, as shown in Fig. 2.7. A UWB pulse of 70-ps wide from the Hyperlabs HL9200 pulse generator is directly transmitted. On the receiver side, the received signal is first amplified by a low-noise amplifier and then sampled by the Agilent 81004A high-speed Digital Sampling Oscilloscope (DSO). Both the Tx and Rx use the Electrometric EM-6865 biconical, omnidirectional antennas with vertical polarization. All the measurement was conducted in a lab at the University of Victoria. The details of the measurement setup, system architecture and floor plan of the building, can be found in [38].
Figure 2.7: The photo showing the BSE propagation measurement setup.

Figure 2.8: The obstructing positions for body shadowing measurements.
We measured the shadowing effect with the person standing on a predetermined $14 \times 5$ grid shown in Fig. 2.8. The distance between two adjacent measuring points is 30 cm and the distance between the two antennas is 4.5 m.

### 2.7.2 BSE Measurement Results

According to Proposition 1, the power attenuation for symmetric blocking positions, $(x, y), (x, -y), (D - x, y)$ and $(D - x, -y)$, should be the same. But due to the randomness of the propagation surroundings such as the floor plan and the furniture, the measurement results may not be always consistent. To eliminate the effect of the surroundings and get more accurate results, we use the average power attenuation of the four symmetric points.

We now compare the measurement results and the analytical results of the (2.12) and (2.13) in Section 2.4. First, Fig. 2.9 shows the BSE when a person is standing along the lines perpendicularly crossing the LOS path at different distances to the Rx, denoted as $D'$. It can be seen that when the obstructing position is close to the Rx, both equations can give good estimation of the power attenuation. Because the BSE is dominated by the shadowing on the Rx antenna, (2.12) which ignores the shadowing effect on the Tx is still reasonably accurate. However, when the person is standing in the middle area between the transceivers, (2.12) underestimates the BSE because the shadowing effect on the Tx is comparable to that on the Rx. In these scenarios, the results of (2.13) are close to the measurement since it has captured both shadowing effects.

The contours of the BSE over the two-dimensional plane is plotted in Fig. 2.10. The $x$-axis and $y$-axis represent the coordinates of the obstructing position. As we can see, the results from the proposed BSE model match the measurement results well.
Figure 2.9: The BSE for a person moving along paths perpendicular to LOS (*-*: measurement results; - -: analytical results of (2.12); —: analytical results of (2.13)).
Figure 2.10: The contours of the BSE with a person moving on the 2-dimensional plane (—: analysis; - -: measurement).

Figure 2.11: The contours of the received SNR with BSE.
Table 2.2: Parameters of the Markov model

<table>
<thead>
<tr>
<th>$n$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_n(m^2)$</td>
<td>10.394</td>
<td>6.325</td>
<td>4.324</td>
<td>0.3195</td>
</tr>
<tr>
<td>$\lambda_n$/s</td>
<td>0.012</td>
<td>0.010</td>
<td>0.029</td>
<td>0</td>
</tr>
<tr>
<td>$\mu_n$/s</td>
<td>0</td>
<td>0.010</td>
<td>0.029</td>
<td>0.391</td>
</tr>
<tr>
<td>$\pi_n$</td>
<td>0.375</td>
<td>0.457</td>
<td>0.156</td>
<td>0.012</td>
</tr>
<tr>
<td>Data Rate (Mbps)</td>
<td>200</td>
<td>160</td>
<td>106.7</td>
<td>80</td>
</tr>
<tr>
<td>FER $\varepsilon_n$(×10^-2)</td>
<td>0.29</td>
<td>0.32</td>
<td>0.09</td>
<td>15.94</td>
</tr>
<tr>
<td>Throughput $\bar{H}_n$(Mbps)</td>
<td>126.45</td>
<td>107.97</td>
<td>80.9</td>
<td>54.54</td>
</tr>
</tbody>
</table>

### 2.7.3 Channel Modeling Results

As an example of the channel modeling, we consider a rectangular room of $7 \times 6 \text{ m}^2$ where the UWB transceivers are mounted on the walls with distance of 7 m. To evaluate the 90-th percentile system performance (the performance corresponding to the 90-th best channel), we set the total channel gain $X = -3.84 \text{ dB}$. According to the link budget of the MB-OFDM systems [1], the received SNR without shadowing is $\gamma_D = 9.22 \text{ dB}$.

The received SNR with a person standing at any position is calculated by (2.15). The payload of each physical-layer frame is 1,500 bytes. In order to ensure the FER not higher than 0.01, the minimal received SNR required for the date rates of 200, 160, and 106.7 Mbps are $\gamma = 8.67$, 7.70 and 5.94 dB respectively [1]. When the SNR is below 5.94 dB, the data rate of 80 Mbps is used.

1) Channel States:

The contours of the SNR thresholds are plotted in Fig. 2.11. The three contours divide the region into four zones, which corresponds to four channel states. The system should use the appropriate data rate when the person is standing in a particular zone.

The average FER of each state is obtained from (2.17) and listed in Table 2.2. If single frame transmission mode is employed and there is no packet error, the throughput of the four transmission modes is $H = 127.25$, 108.32, 80.98 and 80 Mbps, respectively [1]. The average throughput of each channel state is calculated by (2.18) and plotted in Fig. 2.12-(a). It can be seen that the throughput decreases dramatically as the person gradually obstructs the main transmission paths, resulting in severely degraded link performance.

2) Transition Rates and Steady-state Probabilities:
Figure 2.12: Average throughput and steady-state probabilities of the channel states

Figure 2.13: Throughput fluctuation of a MB-OFDM link
In this example, in order to compare the two mobility models, we assume that there is always a person in the room. For the ESMM, we set $T = 4 \, \text{s/m}^2$ and $\alpha = 1/2$. The transition rates of the Markov channel model are obtained by (2.19) and (2.20), respectively, and are listed in Table 2.2. The people arrival rate, $\lambda_P$, can be estimated by $\lambda_P = 1/(A_0 \bar{t})$ where $A_0$ is the area of zone $Z_0$ (outside the contour of $\Gamma = 8.67 \, \text{dB}$.) The steady-state probabilities are obtained by (2.21).

For the RWMM, we assume that the moving speed is uniformly distributed in $[0.5, 1] \, \text{m/s}$ and the pause time between $[30, 120] \, \text{seconds}$. Using the RWMM, we can get the track of the person’s movement and which obstructing zone the person is staying in at any moment. The steady-state probabilities of the Markov channel model with the two mobility models are plotted in Fig. 2.12-(b).

(3) Link Throughput Variation:

Fig. 2.13 shows the traces of the link throughput, which are generated by the Markov model with ESMM and RWMM, respectively. Frequent fluctuation of the throughput from 120 Mbps to less than 60 Mbps can be observed, which can degrade the QoS of the on-going transmissions severely.

It can been seen that, relatively speaking, with the ESMM the person has higher probability to stay in the central region of the simulation area, while with the RWMM, the probability to stay in a zone is basically proportional to the area of the zone. The mobility model can be selected according to the specific environments under investigation.

2.8 Summary

In this chapter, we have investigated the BSE on indoor UWB channels. We have derived the APSD of the indoor UWB signals. Then, the power attenuation has been estimated based on the APSD and the obstructing position. Furthermore, a packet-level channel model has been proposed for the temporal variation of the UWB channels caused by the random movement of a person.

The proposed model is of high practical value as an analysis and simulation tool for UWB systems. Based on the channel model and the time-coherence property, we can optimize the channel estimation and power control mechanisms to improve the transmission efficiency. The model also promotes the research on the cross-layer designs. For example, the queuing behavior at the link layer and the temporal variation of the realistic UWB channels can be analyzed and simulated jointly, which is im-
important for improving QoS provisioning in WPANs. In Chapters 5 and 6, this model will be used to build analytical models for link- and application-layer performance evaluation. The work in [44] also use this model to analyze the reservation-based MAC of WPAN with multimedia traffic. The proposed packet-level channel model can also be easily incorporated into network simulators like NS-2 or GloMoSim, so the WPANs in realistic UWB propagation environments can be simulated.

### 2.9 Symbol List

- $a_{k,l}$: gain of the $k$-th ray in the $l$-th cluster
- $A_n$: area of the zone $Z_n$
- $D$: distance between transmitter and receiver
- $E_b/N_0$: average received SNR
- $E_r(\theta_1, \theta_2)$: remaining received power with BSE on the Rx antenna
- $E_t(\theta_3, \theta_4)$: remaining received power with BSE on the Tx antenna
- $f_\theta(x|\tau)$: PDF of the incident angle w.r.t the LOS
- $\bar{H}_n$: throughput of the $n$-th channel state
- $N$: number of contours
- $\overline{P}_{k,l}$: average received power density conditioned on $\tau_{k,l}$
- $P(\theta)$: APSD of a CIR realization given the cluster delay and ray delay
- $\overline{P}(\theta)$: average APSD (excluding the LOS component)
- $p'(\theta)$: approximated APSD using modified Laplacian distribution
- $r$: radius of body model cylinder
- $S_n$: the $n$-th channel state
- $t_{k,l}$: delay of the $k$-th ray in the $l$-th cluster w.r.t cluster arrival
- $\bar{t}_n = A_nT$: average duration of state $S_n$
- $T$: average duration the person staying in a unit area
- $T_l$: delay of the $l$-th cluster
- $X$: log-normal total CIR attenuation
- $Z_n$: zone encompassed by the $n$-th contour line
- $\alpha$: probability of moving to the inner zone (from $S_n$ to $S_{n+1}$)
- $\chi(x,y)$: shadowing effect on both antennas
- $\chi_r(x,y)$: BSE on the Rx antenna given person’s position $(x,y)$
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon_n$</td>
<td>average FER of the $n$-th channel state</td>
</tr>
<tr>
<td>$\varepsilon(\gamma')$</td>
<td>FER with SNR of $\gamma'$ payload size of 1024 bytes.</td>
</tr>
<tr>
<td>$\gamma'(D, x, y)$</td>
<td>average received SNR with a person standing at $(x, y)$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>ray power exponentially decaying factor in Section 2.3, otherwise SNR</td>
</tr>
<tr>
<td>$\Gamma$</td>
<td>cluster power exponentially decaying factor</td>
</tr>
<tr>
<td>$\Gamma_n$</td>
<td>SNR thresholds for the $N$ contours ($n = 1, 2, \ldots, N$)</td>
</tr>
<tr>
<td>$\lambda_n, \mu_n$</td>
<td>channel state transition rates</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>ray arrival rate within each cluster</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>cluster</td>
</tr>
<tr>
<td>$\Omega_{k,l}$</td>
<td>mean energy of the $k$-th ray in the $l$-th cluster</td>
</tr>
<tr>
<td>$\Omega_0$</td>
<td>the mean energy of the first path of the first cluster</td>
</tr>
<tr>
<td>$\phi_{k,l}$</td>
<td>angular spread of the $k$-th ray in the $l$-th cluster</td>
</tr>
<tr>
<td>$\pi_n$</td>
<td>steady-state probability of the channel state $S_n$</td>
</tr>
<tr>
<td>$\sigma_X^2$</td>
<td>variance of $X$</td>
</tr>
<tr>
<td>$\sigma_1, \sigma_2$</td>
<td>coefficients of multipath gain $a_{k,l}$</td>
</tr>
<tr>
<td>$\tau_{k,l}$</td>
<td>total delay of the $k$-th ray in the $l$-th cluster</td>
</tr>
<tr>
<td>$\tau_m$</td>
<td>delay threshold in APSD</td>
</tr>
<tr>
<td>$\theta$</td>
<td>incident angle with respect to the LOS</td>
</tr>
<tr>
<td>$\theta_1 - \theta_2$</td>
<td>shadowing angular range on Rx</td>
</tr>
<tr>
<td>$\theta_3 - \theta_4$</td>
<td>shadowing angular range on Tx</td>
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Chapter 3

A Packet-Level Model for Wireless Multi-carrier Systems

3.1 Motivation and Contributions

In Chapter 2, we have designed a packet-level model for indoor UWB communication systems considering body shadowing effect in indoor environments. On the other hand, to meet the ever-increasing demand for higher data rate and better QoS anywhere, anytime, the wideband communications have also been widely deployed for outdoor wireless connectivity, such as the IEEE 802.16 and MBWA. In the following two chapters, we will investigate and model the mobile wideband wireless systems. In this chapter, we consider the general multi-carrier systems, while OFDM which is an important special multi-carrier communication technology (de/modulation are implemented with Inverse Discrete Fourier Transform (IDFT) and Discrete Fourier Transform (DFT) with cyclic prefix) will be modeled in the next chapter.

For wideband communications in a mobile environment, the wireless channel is normally undergoing time-varying and frequency-selective fading, which has significant impact on the transmission performance. In order to mitigate the Inter-symbol Interference (ISI) associated with high data rate transmissions, multi-carrier technology converts the wideband channel into multiple narrow-band subchannels by dividing the spectrum equally. A multi-carrier frequency-selective fading channel is essentially different from the traditional single-carrier flat-fading channel.

As mentioned in Section 1.2.1, the packet-level models for flat fading wireless channel have been widely used in research. However, to the best of our knowledge,
there is no such model for wideband communication systems over frequency-selective fading channels available in the literature.

The motivation of our work in this chapter is to develop the packet-level model for multi-carrier wideband systems in the mobile propagation environments. We consider that the channel experiences frequency-selective fading over the total bandwidth and each subchannel follows identical Nakagami-\( m \) distribution. The subchannels within the coherence bandwidth are correlated to each other. We also assume block fading for the time-variation of each subchannel. The contributions in this chapter are:

1. We propose a propagation model for the multipath Nakagami-\( m \) fading channel, and derive the Level Crossing Rate (LCR) of the amplitude and SNR of the subchannels when the subcarrier frequency changes (\textit{i.e.}, the second-order statistics of the channel variation with frequency).

2. By partitioning the received SNR of each subchannel into finite states, we create a FSMC in the frequency domain by which the state of one subchannel is generated according to the neighboring subchannel due to the correlation between them.

3. By combining the proposed frequency-domain FSMC model and the time-domain FSMC for Nakagami-\( m \) fading [7], a complete packet-level model for the multi-carrier system is developed.

Using the proposed packet-level model, the states of the subchannels can be easily generated. The correlation among them and the Nakagami-\( m \) distribution of each subchannel is maintained.

### 3.2 Related Work

The packet-level model for flat fading wireless channels using a FSMC has been proposed and verified extensively. Starting from the early work of the Gilbert-Elliot two-state channel model [45], the Markov Chain model with multiple states was proposed for Rayleigh fading channel. by [5] and later the packet-level model was refined in [6]. The LCR of a Nakagami-\( m \) fading channel (the second-order statistics of the time-variation of the CIR) was derived in [46]. Then, based on the SNR LCR, the FSMC for slow Nakagami-\( m \) fading channels was designed recently in [7].
These models for narrow-band flat-fading channels have been widely used. In [6], the authors used the model of Rayleigh fading channels to derived the channel capacity from the point of view of information theory. The work in [47] used the channel model to evaluate the performance of Hybrid-ARQ over Rayleigh fading channels. The performance of the Dly-ACK mechanism defined in the IEEE 802.15.3 standard over Rayleigh fading channels was studied in [48], based on a three-state Markov chain channel model to approximate the correlated transmission errors caused by channel fading.

However, to the best of our knowledge, there is no packet-level model proposed for wideband systems over time-varying frequency-selective channels.

### 3.3 Multipath Nakagami-

The Nakagami-

- Fading Propagation Model

The Nakagami-

- distribution has raised attention because of its good fit to the empirical fading signal measurement and generality. By adjusting the parameter 

- , it can model signal fading with different severity, e.g., the Rayleigh fading ( ) and Rician fading. Therefore, in our work, we consider that each subcarrier has the Nakagami-

- fading.

The PDF and CDF of the envelop \( r \) of a Nakagami-

- fading signal are given by, respectively

\[
\begin{align*}
    p(r) &= \frac{2}{\Gamma(m)} \left( \frac{m}{\Omega} \right)^{m} r^{2m-1} e^{-\frac{m}{\Omega} r^2}, \\
    F(r) &= \frac{1}{\Gamma(m)} \gamma\left( m, \frac{m}{\Omega} r^2 \right),
\end{align*}
\]

where \( \Gamma(x) = \int_{0}^{\infty} e^{-t} t^{x-1} dt \) is the Gamma function and \( \gamma(x, \alpha) = \int_{0}^{\alpha} e^{-t} t^{x-1} dt \) is the incomplete Gamma function of the first kind. \( \Omega = E[r^2] \) is the average power of the received signal. \( m = \frac{E[S]}{\text{var}(S)} \geq \frac{1}{2} \) is the inverse of the normalized variance of \( r^2 \), so it controls the fading severity. Ref. [46] built a propagation model for the Nakagami-

- fading signal based on the well-known Jakes’ model [49]. The model showed that \( r \) can be considered as the square root of the sum of squares of \( m \) independent Rayleigh or \( 2m \) independent Gaussian variates. The higher order statistics, the LCR and Average Fade Duration (AFD), were then derived.

However, the model of [46] only presents the narrow-band flat-fading. In a wideband frequency-selective channel, the difference in the delay of the multiple paths results in the time-spread of the channel and the different phase shift on the carri-
ers. The normalized Power Delay Profile (PDP) can be regarded as the probability distribution of the signal delay over multiple paths. Based on this consideration, we extend the model proposed in [46] as follows.

Let \( x_i(t) \) and \( y_i(t) \) represent, respectively, the in-phase and quadrature components of the \( i \)-th narrow-band process of the signal, and each is composed of \( N \) multipath waves

\[
x_i(t) = \sqrt{2}\sigma \sum_{j=1}^{N} a_{ij} \cos(\omega_{ij} t + \phi_{ij}),
\]

\[
y_i(t) = \sqrt{2}\sigma \sum_{j=1}^{N} a_{ij} \sin(\omega_{ij} t + \phi_{ij}),
\]

where \( N \) is the number of sinusoidal waves and is assumed to be large enough so that \( x_i(t) \) and \( y_i(t) \) can be considered as Gaussian processes due to the central limit theorem. \( a_{ij} \) satisfies the ensemble average \( \langle \sum_{j=1}^{N} a_{ij}^2 \rangle = 1 \). \( \sigma \) is the standard deviation of \( x_i \) and \( y_i \) which determines the average power of the Nakagami-\( m \) signal.

\( \omega_{ij} = 2\pi f_m \cos(\varphi_{ij}) \) is the Doppler Frequency of the \( j \)-th wave. \( f_m = v f_c / c \), where \( v \) is the velocity of the mobile user, \( f_c \) is the carrier frequency, and \( c \) is the light speed. \( \varphi_{ij} \) is the angle of arrival of the wave and is assumed to be uniformly distributed over \([0, 2\pi)\). Hence, \( \omega_{ij} t \) is the phase shift in the received wave due to the Doppler frequency.

Phase shift \( \phi_{ij} \) is defined as \( \phi_{ij} = 2\pi \tau_{ij} C_f f' \), where \( \tau_{ij} \) is the random excess delay of the \( j \)-th path, \( C_f = 100 \text{ MHz} \) is a constant and \( f' \) is the frequency of the carrier in the unit of 100 MHz (here we use 100 MHz as the frequency unit for easy presentation because the carrier frequencies are usually in the order of GHz). We normalize the PDP to obtain the probability distribution of \( \tau_{ij} \). For example, for the exponentially decaying PDP, the PDF of the excess delay can be approximated as \( p(\tau) = \frac{1}{\beta} \exp \left( -\frac{\tau}{\beta} \right) \), where \( \beta \) is the root mean square of the delay \( \beta = \tau_{\text{rms}} = \sqrt{E[\tau^2] - E[\tau]^2} \). \( \phi_{ij} \) is the phase shift on the carrier due to the time delay of the multipaths.

Let \( r_0^2 = x_0^2 \) (or equivalently \( r_0^2 = y_0^2 \)) and \( r_i^2 = x_i^2 + y_i^2 \). It is known that \( r_0 \) is semipositive Gaussian distributed whereas \( r_i \)'s are Rayleigh distributed. The envelop \( r \) of the fading signal is defined as

\[
r^2 = r_0^2 + \sum_{i=1}^{m-1/2} r_i^2, \quad m \text{ is an integer and half}
\]
or
\[ r^2 = \sum_{i=1}^{m} r_i^2, \quad m \text{ is an integer} \quad (3.6) \]

Following the approach in [46], we can prove that \( r \) fits the Nakagami-m distribution exactly, with parameter of \( m \) and \( \Omega = 2m\sigma^2 \).

### 3.4 LCR in Frequency Domain

In a multi-carrier frequency-selective channel, the channel frequency response (i.e., the amplitude of the subcarriers) varies over the total frequency bandwidth. The coherence bandwidth \( B_c \), which is inversely proportional to \( \tau_{\text{rms}} \), indicates the correlation of the frequency response. In other words, the variation of the amplitudes of the subcarriers over the frequency is related to \( B_c \), similar to that the variation of the CIR over time depends on the channel coherence time \( T_c \).

In order to present the variation of the amplitude of different subcarriers in the frequency domain, we introduce the LCR of the channel frequency response. The LCR in the frequency domain can be regarded as the counterpart of the LCR in the time domain, and it refers to the expected rate at which the amplitudes of the subcarriers cross a given level \( R \) in the positive direction when the frequencies of the subcarriers increase over a certain bandwidth.

Here we focus on the model in (3.6). The derivation for case in (3.5) is a direct extension and the same result can be obtained. The derivative \( \dot{r} \) of \( r \) with respect to frequency \( f' \) (defined earlier) is

\[ \dot{r} = \frac{dr}{df} = \sum_{i=1}^{m} \frac{r_i}{r} \dot{r}_i. \quad (3.7) \]

As shown in [49, 46], the derivatives \( \dot{r}_i \), \( i = 1, \cdots, m \), are Gaussian distributed random variables with zero-mean and standard deviation \( \sigma_i \). In addition, \( \sigma_i \) are identical for \( i = 1, \cdots, m \):

\[ \sigma_i = 2\pi\sigma_{\text{rms}}C_f = \dot{\sigma}. \quad (3.8) \]

Given all the individual amplitude \( r_i \) and therefore \( r \), the distribution of \( \dot{r} \) follows Gaussian distribution with zero mean and standard deviation \( \sigma_{\dot{r}} = \dot{\sigma} \). Thus, the PDF
of the frequency derivative $\dot{r}$ conditioned on $r$ is

$$p(\dot{r}|r) = \frac{1}{\sqrt{2\pi}\dot{\sigma}} e^{(-\frac{\dot{r}^2}{2\dot{\sigma}^2})}$$  \hspace{1cm} (3.9)$$

Eq. (3.9) shows that $p(\dot{r}|r)$ is actually independent of $r$, and hence $p(\dot{r}) = p(\dot{r}|r)$ and $p(\dot{r}, r) = p(\dot{r}) \times p(r)$.

According to the definition of LCR, $N_R = \int_{0}^{\infty} \dot{r} p(\dot{r}, r = R) d\dot{r}$, the LCR in the frequency domain can be obtained as

$$N_R = p(r = R) \int_{0}^{\infty} \dot{r} p(\dot{r}) d\dot{r} = \frac{\dot{\sigma}}{\sqrt{2\pi}} p(r = R).$$  \hspace{1cm} (3.10)$$

From (3.1), (3.8) and (3.10), we can get

$$N_R = 2\sqrt{\pi} r_{\text{rms}} C_f \frac{m^{m-1/2}}{\Gamma(m)} \rho^{2m-1} e^{-m\rho^2},$$  \hspace{1cm} (3.11)$$

where $\rho = R/r_{\text{rms}}$, and $r_{\text{rms}} = \sqrt{\Omega} = \sqrt{E[r^2]}$ is the root mean square of the envelope $r$.

### 3.5 FSMC in Frequency Domain

#### 3.5.1 Markov Model Design

As mentioned in Section 3.1, each subchannel is Nakagami-$m$ flat fading. Let $E_s$ be the average energy per symbol and $N_0$ the single-sided power spectral density of the noise. $\gamma = \frac{r^2 E_s}{N_0}$ is the post-detection SNR per symbol of the signal in one subchannel and $\gamma$ is Gamma distributed [7, 50]. The PDF and CDF are, respectively,

$$p_\gamma(x) = \left(\frac{m}{\overline{\gamma}}\right)^m x^{(m-1)} e^{-\frac{m}{\overline{\gamma}} x},$$  \hspace{1cm} (3.12)$$

$$F_\gamma(x) = \frac{\gamma \left(m, \frac{x}{\overline{\gamma}}\right)}{\Gamma(m)},$$  \hspace{1cm} (3.13)$$

where $\overline{\gamma} = E[\gamma] = \frac{\Omega E_s}{N_0}$ is the average SNR.

We partition the received SNR $\gamma$ into $K$ intervals with thresholds $\Gamma_k$, $k = 1, 2, \cdots, K-1$, and also set $\Gamma_0 = 0$ and $\Gamma_K = \infty$, as shown in Fig. 3.1. Each SNR interval,
$S_k = [\Gamma_{k-1}, \Gamma_k) \ (k = 1, 2, \cdots, K)$, is defined as a state of a subchannel. We assume block fading of the subchannel variation in the time domain. Thus, during the transmission of a data block (e.g., a packet) in the subchannel, the received SNR stays in one interval $\gamma \in [\Gamma_{k-1}, \Gamma_k)$. Then, during the next packet, the subchannel may change to another state.

If the frequency difference of two adjacent subchannels is small enough (i.e., the frequency interval between the subchannels $\Delta f$ is much smaller than the coherence bandwidth $B_c$), given the state of one subchannel, the state of its neighboring subchannel can only be in the same state or the adjacent states due to the correlation between the subchannels. We define the frequency-domain fading rate as $\tau_{\text{rms}}$ times the subchannel frequency interval $\Delta f$. If the fading rate is much smaller than 1, $\Delta f$ is much smaller than the coherence bandwidth $B_c$ and we have the above property.

Furthermore, we can see that the state of one subchannel is only related to its adjacent subchannels. In other words, if the state of the $n$-th subchannel is given, the state of the $(n+1)$-th channel is only determined by the $n$-th subchannel and is irrelevant to the $(n-1)$-th, $(n-2)$-th, $\cdots$ subchannels. This memoryless property suggests that we can use the Markov model to describe the variation of the subchannels in the frequency domain. Considering the adjacent state transition between neighboring subchannels, we build a first-order FSMC, as shown in Fig. 3.2. Thus, if the state of one subchannel is known, the state of the next subchannel can be directly generated using this FSMC.

In a practical multi-carrier communication system, if the frequency interval $\Delta f$ is not sufficiently small, we can insert several (e.g., $l$) virtual subchannels between them such that the difference of two neighboring (virtual) subchannels are much smaller than the coherence bandwidth. Thus, the state transitions between virtual subchannels are still a first-order Markovian process. The one-step transition matrix $P$ between (virtual) subchannels can be determined (as will be shown in Section 3.5.3), and then the state transition matrix of the real subchannels is simply $P^l$.

In the following, the FSMC for the subchannels is given by SNR partition, and the state transition matrix and error probability vector derivation.

### 3.5.2 SNR Partitioning for Nakagami-$m$ Fading

The SNR range of each state should be large enough so that the subchannel stays in one state during a packet transmission, and meanwhile it should not be too large
Figure 3.1: Partition of the SNR range of the subchannels.

Figure 3.2: First-order FSMC for the subchannel states in frequency domain.
so that the packet error rate (PER) can be estimated by the average symbol error probability of the state without much discrepancy. Iskander in [7] justified to use EPM to do partitioning which is therefore used throughout this work. The steady-state probabilities $\pi_k$ of the states are all equal, which are

$$
\pi_k = \int_{\Gamma_{k-1}}^{\Gamma_k} p_\gamma(x) dx = F_\gamma(\Gamma_k) - F_\gamma(\Gamma_{k-1}) = \frac{1}{K},
$$

(3.14)

where $k = 1, 2, \ldots, K$ for total $K$ states. From (3.13) and (3.14), we can obtain $\Gamma_k$ by solving the following equations

$$
\gamma \left( m, \frac{m}{\bar{\gamma}} \Gamma_k \right) - \gamma \left( m, \frac{m}{\bar{\gamma}} \Gamma_{k-1} \right) = \frac{\Gamma(m)}{K}, \quad k = 1, 2, \ldots, K,
$$

(3.15)

and $\Gamma_0 = 0$, $\Gamma_K = \infty$, by numerical methods (e.g., the bisection method).

### 3.5.3 State Transition Probabilities

Let $t_{i,j}$ denote the transition probability from states $S_i$ to states $S_j$. Thus, $t_{k,k+1}$ is approximated by the ratio of the LCR at the threshold $\Gamma_{k+1}$ and the average number of subchannels staying in state $S_k$.

From (3.11), the SNR LCR in the frequency domain can be obtained as

$$
N(\Gamma_k) = 2\sqrt{\pi} \frac{\tau_{\text{rms}} C_f}{\Gamma(m)} \left( \frac{m}{\bar{\gamma}} \Gamma_k \right)^{m-\frac{1}{2}} e^{-\frac{m}{\bar{\gamma}} \Gamma_k},
$$

(3.16)

which is the expected number of times the SNR crossing the threshold $\Gamma_k$ in the bandwidth of $C_f$. Thus, the transition probabilities can be approximated as

$$
t_{k,k-1} \approx \frac{N(\Gamma_k)}{L\pi_k}, \quad k = 2, 3, \ldots, K,
$$

$$
t_{k,k+1} \approx \frac{N(\Gamma_{k+1})}{L\pi_k}, \quad k = 1, 2, \ldots, K - 1,
$$

(3.17)

where $L$ is the total number of subcarriers in the bandwidth of $C_f$ and therefore $L\pi_k$ is the average number of subchannels in state $s_k$. Therefore, Eq. (3.17) gives the probability of level crossing in the frequency domain, or equivalently the probability of state transition from $S_k$ to $S_{k-1}$ and from $S_k$ to $S_{k+1}$, respectively. The remaining
probabilities are given by
\begin{align}
t_{1,1} &= 1 - t_{1,2}, \\
t_{K,K} &= 1 - t_{K,K-1}, \\
t_{k,k} &= 1 - t_{k,k-1} - t_{k,k+1}, \quad k = 2, 3, \ldots, K - 1
\end{align}
(3.18)

The transition matrix of the FSMC can be obtained as
\[
P = \begin{bmatrix}
t_{1,1} & t_{2,1} & \cdots & 0 \\
t_{1,2} & t_{2,2} & \cdots & 0 \\
0 & t_{2,3} & \cdots & 0 \\
0 & \cdots & 0 & t_{K,K-1} \\
0 & \cdots & 0 & t_{K,K}
\end{bmatrix}
\] (3.19)

### 3.5.4 Error Probability Vector

When a subchannel is in state $S_k$ (i.e., the received SNR is in the interval of $[\Gamma_{k-1}, \Gamma_k]$), the average symbol error probability can be obtained by:
\[
\varepsilon_k = \frac{1}{\pi_k} \int_{\Gamma_{k-1}}^{\Gamma_k} e(x)p_\gamma(x)dx,
\] (3.20)

where $e(x)$ is the error probability given the SNR of $\gamma = x$ and $p_\gamma(x)$ is the Gamma distribution as in (3.12).

For example, the conditional BER for many coherent modulation schemes can be expressed as $AQ(\sqrt{B\gamma})$, where $Q(x) = \left(1/\sqrt{2\pi}\right) \int_x^\infty e^{-t^2/2}dt$, $B$ is a factor depending on the modulation schemes, and $\gamma$ is the received SNR. The closed form of $\varepsilon_k$ for BPSK, QPSK and DQPSK modulations can be found in [5] and [6].

### 3.6 Packet-level Model for Multi-carrier System

A packet-level model for multi-carrier communication system is designed as shown in Fig. 3.3, which presents the variation of the subchannel states in both the time-domain and frequency-domain. First, we use the time domain FSMC model for Nakagami-$m$ fading [7] to generate the states of the first subcarrier at the packet transmission time. This model has the similar structure as shown in Fig. 3.2, but presents the time-
variation of the flat fading. Given the state of the first subchannel in one time slot, its state in next time slot (transmission time of next packet) can be generated according to the model’s transition probabilities. As mentioned earlier, under the assumption of block fading, the time domain fating rate (the maximal Doppler frequency \( f_m \) times the packet transmission time) is much smaller than 1. Thus, the subchannel remains in the same state during the transmission of a packet.

Then we use the FSMC in the frequency domain proposed above to generate the states of all the other subchannels. In Fig. 3.3, \( S^{(x,y)} \) presents the state of the \( x \)-th subchannel during the \( y \)-th packet transmission. The virtual subchannels may be inserted if necessary. For example, in Fig. 3.3, the 2-nd, 4-th, 6-th, \( \cdots \) subchannels are virtual ones inserted.

As verified by the simulations in the next section, the proposed multi-carrier system model can preserve the correlation between the subchannels and also the Nakagami-\( m \) distribution of each subchannel.

The parameters for this packet-level model (e.g., the transition probabilities and error vector) need to be computed once according to the channel profile and the configuration of the multi-carrier system. Then, in the simulation of packet transmission, only \( 2L \) (\( L \) is the number of subchannels) uniformly distributed random numbers (RVs) need to be generated for each packet. \( L \) RV’s are used to determine the state transition of the subchannels, and the rest \( L \) RV’s to determine if transmission errors happen in each subchannel. This drastically reduces the computational complexity compared to the waveform signal-level simulations.
3.7 Simulation Results

3.7.1 Simulation Settings

The parameters for the simulations are as follows. The velocity is $v = 10 \text{ km/h}$ and the carrier frequency of the first subchannel is $f_1 = 2.4 \text{ GHz}$. The maximum Doppler frequency is $f_m = 22.22 \text{ Hz}$. The total bandwidth of the system has 20 MHz including 512 subchannels, and the total bit rate is 20 Mbps. Thus, the interval between two subchannels is $\Delta f = 39.062 \text{ KHz}$. The packet size is 400 bytes and therefore the packet rate is 6250 packets/s. The channel has an exponentially decaying PDP as shown in Section 3.3.

3.7.2 Propagation Model

The propagation model proposed by (3.3) and (3.4) in Section 3.3 is simulated to generate the envelopes of multiple subchannels. The number of waves is $N = 40$. The cases $m = 1, 2$ and 3.5 are simulated. $\sigma$ is chosen such that the Nakagami-$m$ distribution of the generated envelope is normalized, i.e., $\Omega = 1$. So $\sigma = 0.7071$, 0.5 and 0.3780, respectively. Each case runs for 10 seconds, corresponding to $6.25 \times 10^4$ observations.

Fig. 3.4 compares the CDF between the envelope of one randomly selected subcarrier generated by the propagation model and the theoretical Nakagami-$m$ CDF. Since a change in carrier frequency does not affect the overall fading statistics, the distribution of the subcarriers should be a fixed Nakagami-$m$ distribution, independent of the carrier frequency or Doppler shifting. It can be seen that the propagation model in (3.3) and (3.4) generates the exactly Nakagami-$m$ distributed envelope.

3.7.3 LCR in Frequency Domain

Fig. 3.5 compares the LCR’s of the simulated envelope and the theoretical expression in (3.11). The LCR’s of three different channel delay spread $\tau_{\text{rms}}$ (equivalently three different coherence bandwidth) are simulated. The bandwidth to count the LCR is $C_f = 100 \text{ MHz}$ and the Nakagami-$m$ parameter is $m = 2$. The fifteen thresholds are chosen according to the EPM such that the Nakagami-$m$ distributed amplitude would fit into each interval with equal probability. It can be seen that the larger the delay spreads, the higher the LCR is. This is to be expected: when the coherence
Figure 3.4: CDF of the signal envelope generated by propagation model.

Figure 3.5: LCR in frequency domain, $C_f = 100$MHz
bandwidth decreases, the channel frequency response will vary more significantly.

### 3.7.4 Multi-carrier System Model

We use a 16-state\(^1\) FSMC model to present the variation of the subchannels in the frequency domain. The amplitude of each subchannel was generated using the propagation model and the instantaneous SNR was obtained by \( \gamma = r^2 E_s / N_0 \), with \( E_s / N_0 = 3.01 \) dB. The thresholds of the SNR intervals are chosen by the EPM such that \( \pi_1 = \pi_2 = \cdots = \pi_{16} = 1/16 \). The state transition probabilities of the SNR of neighboring subchannels were averaged over 10-second simulation.

The analytical approximations and simulation results for state transition probabilities, \( t_{i,j} \), and steady-state probabilities, \( \pi_k \), are compared in Fig. 3.6, which shows good agreement. The fading in the frequency domain is slow enough (the frequency fading rate) such that the assumption of state transition among neighboring states only is confirmed by the simulation.

Finally, the distribution of the states of each subchannel generated by the FSMC model is verified. Although the state of one subchannel is generated in the frequency domain by the neighboring subchannel, they should be Nakagami-\( m \) distributed in the time domain and the SNR should have the Gamma distribution. We use the 16-state FSMC for 10-seconds simulation and thus totally \( 6.25 \times 10^4 \) observations for every subchannel are obtained. With the average SNR \( \bar{\gamma} = 3.01 \) dB and the fading parameter \( m = 2 \), Fig. 3.7 illustrates that the distribution of the SNR of a subchannel approximates the Gamma distribution reasonably. The CDF of the simulated SNR is a staircase function because the SNR is generated by the model which has 16 discretized states.

\(^1\)If the SNR intervals for the states are too large, the estimation of the PER using the average BER of the states will not be very accurate. But if the SNR intervals are too small, the transition probabilities to non-adjacent states will not be close to zero [6].
Chapter 3. A Packet-Level Model for Wireless Multi-carrier Systems

Figure 3.6: Analytical and simulation results of $t_{i,j}$ and $\pi_k$ of FSMC in frequency domain ($\tau_{rms} = 200\text{ns}$, $\Delta f = 39.062\text{ kHz}$, and $m = 2$)

Figure 3.7: SNR distribution of one subcarrier ($m = 2, \bar{\gamma} = 2$).
3.8 Summary

This chapter has proposed a packet-level channel model to facilitate analysis and fast simulation of multi-carrier transmission over a frequency-selective Nakagami-$m$ fading channel. The model includes two FSMCs in both the time domain and the frequency domain.

A signal propagation model for the wideband Nakagami-$m$ channel has been first proposed and then the frequency-domain LCR of the amplitude of the subchannels has been introduced. The FSMC model to present the SNR variation in the frequency domain has been obtained based on the theoretical LCR. In the multi-carrier system model, the states of the first subchannel is generated using the time-domain FSMC and the other subchannels are obtained by the frequency-domain FSMC. The Nakagami-$m$ distribution of each subchannel and the correlation between them are preserved using the proposed model.

The simulator developed is thus successful in simulating the packet error profile of multi-carrier systems, where the subchannels have frequency-selective correlated Nakagami-$m$ fading. In addition, because the subchannel states are generated using two FSMCs, the model is very easy to implement in network simulator like NS-2 or GloMoSim, which will be a useful tool for networking research.

3.9 Symbol List

- $B_c$: channel coherence bandwidth
- $f_m$: maximal Doppler frequency
- $F(r)$: CDF of the envelop $r$ of a Nakagami-$m$ fading signal
- $N$: number of of sinusoidal waves of each narrow-band process
- $N_R$: LCE in frequency-domain
- $p(r)$: PDF of the envelop $r$ of a Nakagami-$m$ fading signal
- $p(\tau)$: PDF of the excess delay
- $P$: one-step transition matrix between (virtual) subchannels
- $\dot{r}$: first derivative of $r$ w.r.t frequency $f'$
- $t_{i,j}$: transition probability from states $S_i$ to states $S_j$
- $T_c$: channel coherence time
- $v$: velocity of the mobile user
- $x_i(t), y_i(t)$: in-phase and quadrature components of the $i$-th narrow-band process
\( \Delta f \) frequency interval between the subchannels

\( \varepsilon_k \) average symbol error probability

\( \gamma \) post-detection SNR

\( \Gamma_k \) SNR thresholds for the \( K \) channel states \( k = 1, 2, \ldots, K - 1 \)

\( \omega_{ij} \) Doppler frequency of the \( j \)-th wave

\( \omega_{ij} t \) phase shift in the received wave due to the Doppler frequency

\( \varphi_{ij} \) angle of arrival of the wave

\( \pi_k \) steady-state probabilities

\( \sigma \) standard deviation of \( x_i \) and \( y_i \)

\( \sigma_i \) standard deviation of \( \dot{r} \)
Chapter 4

Markov Modeling for OFDM Systems

4.1 Motivation and Contributions

In Chapter 3, we have modeled the general multi-carrier communication systems over frequency-selective Nakagami-$m$ fading channels. OFDM is an important multi-carrier technology and has been widely adopted in many wireless systems, such as Digital Video Broadcasting (DVB), IEEE 802.11a/g/n (WLAN), IEEE 802.16 (WiMax), IEEE 802.15.3a (WPAN), etc. Therefore, this chapter focuses on the OFDM systems in mobile propagation channels. Different from Chapter 3, we will consider the subchannel correlations in both the time and frequency domains and the salient features of OFDM modulations. In addition, channel coding and interleaving which are commonly implemented in OFDM systems to explore the frequency diversities will also be considered.

The main contributions in this chapter are:

1. We derive the distribution and higher-order statistics of the channel frequency response and the LCR of the SNR of each subchannel in OFDM system.

2. We develop a packet-level model for OFDM systems based on FSMC which captures the time and frequency correlations of the subchannels and presents the stochastic process of the PER.

Because the packet error sequence can be generated by the Markov chain based model directly with low computational complexity, the model can speed up simu-
lations significantly. Furthermore, the model is ready to be incorporated into the analytical framework of upper-layer protocols to evaluate network performance considering the realistic physical layer characteristics.

4.2 Related Work

The study of OFDM communications over fading channels has been an active area. The work in [51] studied transmission of an OFDM signal over multipath Nakagami-\(m\) channels by assuming that the frequency-domain channel response samples were also Nakagami-\(m\) distributed with the same fading parameters as the time-domain channel. Kang \textit{et al.} [50] claimed that the distribution of samples of the channel frequency response could be approximated by another Nakagami-\(m\) distribution with a new fading parameter different from the time-domain fading parameter. However, Du [52] proved that such Nakagami-\(m\) approximation is not reliable and derived the exact distribution and the BER. To the best of our knowledge, there is no packet-level model proposed for OFDM systems over the realistic time-varying frequency-selective channels.

4.3 System Model

4.3.1 OFDM System Model

We consider an OFDM system employing \(N\) subcarriers within the bandwidth of \(W\). The modulated data sequence of each OFDM symbol is denoted as \(\mathbf{D} = [D_0 \ D_1 \ \cdots \ D_{N-1}]\). An \(N_G\)-point Cyclic Prefix (CP) is appended to \(\mathbf{D}\) to eliminate ISI. Suppose one packet requires \(N_{\text{sym}}\) symbols to transmit and thus the transmission time is \(T_P = N_{\text{sym}} T_s (N + N_G)\), where \(T_s = 1/W\) is the signaling interval.

The time-varying frequency-selective channel varies over both the time and frequency domains. We consider that in practical systems the fading rate (\textit{i.e.}, the maximum Doppler shift \(f_d\) times the packet period \(T_P\), as defined earlier) is much smaller than one and thus the channel coherent time is much larger than \(T_P\). As a result, the channel is \textit{slow fading} and it can be assumed that during the transmission of one packet, the channel is stable [5, 6, 7]. Therefore, we use \(T_P\) as the time slot for the discrete-time channel model. We denote \(t\) the index of the time slot.
Chapter 4. Markov Modeling for OFDM Systems

The CIR in the $t$-th time slot ($t = \cdots, -1, 0, 1, 2, \cdots$) is sampled with the time interval of $T_s$. The samples are indicated by $h(t) = [h_0(t) \ h_1(t) \ \cdots \ h_{L-1}(t)]$, where $L$ is the number of non-zero samples. The channel frequency response can be expressed as

$$H_k(t) = \sum_{l=0}^{L-1} h_l(t) e^{-j2\pi \frac{lk}{N}}, \quad k = 0, 1, \cdots, N-1. \quad (4.1)$$

For easy expression, we refer $\{h_l(t)\}$ as the CIR taps and $\{H_k(t)\}$ as the channel frequency response taps.

At the receiver, the output of the $N$-point DFT can be presented as

$$R_k = \sum_{n=0}^{N-1} r_n e^{-j2\pi \frac{nk}{N}} = H_k(t)D_k + V_k(t), \quad (4.2)$$

where $r_n$ is the sample of the received signal, $D_k$ is the useful data symbol and $V_k(t)$ is the channel noise which is modeled as independent identically distributed (i.i.d.) complex Gaussian process with zero mean.

Eq. (4.2) shows that each OFDM subcarrier undergoes a flat fading channel attenuated by the complex coefficient $H_k(t)$. Thus, the received SNR and BER of the $k$th subcarrier depends on the channel gain $|H_k(t)|$. The statistics of $|H_k(t)|$ will be discussed in the next section.

### 4.3.2 Time-varying Frequency-selective Fading Channels

Because of the generality of Nakagami-$m$ fading, we assume that the CIR taps $\{h_l(t)\}$ are mutually independent complex RVs and have Nakagami-$m$ fading. The amplitude of each tap, $|h_l(t)|$, has Nakagami-$m$ distribution, and their phases $\{\theta_l(t)\}$ are mutually independent, uniformly distributed over $[0, 2\pi)$ and independent of the fading amplitudes $\{|h_l(t)|\}$, as given in Section 3.3.

In our work, we use the often referred exponential-decaying power-delay profile for terrestrial channels

$$\Omega_l = \Omega_0 e^{-\frac{\tau_m}{\tau_m}}, \quad l = 0, 1, \cdots, L - 1 \quad (4.3)$$

where $\tau_m$ represents the RMS delay spread.

Reference [53] proposed a fading channel generation procedure which gives the correlated amplitude and phase of the Nakagami-$m$ fading. This fading mechanism
builds in appropriate correlation properties and higher order statistical properties into the generated Nakagami-\(m\) RV. In our work, the CIR taps in the time domain, \(\{h_l(t)\}\), are generated using this procedure [53] individually.

### 4.4 Statistical Characteristics of Channel Frequency Response

#### 4.4.1 Probability Distribution of Subchannel SNR

In the case that \(|h_l(t)|\) has a Nakagami-\(m\) distribution with \(m_l = 1, l = 0, 1, \ldots, L-1\), has a joint complex Gaussian distribution. According to (4.1), the application of DFT yields joint Gaussian RVs. Thus, the envelope of the frequency response tap \(|H_k(t)|, k = 0, 1, \cdots, N-1\) should have a Rayleigh distribution.

For the case of \(m_l \neq 1\), according to [52], the sums of Nakagami-\(m\) distributed RVs do not, in general, have a Nakagami-\(m\) distributed envelope. The exact distribution of \(|H_k(t)|\) becomes intractable when \(L \geq 3\) [52]. But when the number of CIR taps is large, we can expect that \(H_k(t)\) is a complex Gaussian RV by the central limit theorem. Thus, we have the following proposition:

**Proposition 1:** The amplitude of all the channel frequency response taps has the Rayleigh distribution with the average power of

\[
\Omega_k = \sum_{l=0}^{L-1} \Omega_l = \bar{\Omega}, \quad k = 0, 1, \cdots, N - 1.
\]  

(4.4)

The distribution of \(|H_k(t)|\) is verified by simulation. The parameters of the OFDM system and the channel are listed in Table 4.1. \(\Omega_0\) is chosen such that \(\sum_{l=0}^{L-1} \Omega_l = 1\) based on (4.3). Totally 20,000 realizations of the CIR are generated by the Nakagami-\(m\) fading generator, with the time interval of \(T_P = 64\) \(\mu s\). The fading rate \(f_dT_P = 0.0047\) is much smaller than one. The CDF of the amplitude of one channel frequency response tap is shown in Fig. 4.1. It can be seen that \(|H_k(t)|\) can be well modeled by the Rayleigh distribution.

As shown in Section 4.6, the distribution of \(|H_k(t)|\) is verified by simulations. Consequently, with an additive Gaussian noise, the received SNR of each subcarrier,
Table 4.1: System parameters in simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W$</td>
<td>20 MHz</td>
<td>$E_b/N_0$</td>
<td>10 dB</td>
</tr>
<tr>
<td>$N$</td>
<td>128</td>
<td>$\tau_m$</td>
<td>200 ns</td>
</tr>
<tr>
<td>$N_G$</td>
<td>32</td>
<td>$f_c$</td>
<td>2 GHz</td>
</tr>
<tr>
<td>Constellation</td>
<td>QPSK</td>
<td>$v$</td>
<td>20 km/h</td>
</tr>
<tr>
<td>$N_{sym}$</td>
<td>8</td>
<td>$f_d$</td>
<td>37.037 Hz</td>
</tr>
<tr>
<td>$m_l$</td>
<td>2</td>
<td>$\Omega_0$</td>
<td>0.2983</td>
</tr>
</tbody>
</table>

Figure 4.1: Distribution of $|H_k(t)|$
\(\gamma_k(t) = |H_k(t)|^2 \frac{E_k}{N_0}\), is exponentially distributed with the PDF of

\[
p_{\gamma_k}(\gamma) = \frac{1}{\bar{\gamma}} e^{-\frac{\gamma}{\bar{\gamma}}},
\]

(4.5)

where \(\bar{\gamma} = \tilde{\Omega} \frac{E_k}{N_0}\) is the average SNR.

### 4.4.2 Higher-order Statistics of Subchannel SNR

In order to build the packet-level channel model, we need to know the higher-order statistics of \(\gamma_k\), in particular, the LCR which is the expected number of times per second the received SNR \(\gamma_k\) passes downward across a given level \(\Gamma\). We have:

**Proposition 2:** The SNRs of all the channel frequency response taps have the same LCR, which is approximated as:

\[
\Lambda_{\Gamma} = \sqrt{2\pi f_d} \sqrt{\frac{\Gamma}{\bar{\gamma}}} e^{-\frac{\Gamma}{\bar{\gamma}}}. 
\]

(4.6)

The proof of this proposition is given in Appendix B. To verify the derivation, using the same simulation settings listed in Table 4.1, the thresholds \(\Gamma_i, i = 1, 2, \cdots, 7\) are chosen such that \(\gamma_k\) falls in each interval with the same probability of 0.125. The analytical and the simulation results for different maximal Doppler frequency \(f_d\) are shown in Fig. 4.2.
Figure 4.2: LCR of $|H_k(t)|$ (-o-: analytical results; -*- simulation results)
4.5 FSMC Model for OFDM Systems

4.5.1 Definition of Channel States

First, we partition the received SNR of the subcarriers into several non-overlapping intervals of \([\Gamma_u, \Gamma_{u+1})\), where \(u = 1, 2, \ldots, U\) and \(\Gamma_1 = 0, \Gamma_{U+1} = \infty\). We denote the \(u\)th interval as \(I_u\), as shown in Fig. 4.3.

Then, similar to the approach in estimating the channel capacity in time-varying frequency-selective channel [54], we divide the channel bandwidth \(W\) of the OFDM signal into several subbands \(H(b)(t), b = 1, 2, \ldots, B\), with the size of \(W'\), which is equal to or smaller than the channel coherence bandwidth \(B_c\), as shown in Fig. 4.3. Suppose that there are \(B\) subbands and \(S\) subcarriers in each subband. Thus, we can approximate that the SNR of the subcarriers in one subband reside in one SNR interval due to the correlation among them, and the intervals of each subband are time-varying and independent with other subbands.

For OFDM systems, the average BER and the Symbol Error Rate (SER) mainly depends on the subcarriers which are in deep fading. To trade-off between the accuracy and simplicity, we divide the SNR into 3 intervals, \(I_u, u = 1, 2, 3\). \(I_1\) and \(I_2\) have small range because the subbands in \(I_1\) and \(I_2\) are in deep fading and determines the average BER and SER. On the contrary, \(I_1\) can be large because the subbands in it have much smaller BER and does not have significant impact on the average BER and SER.

Thus, the OFDM system on time-varying frequency-selective channels is modeled by a 2-dimensional FSMC, as shown in Fig. 4.4. The rows of the model correspond to the number of subbands in SNR intervals \(I_1\), and the columns correspond to the number of subbands in \(I_2\). Obviously, for channel state \((m, n)\), there are \((B - m - n)\) subbands in \(I_3\). There are totally \((B + 2)(B + 1)/2\) channel states.

4.5.2 State Transition Probabilities

First, the probability that one subband resides in the SNR interval \(I_u\) is:

\[
\eta_u = \int_{\Gamma_u}^{\Gamma_{u+1}} p_\gamma(x)dx = e^{-\frac{\Gamma_{u}}{\bar{\gamma}}} - e^{-\frac{\Gamma_{u+1}}{\bar{\gamma}}}, \tag{4.7}
\]

where \(p_\gamma(x)\) is from (3.12) given by Proposition 1.

Let \(g_{u,v}\) denote the probability for a subband to transit from interval \(I_u\) to \(I_v\)
Figure 4.3: Channel Division in Frequency-Selective Fading

Figure 4.4: The packet-level model for OFDM system
Table 4.2: Channel State Transition

| Condition | Interval change of one subband | Current state | Next state | |
|-----------|-------------------------------|---------------|------------|
| $m + n < B$ | from $I_3$ to $I_2$ | $(m, n)$ | $(m, n + 1)$ | |
| $n > 1$ | from $I_2$ to $I_3$ | $(m, n)$ | $(m, n - 1)$ | |
| $n > 1$ | from $I_2$ to $I_1$ | $(m, n)$ | $(m + 1, n - 1)$ | |
| $m > 1$ | from $I_1$ to $I_2$ | $(m, n)$ | $(m - 1, n + 1)$ | |

after one time slot $T_p$. Because of slow fading of CIR in the time domain, it can be approximated that the SNR of a subband can reside in the original interval or one-step transit to adjacent intervals after one packet period $T_p$ [6, 7]. Thus, we have $g_{1,3} \approx g_{3,1} \approx 0$. Then, the other transition probabilities can be estimated by

$$
\begin{align*}
q(m,n)(m,n+1) &= \binom{B-m-n}{1} g_{3,2}g_{1,1}^m g_{2,2}^n g_{3,3}^{B-m-n-1} \\
q(m,n)(m,n-1) &= \binom{n}{1} g_{2,3}g_{1,1}^m g_{2,2}^{n-1} g_{3,3}^{B-m-n} \\
q(m,n)(m+1,n-1) &= \binom{n}{1} g_{2,1}g_{1,1}^m g_{2,2}^{n-1} g_{3,3}^{B-m-n} \\
q(m,n)(m-1,n+1) &= \binom{m}{1} g_{1,2}g_{1,1}^m g_{2,2}^{n-1} g_{3,3}^{B-m-n} \\
q(m,n)(m,n) &= 1 - \sum_{m' \neq m \text{ or } n' \neq n} q(m,n)(m',n') 
\end{align*}
$$

(4.9)

where $\Lambda(\Gamma)$ is from (4.6) proved by Proposition 2.

Now we discuss the transition probabilities of the overall channel states defined in Fig. 4.4. Again, due to the slow fading property, the probability for two or more subbands to change their intervals simultaneously in one time slot is much smaller than the probability for none or only one subband to change the interval (i.e., the number of subbands times the probability for one subband to change state during one time slot is much smaller than one). Thus, we only consider that at most one subband steps into its adjacent SNR intervals. The 4 scenarios and the resultant channel state transitions, from $(m_t, n_t)$ to $(m_{t+1}, n_{t+1})$, are listed in Table 4.2. The transition probabilities are obtained as
4.5.3 Steady State Probabilities

The steady probability of channel state \((m,n)\) in Fig. 4.4 can be obtained by

\[
\pi(m,n) = \binom{B}{m} \binom{B-m}{n} \eta_1^m \eta_2^n \eta_3^{B-m-n}.
\] (4.10)

4.5.4 PER for Each Channel State

Using the similar approach in Section 3.5.4, when a subband is in the SNR interval \(I_u\), the average BER of the subcarriers in this subband is

\[
\varepsilon_u = \frac{1}{\eta_u} \int_{\Gamma_u}^{\Gamma_u+1} AQ(\sqrt{B\gamma})p_\gamma(x)dx, \quad u = 1, 2, 3
\] (4.11)

where \(\gamma\) is exponentially distributed according to Proposition 1 and \(AQ(\sqrt{B\gamma})\) is the conditional BER for coherent modulations as given in Section 3.5.4. When the channel is in state \((m,n)\), the average BER of the OFDM signal is

\[
\varepsilon(m,n) = \frac{m\varepsilon_1 + n\varepsilon_2 + (B-m-n)\varepsilon_3}{B}.
\] (4.12)

In addition, the interleaving and channel coding are usually implemented in OFDM systems to combat channel fading. As an example, we consider convolutional coding and hard-decision Viterbi decoder which are commonly employed in practice. The union bound of the BER with channel coding can be approximated by Chernoff upper bound [55]

\[
\varepsilon'(m,n) < \sum_{d=d_f}^{\infty} c_d \left[4\varepsilon(m,n)(1-\varepsilon(m,n))\right]^\frac{d}{2},
\] (4.13)

where \(c_d\) is the distance spectrum defined as the sum of bit errors of all error events for code distance \(d\) [56] and \(d_f\) is the free distance of the code.

Finally, if one packet has \(L_b\) information bits, the PER for channel state \((m,n)\) is

\[
e(m,n) = 1 - (1 - \varepsilon'(m,n))^{L_b}.
\] (4.14)

4.6 Simulation Results

We use the system parameters listed in Table 4.1 in the simulation. The Nakagami-\(m\) fading generator described in [53] was developed to generate the CIR taps \(\{h_l(t)\}\).
The channel coherent bandwidth is $B_c \approx 1/\tau_{rms} = 5$ MHz. To estimate the average BER more accurately, we divide the channel into $B = 8$ subbands and each subband has $S = 16$ subcarriers which occupy 2.5 MHz. Simulations have shown that the time-variations of the subbands can be assumed to be independent. The thresholds to partition the SNR intervals are $\Gamma_0 = 0$, $\Gamma_1 = 2$, $\Gamma_2 = 4$, and $\Gamma_3 = \infty$. The guidance to set these thresholds is to allocate small intervals to $I_1$ and $I_2$, as mentioned earlier. The 2-dimensional FSMC model shown in Fig. 4.4 has 45 states. To simplify the model, we ignore the states whose steady state probabilities are less than 0.01. As a result, the remaining 17 states are shown in Fig. 4.5.

We index these channel states with 1 to 17 (the states in the 1st row are assigned the index of 1 to 4, the states in the 2nd row the index of 5 to 8, and so on). The average channel BERs ($\varepsilon_{(m,n)}$) are plotted in Fig. 4.6. Fig. 4.6 suggests that we can further simplify the packet-level model by combining the states which have similar BER. In this example, the states in each row in Fig. 4.5 can be combined together, resulting in the final 5-state channel model.

To validate the model, the waveform simulation is performed. Convolutional coding is employed, using the coding rate $R = 1/2$, constraint length $K = 7$ and generator polynomials of $(133, 171)$ [56]. Totally $10^5$ CIRs are generated and the state of each CIR is determined based on its average BER. $\{\varepsilon'_{(m,n)}\}$ of the 5 system states are shown in Fig. 4.7(a). The distributions of the channel states obtained by the simulation, and the steady state probabilities of the proposed model, are plotted in Fig. 4.7(b).

To further validate the proposed model, we change the thresholds of the SNR intervals to $\Gamma_0 = 0$, $\Gamma_1 = 0.8$, $\Gamma_2 = 1.6$, and $\Gamma_3 = \infty$. We still simplify the channel model by ignoring the states with the steady state probability smaller than 0.01 and combining the states with similar BER. Finally, the simplified channel model has 7 states. The BER (after decoding) and the probability of each state (by simulation and using the proposed model, respectively) are plotted in Fig. 4.8. The state transition probabilities of the proposed packet-level model have also been verified by simulation.

From the numerical results and simulations, we have the following observations: (1) the packet-level channel model can be simplified by ignoring the states with small steady state probabilities, like smaller than 1%; (2) the model can be further simplified by combining some states which have similar BER; (3) we should select SNR thresholds appropriately so different states have significantly different BER performance.
Figure 4.5: Simplified packet-level channel model

Figure 4.6: Average BER of channel states
Figure 4.7: Steady State Probabilities

Figure 4.8: Steady State Probabilities
4.7 Summary

In this chapter, we have investigated the packet transmission of OFDM systems over time-varying frequency-selective fading channels. The distribution and LCR of the channel frequency response have been derived. A packet-level system model has been proposed considering the time and frequency correlations of the channel. The statistics of the transmission errors are properly presented by the model.

Similar to the packet-level model for indoor UWB system in Chapter 2, the proposed model for OFDM in mobile propagation environment is ready to be incorporated into the analysis framework of upper-layer networking protocols. Thus, the performance/QoS (link throughput, delay, etc.) can be analyzed theoretically, which beckons for further research. The model can also be easily built into existing network simulators.

4.8 Symbol List

\begin{align*}
B & \quad \text{number of subbands} \\
B_c & \quad \text{channel coherence bandwidth} \\
D & \quad \text{modulated data sequence of each OFDM symbol} \\
e_{(m,n)} & \quad \text{average FER of channel state } (m, n) \\
f_d & \quad \text{maximum Doppler shift} \\
g_{u,v} & \quad \text{probability for a subband to transit from } I_u \text{ to } I_v \\
h(t) & \quad \text{CIR at the } t\text{-th time slot} \\
H_k(t) & \quad \text{channel frequency response} \\
H_{(b)}(t) & \quad \text{state of the } b\text{-th subband} \\
I_u & \quad \text{SNR intervals, } u = 1, 2, 3 \\
(m, n) & \quad \text{channel state} \\
N & \quad \text{number of subcarriers} \\
N_{Sym} & \quad \text{number of symbols of one packet} \\
q_{(m,n)(m',n')} & \quad \text{channel state transition probabilities} \\
R_k & \quad \text{output of the } N\text{-point DFT} \\
S & \quad \text{number of subcarriers in each subband} \\
T_P & \quad \text{transmission time of one packet} \\
V_k(t) & \quad \text{is the channel noise} \\
W & \quad \text{OFDM system bandwidth}
\end{align*}
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon_{(m,n)}$</td>
<td>average BER of channel state $(m,n)$</td>
</tr>
<tr>
<td>$\varepsilon'_{(m,n)}$</td>
<td>average BER after decoding of channel state $(m,n)$</td>
</tr>
<tr>
<td>$\eta_u$</td>
<td>probability for one subband reside in the SNR interval $I_u$</td>
</tr>
<tr>
<td>$\gamma_k(t)$</td>
<td>received SNR of each subchannel</td>
</tr>
<tr>
<td>$\Gamma_u$</td>
<td>SNR thresholds for subchannels</td>
</tr>
<tr>
<td>$\Lambda_G$</td>
<td>LCR of channel frequency response taps</td>
</tr>
<tr>
<td>$\Omega_l$</td>
<td>average power of $l$-th tap</td>
</tr>
<tr>
<td>$\pi(m,n)$</td>
<td>steady-state probability of channel state $(m,n)$</td>
</tr>
<tr>
<td>$\tau_m$</td>
<td>RMS delay spread</td>
</tr>
</tbody>
</table>
Chapter 5

Joint Error-control Mechanisms over Fading Channels

5.1 Motivation and Contributions

Error-control mechanisms are critical for wireless networks to combat channel fading and ensure efficient resource utilization. To provide reliable data delivery over the wireless fading channels and enhance the bandwidth efficiency, various error-control mechanisms have been adopted in both the PHY and link layers. The Adaptive Modulation and Coding (AMC) in the PHY layer can ensure an acceptable BER by changing the TM in every frame or a burst of frames according to the time-varying channel condition. In the link layer, the packet fragmentation and ARQ schemes have been employed, which are particularly important for marginal links (links with small SNR budget and thus high BER). As defined in [4, 2], a packet from the upper layer, called MAC Service Data Unit (MSDU)\(^1\), may be fragmented by the sender and then reassembled in order at the receiver. The fragments are delivered using the ARQ scheme, such as the Delayed Acknowledgment (Dly-ACK) (described in Section 5.3.3). In the following, we denote the AMC in the PHY layer and the fragmentation and ARQ in the link layer together as the \textit{joint error-control mechanisms}.

On the other hand, the MAC protocol coordinates the network nodes to share the medium and it directly affects the QoS support. The QoS guarantee in the contention-based MAC (such as the Distributed Coordination Function in IEEE

\(^1\)The MSDUs refer to the packets from the upper layer to the MAC layer to transmit. The terms of MSDU and packet are exchangeable in this paper.
802.11) is achieved in a statistical manner, so it is difficult to satisfy the stringent delay requirement of multimedia traffic. Even the prioritized contention cannot guarantee the hard QoS and also may lead to the starvation of low priority flows [57]. Consequently, reservation-based MAC protocols have been adopted in emerging network standards due to their superiority for QoS guarantee, such as in the WiMedia ECMA-368 [2] and IEEE 802.15.3a [4] standards for UWB WPANs. For example, with the Distributed Reservation Protocol (DRP) defined in ECMA-368 [2], by reserving appropriate time slots in each superframe in a distributed manner, users can communicate in a peer-to-peer fashion with guaranteed bandwidth. Different from the traditional Time Division Multiplexing Access (TDMA) protocol where one reserves a number of continuous slots per scheduling period, with general distributed reservation-based MAC, a node may reserve multiple non-continuous slots arbitrarily distributed in a scheduling period.

The AMC in the PHY layer and the packet fragmentation and ARQ in the link layer have been widely adopted. To ensure QoS, we need to quantify the packet loss and delay, considering the wireless channel variation, the error-control mechanisms (AMC, ARQ and fragmentation) and the scheduling in MAC. Combining them together further complicates the network performance study and protocol optimization. How to optimize the error-control mechanisms in both layers jointly for high-rate wireless networks is an open and important issue.

In this chapter, based on the ECMA-368 [2] standardized WPAN and the packet-level UWB channel model proposed in Chapter 2, we investigate the joint error-control mechanisms and the arbitrary reservation-based MAC over fading channels. Different from the previous works studying AMC and ARQ, we consider two more important issues which have great impact on delay and loss performance, the arbitrary reservation pattern in scheduling and the estimation errors in Channel State Information (CSI). More importantly, this work is the first to theoretically study the queueing behavior and transmission process of fragmented packets, and compare the effect of AMC and fragmentation on the network performance. The main contributions of this chapter are:

1. We propose a Markov model to quantify the sender’s queuing behavior, considering the joint error-control, DRP MAC and the UWB channel fading.

2. We derive the transmission delay of a fragmented MSDU delivered by Dly-ACK over the fading channel. Thus, a complete analytical framework to quantify the
network performance in terms of PDR and delay is developed.

3. A cross-layer optimization problem for joint AMC and fragmentation is formulated, and a feasible, sub-optimal joint-adaptation strategy is proposed.

As illustrated by our analysis and simulations, we have the following key observations. 1) The PHY-layer AMC and link-layer fragmentation can both improve the bandwidth utilization and link performance. However, the fragmentation can also improve the queueing behavior of the buffer by allowing packets to be partially delivered, which further reduces the queueing delay and buffer overflow probability. 2) The fragmented packets may need more transmission opportunities to be completely delivered, resulting in larger transmission delay. But the transmission delay increment is marginal compared with the reduced queueing delay. Therefore, fragmentation can outperform the AMC in terms of PDR and delay. 3) The proposed sub-optimal joint-adaptation can effectively combat the channel fading and improve the link throughput and delay performance, and it is easy to implement.

In summary, a complete analytical framework to quantify the network performance in terms of PDR and delay is developed, and also the proposed joint-adaptation is efficient and effective for high-rate wireless networks. Although we use the UWB WPANs as an example, the error-control technologies and the arbitrary reservation-based scheduling are general and widely adopted. Therefore, the proposed analytical framework and the joint error-control are ready to be extended to other practical wireless systems, such as the millimeter-wave based WPANs.

5.2 Related Work

The delay of the traditional TDMA has been modeled extensively (e.g., [58, 59]), without considering the arbitrary reservation slot allocation. Therefore, the previous works for traditional TDMA cannot be applied to DRP. Wu [60] analyzed the queue distribution for DRP and evaluated the effect of reservation pattern on the link delay performance, assuming an ideal channel and ignoring the transmission errors. Liu [44] studied the DRP protocol performance with bursty arrivals over indoor UWB shadowing channel. In these works, the error-control mechanisms, which have significant impact on the delay and throughput, have not been considered.

Some recent works investigated the performance of Dly-ACK, which is an efficient ARQ scheme for high rate networks due to less overhead. Link throughput using Dly-
ACK was derived by considering the effective transmitting time for the payload [61]. In [62], the delay performance was analyzed assuming independent transmission errors. An analytical model for Dly-ACK over wireless Rayleigh-fading channel was developed in [48], which illustrated that the correlation between transmission errors affects link performance considerably.

The cross-layer design combining the AMC in the PHY layer and ARQ in the link layer has been discussed in the literature for traditional wireless networks. In [63], AMC was combined with truncated ARQ in order to maximize the spectral efficiency under prescribed delay and error performance constraints. It is revealed that retransmissions in the link layer relieve the stringent error control requirements in the PHY layer. The joint effects of finite-length queuing and AMC was studied in [8]. Because packet loss can be caused by both transmission error and buffer overflow, the optimization of AMC parameters was developed and the packet loss rate and average throughput were obtained. In [9], the queuing behavior induced by both the truncated ARQ and the AMC scheme was analyzed with an embedded Markov chain. Novel cross-layer designs of joint AMC/ARQ were proposed in [64, 10], where different ARQ schemes and the size of transmitter buffer were considered and a buffer-assisted mode selection strategy for AMC was proposed. The authors developed a Markov chain based analytical framework to investigate the performance different mode selection strategies and buffer management schemes.

However, these previous works did not consider the MAC protocol and assumed full channel access for a wireless link when analyzing the performance, e.g., queueing delay and buffer occupancy. The nodes in practical wireless networks usually have to share the channel using MAC protocols. The channel access opportunities are obtained after a relatively long waiting or competing time, which introduces significant delay in both queueing and delivery of a packet. In addition, in the previous works, by assuming a separate feedback channel without delay, the CSI is always available and accurate. But in practical wireless networks with channel access scheduling, the transmitter has to use the CSI obtained from current frame exchange to decide the TM for the next transmission opportunity, which may not be accurate due to channel variations and the relatively long access interval. Therefore, the effectiveness of AMC can be degraded.

Furthermore, to the best of our knowledge, no previous work has investigated the link-layer packet fragmentation, which also affects the link throughput and delay considerably. Therefore, the queueing behavior and link performance of the joint
error-control mechanisms, also considering the MAC scheduling and channel fading, has not been reported, which motivates the work reported in this chapter.

5.3 System Model

5.3.1 Superframe Structure and DRP

The basic timing structure for ECMA-368 is a superframe. As depicted in Fig. 5.1, a superframe with the duration of $T_{SF} = 65,536 \mu s$ is divided into 256 Media Access Slots (MASs). A MAS lasts for $256 \mu s$ and is the minimum time unit for reservation. Each superframe starts with a beacon period (BP), where the availability Information Element (IE) indicates the current utilization of MASs in the superframe. Then in the Data Transfer Period (DTP), users communicate with each other through contention- or reservation-based channel access.

Each node negotiates with its target to reserve MASs according to its traffic load and QoS requirement. To reduce the delay variation, it is desired to reserve evenly spaced time blocks. However, because the reservation is performed in a distributed manner, the reserved MASs of a source-destination pair can be arbitrarily distributed in one superframe, as shown in Fig. 5.1. A reservation block (RB) is one or multiple continuous MAS(s) reserved by the same user. A user is said to be in service during its RBs, and on vacation otherwise. The duration between two consecutive RBs of the user is called vacation time. Each RB and the preceding vacation time together is named a reservation slot (RS).

We focus on a single pair of users which have reserved $N$ RBs in each superframe, indexed by $n, n = 1, 2, \cdots, N$, as shown in Fig. 5.1. The duration of each block, $\Delta_n$, depends on the number of MASs reserved. The duration of the $n$-th RS is denoted as $T_n$. 

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Figure 5.1: MAS reservation in a superframe

Figure 5.2: The link-layer error-control mechanisms: Dly-ACK and fragmentation [2].
5.3.2 Adaptive Modulation and Coding

Different UWB systems, such as impulse-based DS-UWB [65] and MB-OFDM UWB [1], are all capable of using AMC to adapt to the channel condition and meet the BER requirement. ECMA-368 adopts MB-OFDM technology in the PHY layer, where several TMs are provided by puncturing the $R = 1/3$ convolutional codes and selecting time/frequency domain spreading. Thus, the UWB sender can adjust the data rates from 53.3 to 480 Mbps with different coding gain and diversity gain.

Suppose that the wireless system can support $C$ TMs and denote $\mathcal{M}_c (c = 1, 2, \cdots, C)$ the $c$-th TM. The range of the received SNR $\gamma$ is partitioned into $C$ fading intervals $S_c = [\Gamma_c, \Gamma_{c-1})$, $c = 1, 2, \cdots, C$, and TM $\mathcal{M}_c$ is used when $\gamma \in S_c$ such that the BER is maintained to be the target BER, denoted by $\varepsilon_0$.

The transmission time of a Physical Layer Convergence Protocol (PLCP) frame with payload size of $L$ bytes using TM $\mathcal{M}_c$ is [1]

$$T_F(L, \mathcal{M}_c) = 6 \times \left\lceil \frac{8L + 38}{N_{IBP6S}(\mathcal{M}_c)} \right\rceil \times T_{Sym} + T_{Pre} + T_{Hdr}, \quad (5.1)$$

where $N_{IBP6S}$ is the number of information bit per six OFDM symbols, which depends on the TM (e.g., as listed in Table 5.1); $T_{Sym}$, $T_{Pre}$ and $T_{Hdr}$ are the transmission time of one OFDM symbol, the PLCP frame preamble and frame header, respectively.

Using the Dly-ACK scheme (described in the following subsection), the ACK frame piggybacks the link feedback IE which recommends the adjustment to the data rate and transmission power level. Then, the transmitter may change the TM in the next burst transmission accordingly.

5.3.3 Dly-ACK Scheme and Packet Fragmentation

Fragmentation and Dly-Ack are defined as the link-layer error-control mechanisms in both IEEE 802.15.3a and ECMA-368 standards. In the Dly-ACK scheme as shown in Fig. 5.2-(a), we call the $B$ data frames plus the acknowledge frame a burst transmission. The data frame and the ACK frame are separated by a Short Interframe Spacing (SIFS), and there is a Minimum Interframe Spacing (MIFS) interval between two consecutive data frames. Given the allocated channel time in the $n$-th RB $\Delta_n$, the payload size $L$ of data frames and the TM $\mathcal{M}_c$, the number of frames in a burst,
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called burst size, is

\[ B_{n,c}(L) = \left\lfloor \frac{\Delta_n - T_{ACK} - 2 \times SIFS - GT + MIFS}{T_F(L, M_c) + MIFS} \right\rfloor, \tag{5.2} \]

where \( T_{ACK} \) is the transmission time of the ACK frame and \( GT \) is the guard time.

At the transmitting device (DEV), each packet may be partitioned into several fragments of equal size except the last one. Each fragment is encapsulated in one frame and delivered using the Dly-ACK scheme. Sequence of the fragments is identified by the sequence number (i.e., MSDU number) and the fragment number, as illustrated in Fig. 5.2-(b). The receiving DEV shall reassemble each MSDU in the correct order.

As shown in Fig. 5.1, each RB contains a Dly-ACK burst transmission. Upon reception of the delayed ACK at the end of a RB, the acknowledged fragments are removed from the buffer. If the vacant space in the buffer is not enough for a packet, the new arrived packets will be discarded.

For simplicity, we assume that the packet length is fixed as \( L_P \) bytes and each packet is partitioned into \( M \) (\( M \geq 1 \)) fragments with the length of \( L = \frac{L_P}{M} \) bytes. The sender has a queueing buffer of \( F \) fragments.

\section*{5.3.4 UWB Fading Channels}

We use the channel model proposed in Chapter 2 for the indoor UWB fading channel. We define totally \( C \) channel states which are the received SNR intervals, \( S_c \) (\( c = 1, 2, \cdots, C \)), for the \( C \) TMs. Given the SNR intervals, the average BER of each channel state with a certain TM can be obtained according to the MB-OFDM performance [1].

\section*{5.4 Queueing Analysis}

We focus on the queue of the sender, which can be described using a \( G/G/B(t)/F \) model, as shown in Fig. 5.3. First, the packet arrivals can be approximated as a Poisson process with the average arrival rate of \( \Lambda \) packets/second, and the fragment arrivals are a general process (a packet arrival results in \( M \) fragment arrivals simultaneously). Second, the service time of a fragment depends on the number of transmission trials and the arbitrary vacation periods, which has a general distribu-
tion. Third, using Dly-ACK, multiple fragments are transmitted in burst and may be removed from the buffer simultaneously. If the maximal burst size is $B(t)$ at the time slot $t$, the system can be viewed as having $B(t)$ servers with vacations, where $B(t)$ is random and depends on the TM and RB duration, as shown in (5.2) (therefore it is denoted as $B_{nt,ct}$ in the following discussion). Finally, the sender’s buffer size is $F$ fragments.

Because it is very difficult, if not impossible, to applying the traditional queueing analysis, we model the system based on the RSs in the superframes and build a three-dimensional FSMC, as presented in the following.
Figure 5.3: Link layer queueing model.

Figure 5.4: Embedded Markov chain model.
5.4.1 Markov Model

As mentioned in Section 5.3.1, a superframe is divided into \(N\) RSs from the tagged node's point of view. We define the system state at the beginning of each RS as the triplet of \((n, c, q)\), where \(n \in \{1, 2, \cdots, N\}\) is the index of the RS, \(c \in \{1, 2, \cdots, C\}\) is the channel state and \(q \in \{0, 1, \cdots, F\}\) is the number of fragments in the buffer. The three-dimensional FSMC model can capture the MAC protocol scheduling, channel evolution and queueing behavior. We use the RSs as the time slots of the discrete-time Markov model, and the duration of a time slot durations is not constant but repeats from \(T_1\) to \(T_N\) per scheduling period. There are totally \((F + 1)NC\) states. The state at the time slot \(t\) is denoted as \((n_t, c_t, q_t)\). The structure of the FSMC is shown in Fig. 5.4. The non-null one-step transition probabilities are derived as follows.

1) Arrival Process:

Denote \(a_t\) the number of packet arrivals during the \(t\)-th time slot. Since the queue length is \(q_t\) fragments at the beginning of the slot, only \(\min\{a_t, A_t\}\) packets can enter the queue, where \(A_t = \lfloor \frac{F - q_t}{M} \rfloor\). Denote \(b_t\) the number of accommodated fragments and the Probability Mass Function (PMF) of \(b_t\) can be obtained as

\[
 f_{b_t}(a_t, M|n_t, q_t) = \begin{cases} 
 \frac{(\Lambda T_{n_t})^{a_t}}{a_t!}e^{-\Lambda T_{n_t}} = \Psi(a_t, \Lambda T_{n_t}), & a_t < A_t \\
 1 - \sum_{x=0}^{A_t-1} \frac{(\Lambda T_{n_t})^{x}e^{-\Lambda T_{n_t}}}{x!} = 1 - \sum_{x=0}^{A_t-1} \Psi(x, \Lambda T_{n_t}), & a_t = A_t \\
 0, & a_t > A_t 
\end{cases}
\]

where \(n_t\) is the index of the RS in the \(t\)-th time slot and \(\Psi(\cdot)\) is the Poisson distribution function.

2) Channel State Transition:

For the UWB shadowing channels, the residential time in each channel state (the period the person stays in an obstructing zone) is much longer than the duration of a time slot \(T_n\) \((n = 1, \cdots, N)\), so the probability that channel state transition occurs more than once in one time slot is negligible. Hence, the transition probability can be estimated by

\[
 h_{c,c+1} = \frac{\alpha}{A_t} T_{n_t}, \quad c = 1, 2, \cdots, C - 1, \\
h_{c,c-1} = \frac{(1-\alpha)}{A_t} T_{n_t}, \quad c = 2, 3, \cdots, C, \\
h_{c,c} = 1 - \frac{1}{A_t} T_{n_t}, \quad c = 1, 2, \cdots, C.
\]

3) Queue Service Process:
The maximal burst size in the RB in the $t$-th time slot, denoted as $B_{n_t, c_t}$, can be obtained by (5.1) and (5.2). The number of fragments in the burst is $v_t = \min \{ q_t + b_t, B_{n_t, c_t} \}$. The duration of a RB is of several MASs which is much smaller than the channel coherent time. Therefore, the channel is assumed static within a burst, so the frame error probability is constant.

By using the AMC mechanism, the PHY layer chooses appropriate TM to ensure the target BER. However, the TM is determined by $c_t$ estimated by the receiver during the previous burst. When the current burst is in transmission using TM $\mathcal{M}_{c_t}$, the channel is in state $c_{t+1}$, which can be the same as $c_t$ or its adjacent states. If $c_{t+1} = c_t$, we have the target BER $\varepsilon_0$ and the target FER. If $c_{t+1} = c_t + 1$, the channel condition becomes worse than expected, the BER is $\varepsilon_w > \varepsilon_0$. Similarly, if $c_{t+1} = c_t - 1$ (channel condition becomes better), the BER is $\varepsilon_b < \varepsilon_0$. The FER is $\eta_{c_t, c_{t+1}} = 1 - (1 - \varepsilon)^L$ where $\varepsilon$ is $\varepsilon_0$, $\varepsilon_w$ and $\varepsilon_b$, for the three scenarios, respectively. Because the frame header and the ACK frames are always sent at the base data rate of 53.3 Mbps and protected by the strong error-correction coding (concatenation of Reed-Solomon and convolutional coding), we assume that they can be correctly received.

If $d_t$ frames are correctly received in a burst transmission during time slot $t$, they will be removed from the buffer. $d_t$ is of binomial distribution with PMF of

$$f_{d_t}(x|v_t, c_t, c_{t+1}) = \binom{v_t}{x} (1 - \eta_{c_t, c_{t+1}})^x \eta_{c_t, c_{t+1}}^{v_t-x} = \Phi \left( x, v_t, 1 - \eta_{c_t, c_{t+1}} \right), \quad (5.3)$$

where $\Phi(\cdot)$ is the binomial distribution function.

4) System State Transition Probabilities:

The RS index in the $(t+1)$-th time slot is $n_{t+1} = (n_t \mod N) + 1$ and the queue length at the beginning of the time slot is $q_{t+1} = q_t + b_t - d_t$. The transition probability from state $(n_t, q_t, c_t)$ to state $(n_{t+1}, q_{t+1}, c_{t+1})$ is

$$Pr \{(n_{t+1}, q_{t+1}, c_{t+1})|(n_t, q_t, c_t)\} = Pr \{c_{t+1}|c_t, n_t\} Pr \{b_t - d_t = q_{t+1} - q_t|n_t, c_t, q_t, c_{t+1}\}. \quad (5.4)$$

The PMF of the random variable $b_t - d_t$ can be obtained by

$$f_{b_t - d_t}(x|n_t, c_t, c_{t+1}, q_t) = \sum_{y=0}^{A_c M} f_{b_t}(y|n_t, q_t) f_{d_t}(y - x|b_t, q_t, c_t, c_{t+1}), \quad (5.5)$$

where $f_{b_t}$ and $f_{d_t}$ are given in (5.3) and (5.3), respectively.
We organize the transition probability from state \((n, c, q)\) to all the system states in a column vector as
\[
P_{(n,c,q)} = [Pr\{(1,1,0)|(n,c,q)\} \cdots Pr\{(N,C,F)|(n,c,q)\}]^T.
\]
(5.6)

Then, the state transition probability matrix can be obtained as
\[
P = [P_{(1,1,0)} \cdots P_{(1,C,F)} \cdots P_{(N,1,0)} \cdots P_{(N,C,F)}].
\]
(5.7)

5) Stationary Distribution:

Let \(\pi_{(n,c,q)}\) be the steady-state probability of \((n,c,q)\) and define the column vector of the steady-state distribution as
\[
\Pi = [\pi_{(1,1,0)} \cdots \pi_{(1,C,F)} \cdots \pi_{(N,1,0)} \cdots \pi_{(N,C,F)}]^T,
\]
which can be solved by the following linear equations:
\[
\left\{
\begin{array}{l}
\Pi = PP,
\sum_{n=1}^{N}\sum_{c=1}^{C}\sum_{q=0}^{F}\pi_{(n,c,q)} = 1.
\end{array}
\right.
\]

Finally, denote \(Q\) the queue length at the beginning of a RS. Then the stationary distribution of \(Q\) is
\[
f_Q(q) = \sum_{n=1}^{N}\sum_{c=1}^{C}\pi_{(n,c,q)}.
\]
(5.8)

5.4.2 Packet Drop Rate

Considering that AMC in the PHY layer can bound the BER, the probability that a frame is discarded due to excessive retransmissions is negligible. Because of the arbitrary length of vacation time, we evaluate the buffer overflow probability and PDR for each RS.

Denote the queue length at the beginning of the \(n\)-th RS in the superframe as \(Q_n\). First, the stationary distribution of \(Q_n\) is
\[
f_{Q_n}(q) = \sum_{c=1}^{C}\pi_{n,c,q}.
\]
(5.9)

Let \(A_n\) denote the maximal number of packets accommodated in the \(n\)-th slot. The PMF of \(A_n\) is
\[
f_{A_n}(x) = \sum_{q=F-(x+1)M+1}^{F-xM} f_{Q_n}(q), \ x = 0, 1, \cdots, \lfloor \frac{F}{M} \rfloor.
\]

The number of dropped packets during the \(n\)-th RS is denoted as \(D_n\) and thus \(a_n = A_n + D_n\) is the total number of packets arrived during the slot. The conditional
probability of $D_n$ is $f_{D_n}(x|A_n = y) = f_{a_n}(x + y) = \Psi(x + y, \Lambda T_n)$. Thus, the average number of dropped packets in the $n$-th slot is

$$
\bar{D}_n = \sum_{y=0}^{\lfloor \frac{F}{M} \rfloor} \sum_{x=1}^{\infty} xf_{D_n}(x|A_n = y)f_{A_n}(y) 
= \sum_{y=0}^{\lfloor \frac{F}{M} \rfloor} \sum_{x=1}^{\infty} \left[ x\Psi(x + y, \Lambda T_n) \sum_{q=F-(y+1)M+1}^{F-yM} f_{Q_n}(q) \right].
$$

(5.10)

Finally, given the average number of packets dropped in one superframe, the PDR is

$$
\bar{D} = \frac{\sum_{n=1}^{N} \bar{D}_n}{\Lambda T_{SF}}.
$$

(5.11)

### 5.4.3 Queuing Delay

For a tagged packet, the total delay consists of the queuing delay and the transmission delay. The queuing delay of a fragmented packet is defined as the duration from the packet arrival instant till the beginning of the earliest RB in which the first fragment of the packet is transmitted. The transmission delay is the time interval from the transmission of the first fragment until all the fragments of the packet are correctly received. In this subsection, we derive the queuing delay distribution. The transmission delay will be discussed in the following section.

The queuing delay of a packet contains two parts: the delay to the end of the RS in which the packet arrives, and the delay to the RB where the first fragment is transmitted. For the system state $(n, c, q)$, the buffer can at most accommodate $A_q = \lfloor \frac{F-q}{M} \rfloor$ new packets. The average number of the accommodated packets is

$$
\bar{a}_{n,q} = \sum_{x=0}^{A_q-1} x\Psi(x, \Lambda T_n) + A_q \left[ 1 - \sum_{x=0}^{A_q-1} \Psi(x, \Lambda T_n) \right].
$$

(5.12)

Because the average arrival interval is $\delta = \frac{1}{A}$, the expected arriving instant of the $i$-th ($i = 1, 2, \cdots, A_{n,q}$) packet is $i\delta$ w.r.t. the beginning of the RS.

The number of fragments in the buffer when the $i$-th packet arrives is $Q_i = q + (i - 1)M$. Let $G_i$ denote the expected number of RSs the $i$-th packet experiences while it is waiting in the buffer before its first fragment being transmitted. $G_i$ is
obtained by

\[ G_i = \begin{cases} 
1, & Q_i < B_{n,c} \\
\min \left\{ x \mid \sum_{x=2}^{\infty} B_g(n+x-2,c)(1-\eta_0) + B_g(n+x-1,c) > Q_i \right\}, & Q_i > B_{n,c}
\end{cases} \quad (5.13) \]

where \( B_{n,c} \) is the burst size of the \( n \)-th RB using TM \( \mathcal{M}_c \), as given in (5.2), and 

\[ g(x) = \left[ \left( x - 1 \right) \mod N \right] + 1. \]

Thus, the total queueing delay for the \( i \)-th packet is

\[ \zeta_i = \sum_{j=n}^{n+G_i-1} T_{g(j)} - i\delta - \Delta_g(n+G_i-1). \quad (5.14) \]

The average queueing delay of the packets arriving during the system state \((n, c, q)\) is \( \bar{\zeta}_{(n,c,q)} = \frac{1}{A_q} \sum_{i=1}^{\tilde{a}_{n,q}} \zeta_i \). Thus, the average queueing delay for all the system states is

\[ \bar{\tau}_q = \sum_{n=1}^{N} \sum_{c=1}^{C} \sum_{q=0}^{F-M} \bar{\zeta}_{(n,c,q)} \pi_{(n,c,q)} = \sum_{n=1}^{N} \sum_{c=1}^{C} \sum_{q=0}^{F-M} \left( \frac{1}{A_q} \sum_{i=1}^{\tilde{a}_{n,q}} \zeta_i \right) \pi_{(n,c,q)}. \quad (5.15) \]

### 5.5 Transmission Delay of Fragmented Packets

To quantify the transmission delay of a fragmented packet, we first obtain the PMF of the number of burst transmissions needed for a packet, and then the transmission delay is acquired by considering the reservation pattern in the superframe.

#### 5.5.1 Transmission Process of Fragmented Packets

We index the earliest burst in which the first fragment of the tagged packet is transmitted as the first burst, and the following burst is the second one, and so on. A fragment is called imported in a burst when it is transmitted for the first time. Suppose that the last fragment of the tagged packet is imported in the \( U \)-th burst. The number of fragments imported in the \( u \)-th (\( u = 1, 2, \cdots, U \)) burst is denoted as \( m_u \). The vector of \( \mathbf{m}_U = [m_1 \ m_2 \ \cdots \ m_U] \) is called import vector and we have \( \sum_{u=1}^{U} m_u = M \). The import process and the transmission process both depend on the burst size \( u \) and the FER of each burst transmission.
5.5.2 PMF of the Number of Bursts for One Packet

With slow fading, the probability for the channel to change state during the transmission of one packet is much less than the probability to stay in the same state. Therefore, due to the space limit, we assume that the channel is constant during the transmission of the tagged packet, and thus the FER is $\eta_0$ as defined earlier. The analysis for the scenario that the channel state changes can be found in [24].

Let $W'_u$ denote the index of the burst where one of the $m_u$ fragments, which is imported in the $u$-th burst, is delivered. The PMF and CDF of $W'_u$ are, respectively:

$$ f_{W'_u}(w) = (1 - \eta_0)\eta_0^{w-u}, \quad w \geq u $$  \hspace{1cm} (5.16)

and

$$ F_{W'_u}(w) = \sum_{x=u}^{w} (1 - \eta_0)\eta_0^{x-u} = 1 - \eta_0^{w-u+1}. $$  \hspace{1cm} (5.17)

Note that $W'_u$ for each of the $m_u$ fragments are i.i.d. random variables. Denote $W_u$ the burst when all the $m_u$ fragments are received. The CDF of $W_u$ is

$$ F_{W_u}(w|m_u) = [F_{W'_u}(w)]^{m_u} = (1 - \eta_0^{w-u+1})^{m_u}, \quad w \geq u. $$  \hspace{1cm} (5.18)

Denote $W$ the last burst when all the $M$ fragments have been delivered. Given the import vector $m_U$ (the import process includes $U$ bursts), the conditional CDF of $W$ is

$$ F_W(w|m_U) = \prod_{u=1}^{U} F_{W_u}(w) = \prod_{u=1}^{U} (1 - \eta_0^{w-u+1})^{m_u}, \quad w \geq U. $$  \hspace{1cm} (5.19)

Finally, the unconditional CDF of $W$, i.e., the probability that the tagged packet can be delivered within $w$ bursts, is

$$ F_W(w) = \sum_{U=1}^{w} F_W(w|m_U)Pr\{m_U\}, $$  \hspace{1cm} (5.20)

where $Pr\{m_U\}$ is the probability of the import vector $m_U$. Then the PMF of $W$ can be obtained by $f_W(w) = F_W(w) - F_W(w - 1)$. 
5.5.3 Import Process

Because the import process is related to the burst size, we evaluate \( \Pr \{ m_U \} \) for each RB. Suppose that the tagged packet is first imported in the \( n \)-th RB. At the beginning of the RB, the number of fragments in the buffer is \( Q'_n = Q_n + b_n \), where \( Q_n \) is the queue length at the beginning of the RS as defined earlier and \( b_n \) is the fragment arrivals during the RS. If the TM is \( M_c \) and \( Q'_n > B_{n,c} \), the burst transmission in the RB will be full and there is at least one fragment in the buffer not transmitted. We call such scenario as being saturated.

1) For \( U = 1 \)

We first consider the saturated case. Here we make two approximations. First, because the current burst is saturated, we assume that the previous burst is full (which happens with high probability). Second, the number of the remaining fragments of the previous packet which have not been imported yet is uniformly distributed over \([1, M - 1]\). As shown in the numerical results, these approximations do not affect the accuracy of the analytical results.

Thus, the number of the fragments of new packets which can be imported in the burst is

\[
V = \left[ B_{n,c} - B_{g(n-1,c)}(1 - \eta_0) - \frac{M - 1}{2} \right],
\]

where \( \lceil \cdot \rceil \) rounds the value inside to the nearest integer. Since the number of packets completely imported is \( \lfloor \frac{V}{M} \rfloor \) and the last packet is partially imported, the probability for one packet to be completely imported \( (U = 1) \) is

\[
\Pr \{ U = 1 \mid Q'_n > B_{n,c} \} = \frac{\lfloor \frac{V}{M} \rfloor}{\lfloor \frac{V}{M} \rfloor + 1}.
\]

Second, for unsaturated scenario, because all packets in the buffer can be completely imported, we have \( \Pr \{ U = 1 \mid Q'_n \leq B_{n,c} \} = 1 \).

The PMF of \( Q'_n \) can be obtained by

\[
f_{Q'_n}(q) = \sum_{x=0}^{q} f_{Q_n}(x) f_{b_n}(q - x | n, x),
\]

where \( f_{Q_n}(x) \) and \( f_{b_n}(x) \) are given in (5.9) and (5.3), respectively. Thus, the probability for the \( n \)-th RB to be saturated is \( \Pr \{ Q'_n > B_{n,c} \} = \sum_{q=B_{n,c}+1}^{F} f_{Q'_n}(q) \).
Finally, the probability for a packet to be imported completely in one burst is

\[
\Pr\{U = 1\} = \Pr\{U = 1|Q'_n > B_{n,c}\}\Pr\{Q'_n > B_{n,c}\} \\
+ \Pr\{U = 1|Q'_n \leq B_{n,c}\}\Pr\{Q'_n \leq B_{n,c}\} \\
= 1 - \left(1 - \frac{\lfloor V_M \rfloor}{V_M} + 1\right) \sum_{q=B_{n,c}+1}^{F} f_{Q'_n}(q). \tag{5.24}
\]

Obviously, when \( U = 1 \), the import vector is simply \( \mathbf{m}_1 = [M] \).

2) For \( U > 1 \)

The import vector is \( \mathbf{m}_U = [m_1 \ m_2 \ \cdots \ m_U] \), where \( m_u \in \{1, 2, \cdots, M - 1\} \) for \( u = 1 \) or \( U \), and \( m_u \in \{0, 1, \cdots, M - 2\} \) for \( 1 < u < U \). First, \( m_1 \) is approximated to be uniformly distributed and the PMF is \( f_{m_1} = \frac{1}{M-1} \). Then, \( m_u \) fragments being imported in the \( u \)-th (\( 1 < u < U \)) burst means that exactly \( m_u \) fragments are successfully delivered in the previous burst, which is in the \( g(n + u - 2) \)-th RB. Therefore, the PMF of \( m_u \) can be obtained as \( f_{m_u}(x|n, c) = \Phi(x, B_{g(n+u-2),c}, 1 - \eta_0) \) where \( 0 \leq x \leq M - 2 \). Finally, the probability for the last \( m_U \) fragments to be imported in the \( U \)-th burst (so the import process includes \( U \) bursts) is \( f_{m_U}(x|n, c) = \sum_{y=x}^{B_{g(n+U-2),c}} \Phi(y, B_{g(n+U-2),c}, 1 - \eta_0) \) where \( 1 \leq x \leq M - 1 \).

Thus, the probability of the import vector given that the packet’s first fragment is imported in the \( n \)-th RB and the TM is \( \mathcal{M}_c \) is

\[
\Pr\{ \mathbf{m}_U = [m_1 \ m_2 \ \cdots \ m_U]|n, c\} = \Pr\{U > 1\} f_{m_1}(m_1)f_{m_2}(m_2|n, c)\cdots f_{m_U}(m_U|n, c) \\
= (1 - \Pr\{U = 1\}) \frac{1}{M-1} \left[\prod_{u=2}^{U-1} \Phi(m_u, B_{g(n+u-2),c}, 1 - \eta_0)\right] \\
\sum_{y=x}^{B_{g(n+U-2),c}} \Phi(y, B_{g(n+U-2),c}, 1 - \eta_0). \tag{5.25}
\]

By plugging (5.25) into (5.20), \( F_W(w|n, c) \) can be obtained.

### 5.5.4 Transmission Delay

If all \( M \) fragments are delivered in \( w \) bursts, the transmission delay is \( \Delta_n + \sum_{j=n+1}^{n+w-1} T_{g(j)} \).

The average transmission delay for a packet which is first time imported in the \( n \)-th
RB is
\[
\bar{\xi}_{n,c} = \sum_{w=1}^{\infty} f_W(w|n,c) \left( \Delta_n + \sum_{n'=n+1}^{n+w-1} T_{n'} \right).
\]
(5.26)

To estimate the average transmission delay using TM $M_c$, we need to determine the probability for one packet to be first time imported in the $n$-th RB, denoted as $p_{n,c}$. We propose Algorithm 1 to estimate $p_{n,c}$.

**Algorithm 1** Throughput estimation of each RB

1. $n_0 \leftarrow \arg \max_n (B_{n,c} - \lambda_n)$
2. $Queue \leftarrow 0$
3. for $j = n_0 + 1$ to $n_0 + N$ do
4. \hspace{1em} $n \leftarrow g(j)$
5. \hspace{1em} $H_{n,c} \leftarrow \min(B_{n,c}, Queue + \lambda_n)$
6. \hspace{1em} $Queue \leftarrow Queue + \lambda_n - H_{n,c}$
7. end for

Then, the probability for one packet to be first imported in the $n$-th RB is $p_{n,c} = \frac{H_{n,c}}{\sum_{n=1}^{N} H_{n,c}}$. Finally, the average transmission delay of a packet is
\[
\bar{\xi}_c = \sum_{n=1}^{N} p_{n,c} \bar{\xi}_{n,c}.
\]
(5.27)

### 5.6 Joint Error-control Mechanism Optimization

In Sections 5.4 and 5.5, we have studied the performance of joint error-control mechanism. How to optimize the TM (i.e., the SNR boundaries), the target BER and the fragment size to achieve best performance is an open issue. In [61], optimal ACK scheme was presented by adapting the payload size only. Here, we define the optimization problem as maximizing the link throughput via jointly arranging the TM and fragment size of both layers.

#### 5.6.1 Throughput Optimization Problem

Since the BER depends on both the received SNR $\gamma$ and the TM, it is denoted as $\varepsilon(\gamma, M_c)$. Given the channel time allocated to the tagged user, $\Delta_n (n = 1, 2, \cdots, N)$,
the link throughput of the saturated sender can be expressed as

\[ H(\gamma, M_c, L) = \frac{8}{T_{SF}} \left( \sum_{n=1}^{N} B_{n,c} \right) \left[ 1 - \varepsilon(\gamma, M_c) \right]^{8L} L, \tag{5.28} \]

where \( B_{n,c} \) is given by (5.2). To maximize \( H(\gamma, M_c, L) \) given \( \gamma \), the two-step numerical search for the optimal system parameters is as follows.

First step, we determine the optimal fragment size of each TM for fixed SNR. Using a smaller fragment size leads to higher percentage of the overheads (the fixed frame header, interframe spacing time and ACK) and thus reduces channel utilization. But with error-prone channel condition, a larger frame is more likely to be corrupted and thus the link throughput may be reduced.

We can approximate the transmission time of a data frame in (5.1) by

\[ T'_F \approx \frac{48LT_{Sym}}{N_{IBP6S}} + T_{Pre} + T_{Hdr}. \tag{5.29} \]

By plugging (5.29) and (5.2) (ignoring the flooring function) into (5.28), we can get the throughput as

\[ H' \approx X \frac{L \left[ 1 - \varepsilon(\gamma, M_c) \right]^{8L}}{L + Y}, \tag{5.30} \]

where

\[ X = \frac{N_{NIBP6S}}{6T_{Sym}T_{SF}} \sum_{n=1}^{N} (\Delta_n - T_{ACK} - 2SIFS + MIFS), \]

\[ Y = \frac{N_{NIBP6S}}{48T_{Sym}} (T_{Pre} + T_{Hdr} + MIFS). \tag{5.31} \]

Taking the first derivative of (5.30) and setting it to zero, the approximate optimal fragment length can be obtained as

\[ L^*_c(\gamma) \approx \frac{-8Y \ln(1 - \varepsilon) - \sqrt{[8Y \ln(1 - \varepsilon)]^2 - 32Y \ln(1 - \varepsilon)}}{16 \ln(1 - \varepsilon)}. \tag{5.32} \]

Second step, we can determine the optimal TM for any given SNR \( \gamma \) by \( c^* = \arg \max_c \{ H(\gamma, M_c, L^*_c(\gamma)) \} \), so the TM \( M_c^* \) (with the corresponding optimal fragment size) has the maximal throughput. Finally, the SNR interval, \( S_c \), can be obtained as the SNR range where \( M_c \) is the optimal one.
5.6.2 Suboptimal Joint Error-control Mechanism

According to the numerical results in Section 5.7.1, for a fixed TM, the optimal payload size varies significantly with SNR of $\gamma \in [\Gamma_C, \Gamma_0]$, which introduces considerable implementation complexity because the system needs to change the fragment size with the time-varying SNR frequently. On the other hand, once the AMC is adopted and the appropriate TM is selected, so long as the fragment size is chosen within the appropriate range, (e.g., from 370 bytes to 2730 bytes for TM $M_3$), the throughput remains almost the same.

This observation suggests to use a fixed fragment length to approximate the optimal ones for a relatively wide range of SNR with the support of AMC in the PHY layer, which can greatly simplify the implementation of fragmentation in practical systems. For simplicity, we select the fragment size of $L^* = 1000$ bytes for marginal links. As shown in the numerical results, the performance of this suboptimal strategy with fixed $L^*$ and optimal TM is quite close to the optimal one. In addition, the performance analytical model proposed in Sections 5.4 and 5.5 is directly applicable for this suboptimal error-control mechanism.

5.7 Performance Evaluation

We simulate a typical WPAN deployed in an indoor environment. The received SNR varies in the range of [1, 7] dB due to the shadowing effect. The four TMs of 53.3, 80, 106.7 and 160 Mbps which can operate in this range are considered. The packet size is 4 KB (the maximal allowable payload size of a PLCP frame). Using the parameters of ECMA-368, we first calculate the saturation throughput of different error-control mechanisms, and obtain the optimal SNR partition and BERs of the AMC. Then, the queueing and transmission processes are simulated and different error-control mechanisms are compared.

5.7.1 Optimal TM and Fragment Size

Fig. 5.5 shows the throughput vs. fragment size with given SNR of $\gamma = 2.16, 4.16$ and 8.16 dB, respectively. It can be seen that the throughput is affected by the

\[^{2}\text{If the received SNR is larger, the TMs with higher data rates, like 200, 320, 400 and 480 Mbps can be used, and the approach is still applicable.} \]
fragmentation considerably for a given SNR. As expected, for a given SNR and a TM, an optimal fragment size exists which results in the largest throughput.

The optimal TM and fragment size have been calculated according to Section 5.6 and listed in Table 5.1. For example, when the SNR is in the range of [6.15, 7) dB, the best TM is 160 Mbps, and the optimal payload size varies from 820 bytes (when SNR is 6.15 dB) to 2620 bytes (when SNR is 7 dB). To compare the performance gain, Fig. 5.6 shows the throughput of five adaptation strategies: 1) the optimal strategy, 2) the fragment-adaption strategy using optimal fragment size and fixed TM (106.7 Mbps), 3) the TM-adaptation strategy using the optimal TM without fragmentation ($M = 1$), 4) the suboptimal joint error-control designed in Section 5.6.2 (optimal TM with fixed fragment size of 1000 bytes), referred as joint-adaptation, and 5) the non-adaptive strategy using 106.7 Mbps and no fragmentation. We have the following observations.

First, the joint error-control by combining the AMC and fragmentation can increase the throughput significantly, especially for low SNR range. For example, when $\gamma = 3.5$ dB, the optimal strategy is $M_c^* = 80$ Mbps and $L^* = 930$ bytes, and it can achieve around 64 Mbps throughput. But the throughput is almost zero for the non-adaptive strategy and 35 Mbps only for the fragment-adaptation (the scenario studied in [61]).

Second, as discussed in Section 5.6, the suboptimal joint-adaptation can achieve close to optimal performance with much simpler implementation because frequently changing fragment size is avoided.

Third, as shown in Table 5.1, the average BERs of different TMs within their corresponding SNR intervals are in the same order. Therefore, we can approximate the target BER of the AMC by the average BER of all TMs, denoted as $\varepsilon_0 = 9.59 \times 10^{-6}$. Furthermore, if the TM $M_c$ ($c = 1, 2, 3$) is used but the channel state changes to the adjacent state $S_{c+1}$ (as mentioned in Section 5.4.1), the BER $\varepsilon_w$ of each $M_c$ is all closed to each other and can be approximated by $\varepsilon_w = 2.55 \times 10^{-4}$. Similarly, for the scenario that $M_c$ ($c = 2, 3, 4$) is used but the channel changes to $S_{c-1}$, the BERs are similar and can be approximated by $\varepsilon_b = 2.62 \times 10^{-7}$.

### 5.7.2 Queueing and Transmission Simulations

1) **Simulation Settings:**

Using the SNR range of each TM listed in Table 5.1 as the boundaries of the
Figure 5.5: Link throughput vs. fragment size.

Table 5.1: Transmission Modes in MB-OFDM

<table>
<thead>
<tr>
<th>$c$</th>
<th>Data Rate (Mbps)</th>
<th>$N_{IBP6S}$</th>
<th>SNR interval $[\gamma_{c-1}, \gamma_c]$ (dB)</th>
<th>Optimal Payload $L_c^*$ (bytes)</th>
<th>$\varepsilon_0$ ($\times10^{-6}$)</th>
<th>$\varepsilon_w$ ($\times10^{-4}$)</th>
<th>$\varepsilon_b$ ($\times10^{-7}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>160</td>
<td>300</td>
<td>[6.15, 7)</td>
<td>820 $\sim$ 2620</td>
<td>8.74</td>
<td>2.55</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>106.7</td>
<td>200</td>
<td>[4.45, 6.15)</td>
<td>870 $\sim$ 3640</td>
<td>6.37</td>
<td>2.16</td>
<td>1.57</td>
</tr>
<tr>
<td>3</td>
<td>80</td>
<td>150</td>
<td>[2.85, 4.45)</td>
<td>370 $\sim$ 2730</td>
<td>15.9</td>
<td>2.95</td>
<td>3.64</td>
</tr>
<tr>
<td>4</td>
<td>53.3</td>
<td>100</td>
<td>[1, 2.85)</td>
<td>270 $\sim$ 2580</td>
<td>7.33</td>
<td>-</td>
<td>2.66</td>
</tr>
</tbody>
</table>

Figure 5.6: Throughput of different error-control strategies.
channel states, the obstructing zones are obtained according to Section 2.6. Assuming that $\alpha = \frac{1}{2}$, the state transition rates of the FSMC channel model are $\mu_{1,2} = 0.20$, $\mu_{2,3} = \mu_{2,1} = 0.11$, $\mu_{3,4} = \mu_{3,2} = 1.02$ and $\mu_{4,3} = 3.82$. Then the transition probabilities of the channel states during each RS can be obtained from (5.3). In the link layer, we assume that the tagged user is allocated two RB per superframe and eight MASs in each block which are located at 129 $\sim$ 136 and 193 $\sim$ 200 (the numbers denote the MAS index $\in \{1, 2, \ldots, 256\}$).

When the payload size is 4 KB (no fragmentation), the burst size of Dly-ACK in each RB are 9, 6, 4 and 3 frames for the 4 TMs, respectively. When the payload size is 1000 bytes, the burst size are 32, 22, 17 and 12 frames, respectively. In Figs. 5.7 to 5.12, the dashed lines represent our analytical results, while the solid lines represent the simulation results.

2) Simulation Results:

Fig. 5.7 shows the CDF of the stationary queueing length distribution with the buffer size of 80 KB. The good agreement between the analytical and simulation results validates the accuracy of our analysis. We can see that fragmentation makes significant difference in queue length distribution. With fragmentation ($M = 4$), the queue length has much higher probability to have small values (e.g., smaller than 20 KB with probability of 60%); without fragmentation, the queue length has large dynamics (e.g., larger than 20 KB with probability of 65%). This is because the link throughput is increased by using fragmentation and, more importantly, a packet can be partially delivered. Thus, fragmentation can also improve the queueing behavior of the buffer and thus helps to accommodate bursty traffic.

Fig. 5.8 shows the PDR of three error-control strategies. The fragment-adaptation has lower PDR than the TM-adaptation. Both adaptation mechanisms can increase channel utilization by reducing FER. But the fragment-adaptation can improve the queue length distribution and thus further reduce the probability of buffer overflow. However, the PDR of the fragment-adaptation is still much higher than that of the joint-adaptation when the channel condition is bad (like in channel state $S_4$). The joint-adaptation mechanism has the lowest average PDR.

Fig. 5.9 shows the average queueing delay, where the fragment-adaptation has the best performance. Note that the payload size of the fragment-adaptation is always the optimal one, while it is fixed as $L = 1000$ bytes for the joint-adaptation (the suboptimal strategy). Therefore, the queuing delay of the joint-adaptation is slightly larger.
Figure 5.7: Stationary distribution (CDF) of queue length.
Figure 5.8: Packet drop rate of the three error-control mechanisms.

Figure 5.9: Queueing delay of the three error-control mechanisms.
In the following, we investigate the transmission delay. To validate our analysis, Fig. 5.10 shows $f_W(w)$ of a fragmented packet ($M = 4$) for channel states $S_1$ and $S_4$. The analytical and simulation results match quite well. Most packets can be delivered in one or two bursts. In the bad channel state $S_4$, the probability of more bursts to deliver a packet is increased, as expected.

The average transmission delays are compared in Fig. 5.11. If fragmentation is used, the fragments of one packet are usually imported through several bursts and thus requires more bursts to deliver. Therefore, the joint-adaptation has larger transmission delay than the TM-adaptation. However, the fragment-adaptation can provide the smallest transmission delay. This is because when the channel state is good (like $S_0$), the packets are not fragmented and the transmission delay is similar to that of the TM-adaptation. On the other hand, when the channel state is bad (like $S_3$), the fragment-adaptation can use smaller fragment size to reduce the FER and retransmissions. In addition, the burst size is increased and the probability to import the whole packet in one burst ($U = 1$) is still high.

Another point is that if the packets are fragmented, the transmission delay is also related to the queuing behavior. As shown in Fig. 5.11, the transmission delay of the TM-adaptation (no fragmentation) is constant. But for the payload- and joint-adaptation, the transmission delay is smaller with the small buffer size (like 40 KB) than with large buffer. This is because, with smaller buffer, all fragments of one packet are more likely to be imported in less bursts due to the smaller queue length (e.g., the probability of $U = 1$ is higher). Thus, the transmission delay is reduced. Finally, we can observe a gap between the analytical and simulation results. This is because it is difficult to get accurate probability for one packet to be first imported in the $n$-th RB. Instead, we use Algorithm 1 to obtain an approximation of $p_{n,c}$.

Finally, Fig. 5.12 shows the system performance, i.e., PDR versus average link delay (queueing delay plus transmission delay). Although, as mentioned earlier, fragment-adaptation has the smallest queuing and transmission delay, by using the optimal payload size, given the link delay, the joint-adaptation provides the lowest PDR. This is because the channel utilization of fragment-adaptation is much lower than that of joint-adaptation in bad channel states, which results in much higher PDR. The advantages of joint-adaptation is more significant under bad channel conditions, which results in the best overall performance over the fading channel.
Chapter 5. Joint Error-control Mechanisms over Fading Channels

Figure 5.10: PMF of W.

Figure 5.11: Transmission delay of the three error-control mechanisms.
Figure 5.12: System performance of the three error-control mechanisms.
3) **Discussions:**

In summary, the TM- and fragment-adaptation are both beneficial for throughput and channel utilization efficiency. Fragment-adaptation is more efficient in improving both PDR and delay, because fragmentation can also improve the queueing behavior.

The fragments of a packet may need to be imported through multiple bursts and thus more bursts are required to deliver the whole packet. However, the transmission delay increment is marginal compared with the reduced queueing delay.

The analytical and simulation results show that the TM- and fragment-adaptation alone cannot ensure system performance under bad channel conditions. The joint-adaptation can effectively combat the channel fading and further improve the system performance.

### 5.8 Summary

We have comprehensively studied the performance of error-control mechanisms and reservation-based MAC for wireless networks over fading channels. A general analytical queueing model has been presented and then a suboptimal joint-adaptation mechanism has been proposed. It has been shown that the fragment-adaptation can improve the queueing behavior of the buffer and outperforms the TM-adaptation for PDR and packet delay. However, due to the limited adaptivity, both mechanisms cannot ensure bandwidth efficiency in bad channel conditions. The proposed suboptimal joint-adaptation can provide the satisfactory overall system performance and it is also simple to implement.

The analysis in this chapter also leads a step toward further understanding the UWB network capacity. It beckons more in-depth investigation in this new area, for example, how to optimize the network scheduling to mitigate the fading of the UWB shadowing channels.

### 5.9 Symbol List

- $a_t$: number of packets arrivals during the $t$-th time slot
- $\bar{a}_{n,q}$: average number of accommodated packets (slot: $n$; queue length: $q$)
- $A_n$: maximal number of packets accommodated during the $n$-th slot
- $A_t$: maximal number of packets to accommodate during the $t$-th time slot
\(b_t\) number of accommodated fragments during the \(t\)-th time slot
\(B_{n,c}(L)\) burst size of the \(n\)-th RB with payload size of \(L\) bytes using TM \(M_c\)
\(c\) index of channel state \(c \in \{1, 2, \cdots, C\}\)
\(C\) number of fading intervals (TM)
\(d_t\) number of fragments correctly received during the \(t\)-th time slot
\(D_n\) total number of dropped packets during the \(n\)-th slot
\(\bar{D}_n\) average number of dropped packets during the \(n\)-th slot
\(F\) buffer size (fragments)
\(G_i\) expected number of RSs the \(i\)-th packet experiences waiting in buffer
\(GT\) guard time
\(h_{c,c+1}\) channel state transition probability
\(H(\gamma, M_c, L)\) link throughput of the saturated sender
\(H'\) approximate throughput
\(L^*\) fixed suboptimal fragment size of (bytes)
\(L^*_c(\gamma)\) approximate optimal fragment length
\(L_P\) packet length (bytes)
\(m_u\) number of fragments imported in the \(u\)-th burst
\(M\) number of fragments of each packet \((M \geq 1)\)
\(M_c\) the \(c\)-th TM \((c = 1, 2, \cdots, C)\)
\(M_c^*(\gamma)\) optimal TM for given SNR \(\gamma\)
\(n\) index of the RS \(n \in \{1, 2, \cdots, N\}\)
\(N\) number of RBs in each superframe
\(N_{IBP6S}\) number of information bit per six OFDM symbols
\(p_{n,c}\) probability for one packet to be imported in the \(n\)-th RB
\(P_{(n,c,q)}\) transition probability vector from state \((n, c, q)\)
\(P\) state transition probability matrix
\(q\) number of fragments in the buffer \(q \in \{0, 1, \cdots, F\}\)
\(Q\) queue length at the beginning of a RS
\(Q_i\) queue length when \(i\)-th packet arrives
\(Q_n\) queue length at the beginning of the \(n\)-th RS
\(S_c\) the \(c\)-th fading interval (channel state)
\(T_{ACK}\) transmission time of the ACK frame
\(T'_{F}\) approximate data frame transmission time
\(T_F(L, M_c)\) transmission time of a PLCP frame (payload size: \(L\) bytes; TM: \(M_c\))
\(T_n\) duration of the \(n\)-th RS
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{SF}$</td>
<td>superframe duration</td>
</tr>
<tr>
<td>$U$</td>
<td>number of bursts the tagged packet is imported</td>
</tr>
<tr>
<td>$v_t$</td>
<td>number of fragments in the burst during the $t$-th time slot</td>
</tr>
<tr>
<td>$V$</td>
<td>number of the fragments of new packets imported in a burst</td>
</tr>
<tr>
<td>$W$</td>
<td>the burst when all the $M$ fragments have been delivered</td>
</tr>
<tr>
<td>$W'_u$</td>
<td>the burst a fragment is delivered which imported in the $u$-th burst</td>
</tr>
<tr>
<td>$W_u$</td>
<td>the burst when all the $m_u$ fragments are delivered</td>
</tr>
<tr>
<td>$\delta$</td>
<td>average packet arrival interval</td>
</tr>
<tr>
<td>$\Delta_n$</td>
<td>duration of the $n$-th block</td>
</tr>
<tr>
<td>$\varepsilon_0, \eta_0$</td>
<td>target BER or FER</td>
</tr>
<tr>
<td>$\varepsilon_w, \eta_w$</td>
<td>BER or FER with channel condition worse than expected</td>
</tr>
<tr>
<td>$\varepsilon_b, \eta_b$</td>
<td>BER or FER with channel condition better than expected</td>
</tr>
<tr>
<td>$\varepsilon(\gamma, \mathcal{M}_c)$</td>
<td>BER with SNR $\gamma$ and TM $\mathcal{M}_c$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>received SNR</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>packet arrival rate (packets/second)</td>
</tr>
<tr>
<td>$m_U$</td>
<td>import vector</td>
</tr>
<tr>
<td>$\Phi(\cdot)$</td>
<td>binomial distribution function</td>
</tr>
<tr>
<td>$\pi(n,c,q)$</td>
<td>steady-state probability of $(n,c,q)$</td>
</tr>
<tr>
<td>$\Pi$</td>
<td>steady-state distribution vector</td>
</tr>
<tr>
<td>$\Psi(\cdot)$</td>
<td>Poisson distribution function</td>
</tr>
<tr>
<td>$\bar{\tau}_q$</td>
<td>average queueing delay for all the system states</td>
</tr>
<tr>
<td>$\bar{\xi}_c$</td>
<td>average transmission delay of a packet</td>
</tr>
<tr>
<td>$\bar{\xi}_{n,c}$</td>
<td>average transmission delay for a packet imported in the $n$-th RB</td>
</tr>
<tr>
<td>$\zeta_i$</td>
<td>total queueing delay for the $i$-th packet</td>
</tr>
<tr>
<td>$\bar{\zeta}_{(n,c,q)}$</td>
<td>average queueing delay the state $(n,c,q)$</td>
</tr>
</tbody>
</table>
Chapter 6

Admission Control for IPTV over UWB Channels

6.1 Motivation and Contributions

Future WPANs based on UWB technologies are anticipated to support high quality multimedia applications such as IPTV in office or residential buildings. Chapter 2 has analyzed the BSE and proposed the packet-level UWB channel model. By incorporating this channel model into the link-layer performance analysis and simulation framework, Chapter 5 has revealed the significant impact of the temporal variation of UWB channels on the link-layer throughput and delay. To support in-home distribution of multimedia applications such as IPTV, it is crucial to examine the effect of the BSE on the application-layer QoS metrics such as video PLR, delay and delay jitter.

An immediate question is how many IPTV streams can be supported simultaneously with satisfactory QoS requirements, i.e., a bounded delay and packet loss rate?

The quantitative analysis of the PLR is an important but challenging issue. The main difficulties are coming from twofold. First, with using the state-of-the-art video codecs with high compression ratio, the IPTV traffic is highly bursty. Second, the service data rate of the UWB link is time-varying, due to the random BSE on the channel. An analytical framework can be developed by combining the fluid-flow model of the video traffic and the packet-level UWB channel model. Although this approach can give us the precise PLR, the computational complexity is very high.

In this chapter, we investigate how the BSE affects the UWB-based IPTV in-home distribution. Because our objective is to obtain the admission region, it is not...
necessary to obtain the exact PLR. By considering the characteristics of the video streams coded in MPEG-4/AVC (H.264) standard and the channel variation caused by BSE, we derive the upper bound of the PLR and then the admission region for IPTV services with or without the presence of BSE can be obtained with much lower computational complexity. The numerical results illustrate the effectiveness of the proposed algorithm and also highlights that the BSE of moving people can dramatically affect the network service quality, which leads to a much smaller admission region for IPTV indoor distribution.

6.2 Related Work

Video performance and admission regions in wired networks have been heavily investigated in the literature. A classic analytical framework using fluid-flow models has been developed in 1980s [11]. With the fluid-flow model, the equilibrium queue distribution can be derived. Then, we can determine the admission region of video traffic, i.e., given the buffer size, how many video flows can be supported with guaranteed PLR (where packet losses are mainly due to buffer overflow). We can also calculate the effective capacity of video flows [66] and allocate bandwidth to video traffic accordingly. Mitra extended the fluid-flow model to consider multiple video sources over multiple servers with variable service rates [67].

We can directly apply the fluid-flow analytical model to study the video performance over time-varying wireless links with different resource allocation schemes [12, 13, 14]. As wireless links are usually error-prone, in [15, 16], the authors studied the video performance over non-contention wireless networks considering the transmission error profile of wireless links.

To the best of our best knowledge, there is no previous work studying the video performance over UWB fading channels. Although we can apply the existing fluid-flow model to the WPANs combining the proposed packet-level UWB channel model, one major obstacle for utilizing the model is the high computation complexity. Obtaining and solving a set of big transition matrices for both time-varying video source and channel may not be feasible in real-time, which prevent the fluid-flow model from implementing in on-line control functions such as the admission control in wireless networks. To better facilitate system design, the motivation of our work in this chapter is to propose a simple and yet accurate algorithm to estimate network performance by considering the characteristics of the video source and the UWB shadowing.
Chapter 6. Admission Control for IPTV over UWB Channels

6.3 System Model

In this section, we briefly describe the network system we use for performance evaluation, including the physical, link and application layers.

6.3.1 IEEE 802.15.3 WPAN

In this work we consider the IEEE 802.15.3 standardized WPAN. The physical layer employs the MB-OFDM technology with AMC, as described in Section 5.3.2. Similar to ECMA-368 [2] as described in Section 5.3.1, IEEE 802.15.3 [4] also adopts the reservation-based MAC to improve QoS provisioning. Fig. 6.1 shows the superframe structure, where a Channel Time Allocation (CTA) is allocated to transfer the video data.

Dly-ACK shall be used for directed stream data frames, like the IPTV streams. Therefore, in our system model, we consider the Dly-ACK scheme defined in IEEE 802.15.3 MAC which is slightly different from that in ECMA-368 (as described in Section 5.3.3). Given the channel time $T_C$ (allocated by the piconet coordinator) and

![Diagram](image)

Figure 6.1: Channel time allocation and Dly-ACK scheme in IEEE 802.15.3 MAC.
the transmission time of a data frame $T_F$ from (5.1) (depending on the data rate selected by the PHY layer according to the received SNR), the number of frames in a burst is:

$$N(T_C, T_F) = \left\lfloor \frac{T_C - T_{ACK} - 2 \times SIFS + MIFS}{T_F + MIFS} \right\rfloor,$$

(6.1)

where $T_{ACK}$ is the transmission time of an ACK frame, SIFS and MIFS (Short or Minimum Inter-Frame Spacing) are defined in the MAC layer specifications.

Finally, the ACK frame can piggyback the link-layer feedback Information Element (IE), which contains the recommended adjustment to the data rate and transmission power level. Then, the transmitter may change the TM in the next burst transmission accordingly. Thus, given the channel time allocated, the number of packets which are accommodated in one superframe is time-varying, depending on the channel conditions.

### 6.3.2 IPTV Video Traffic

For IPTV video sources, advanced source coding technologies have been developed to increase the compression ratio and reduce the source data rate. Since H.264 (MPEG-4 Part 10 AVC) has about twice the compression efficiency when compared with that of MPEG-2, it is widely employed to transmit and store High Definition (HD) content. For this reason, we consider H.264/AVC video sources in our system. However, the advanced video compression technologies with higher compression ratio also cause higher traffic burstiness, as shown in Fig. 6.2, and the coded streams become more sensitive to packet delay and loss. Hence, it is important that we obtain an appropriate admission region for IPTV services in UWB networks, to ensure the QoS.

The mini-source Markov chain model, as shown in Fig. 6.3-(b) has been widely used to describe the variable source rates of different GoPs, and particularly it is effective in obtaining the queue distribution when the buffer size is relatively large [68]. Therefore, we use the mini-source traffic model in the analysis and simulation. According to [68], an H.264 video source can be modeled by the multiplexing of $K = 8$ mini sources. Each mini source independently alternates between an “OFF” state and an “ON” state, and $A$ bps are generated during the “ON” state, as shown in Fig. 6.3-(b). The average residence time durations in the “OFF” and “ON” state are $1/\alpha$ and $1/\beta$, respectively. If $M$ video sources are being transmitted simultaneously, the aggregated data rate is then modeled by $8M$ mini sources and their state-vector variation is driven by the underlying Markov chain. Furthermore, in practice, the video
source traffic is usually shaped to reduce the burstiness. For simplicity, we assume that a leaky bucket is used and the maximal data rate is $\Lambda_M$ packets/superframe.

### 6.3.3 UWB Fading Channel

Similar to the work in Chapter 5, we use the channel model proposed in Chapter 2 for the indoor UWB fading channel. We define totally $C$ channel states which are the received SNR intervals, $S_c (c = 1, 2, \cdots, C)$, for the $C$ TMs. We use the RWMM to describe the motion of a person inside the room where a UWB link is carrying several IPTV video streams over the air.

### 6.4 Analysis of Packet Loss Rate

First of all, given the stringent delay constraint of video streaming applications, received packets with excessive delay are useless and will be discarded by the receiver. To bound the queueing delay, the buffer size should be bounded as well. On the other hand, the buffer should still be able to accommodate certain degree of traffic burstiness. Hence, we should first determine an appropriate buffer size, e.g., from 400 to 600 kilobytes according to the video traffic statistics [68], which is also reasonable for home network devices. Given the buffer size, we can determine the maximum number of video streams such that the PLR due to buffer overflow is acceptable, $^{1}$ e.g., less than $10^{-4}$.

As described earlier, with the transmission opportunity in every scheduling cycle, the queue in the sender’s buffer is updated every superframe. Thus, the system can be investigated as a discrete-time system using the duration of a superframe as the time slot. Because the channel variation is caused by people motion, the time granularity for channel variation is much larger than the duration of a superframe. Due to this property, we can assume that the channel is stable for a relatively long period and estimate the PLR based on the stationary distribution of the source data rate.

Suppose that the average data rate of one video stream is $S$ bps, which equals $\bar{\lambda} = (S \cdot T_{SF})/(8L)$ packets/superframe where $T_{SF}$ is the duration of one superframe. The average data rate of $M$ multiplexing streams is $\bar{\Lambda} = M\bar{\lambda}$. The UWB link has $R_c (c = 1, 2, \cdots, C)$ transmission rates calculated by (6.1) (also in the unit of pack-

$^1$With the PHY-layer rate adaptation and the link-layer retransmission, from the viewpoint of upper-layer protocols, packet losses due to transmission errors are negligible.
Figure 6.2: Video frame size vs frame sequence number.

(a) One “ON-OFF” mini-source model

(b) Mini-source Markov chain model for one video source

Figure 6.3: Mini-source model for one video streaming source.
ets/superframe), and $R_C$ is the maximum service rate. Then, given the instantaneous transmission data rate, we can define three categories for the system states, and the PLR can be determined accordingly.

1. If the service rate is $R_c$ and $R_c < \bar{\Lambda}$, the system is in the *overloaded* state and the buffer is always filling and eventually overflows. In the overloaded state, the PLR can be estimated as
   \[ P_o = \frac{\bar{\Lambda} - R_c}{\bar{\Lambda}}. \]  
   (6.2)

2. If the service rate is $R_c$ and $\bar{\Lambda} \leq R_c \leq \Lambda_M$, we define the system in the *underloaded* state. In such a case, although the system utilization rate is smaller than 1, the buffer is occasionally filling and overflows due to the traffic burstiness. The PLR can be estimated as
   \[ P_u = \frac{\sum_{i=m_0}^{M} [(i\bar{\Lambda} - R_c) p_i]}{\bar{\Lambda}}, \]  
   (6.3)

where $\Lambda$ is the output packet rate (packets/superframe) of one mini-source in “ON” state, $m_0$ is chosen such that $m_0\Lambda > R_c > (m_0 - 1)\Lambda$, and $p_i$ is the probability that $i$ mini sources are “ON”. The number of mini sources in “ON” follows binomial distribution as
   \[ p_i = \binom{M}{i} \rho^i (1 - \rho)^{M-i}, \]  
   (6.4)

where $\rho = \alpha/(\alpha + \beta)$ is the probability that a mini source is “ON”.

3. If the service rate is $R_c$ and $R_c > \Lambda_M$, the system is in the *lightly loaded* state. Since the service rate in this case is higher than the highest arrival rate, the buffer is always draining, and the PLR is approximately 0.

Finally, the average PLR is estimated as
   \[ \bar{P}_L = \sum_{c=1}^{C} \pi_c P_L^{(c)}, \]  
   (6.5)

where $\pi_c$ is the probability of the link with data rate $R_c$, which is actually the probability of the moving person staying in the $c$-th region in the SNR contour figure, and $P_L^{(c)}$ is the PLR when the link transmission rate is $R_c$, which is obtained by (6.2), (6.3), or is zero for the overloaded, underloaded, or lightly loaded states, respectively. Thus, the PLR depends on the people’s mobility behavior and the traffic statistics. The appropriate number of IPTV streams should be chosen such that the PLR is
lower than the given threshold.

Note that here we ignore the process for the buffer to change from being empty to being full, which happens after the system changes from an underloaded state to an overloaded state. During this process, the system may be in the overloaded state without packet loss because the buffer has not been full yet. Therefore, the result given by (6.5) is an upper bound of the PLR. Furthermore, we can expect that when the buffer filling process is quick enough (when the buffer size is small or the traffic data rate is high), this upper bound should be tight. We can define the buffer filling ratio as 

\[ r = \frac{i\Lambda - R_c}{B}, \]

where \( B \) is the buffer size in packets and \( i\Lambda > R_c \). Thus, the higher \( r \) is, the tighter the upper bound is. Because our purpose is to obtain the admission region, we focus on the scenarios that the system is close to its capacity and the buffer filling ratio is usually high. Hence, the upper bound can be used for PLR estimation and admission control.

\section{Simulation Results}

In this subsection, we use simulation to verify the PLR analysis and examine the impact of BSE on the IPTV service provisioning. For the indoor UWB channel, we use the packet-level model obtained in Section 2.7.3 with the RWMM. We use the IEEE 802.15.3 MAC standards \cite{IEEE802.15.3}, and assume that a superframe lasts for 30 ms and a CTA of 6.6 ms per superframe is allocated to this pair of users. Link-layer retransmission is used to recover the transmission failures.

For the IPTV traffic, we obtain the parameters of the mini-source model from the H.264 video trace of “From Mars to China” in HDTV format (1920 × 1080i) \cite{H.264}.

\footnote{The trace of the video clip is available at http://trace.eas.asu.edu/h264/mars/}

The mean bit rate of the video stream is 4.85 Mbps, the variance is \( 3.6375 \times 10^{10} \) (bps)\(^2\), the auto-correlation decay coefficient is 0.215 Mbps, and the frame refresh rate is 30 frames/sec. The buffer size at the transmitter (e.g., a home media server) is 600 kilobytes.

The queue length plotted in Fig. 6.4 shows that the buffer overflow occurs when the body shadowing happens and the system is in overloaded states. Also, in such cases, the queue length increases quickly to be full. As mentioned earlier, because the time granularity of the channel variation (caused by people motion) is much larger than that for the video traffic variation, the system stays in the overload or underload states
for a relatively long time. Therefore, the PLR upper-bound estimation presented in Section 6.4 is suitable for this scenario.

The analytical and simulation results of PLR (with and without shadowing) are shown in Fig. 6.5. The analytical upper bound for the scenario without body shadowing is obtained by using the same algorithm presented but setting the UWB service rate as the constant value of $R_C$. If the acceptable PLR is $10^{-4}$, the simulation results show that the system can support $M = 5$ H.264 streams if the random BSE is not considered. But with BSE, the admission region is reduced to $M = 2$ streams only.

Fig. 6.5 also shows the tightness of the analytical upper bound we have derived which can be used to determine the admission control region. For example, for the scenario with body shadowing, the analytical PLR upper bound indicates $\bar{P}_L < 10^{-4}$ when $M = 2$ streams, giving the same admission region as the simulation results. Similarly, the analytical result for the scenario without body shadowing also gives the admission region of $M = 5$ streams.
Figure 6.4: UWB link data rate and queue length evolution.

Figure 6.5: Packet loss rate due to buffer overflow (by assuming the simulation results following normal distribution, the vertical bars shown in the figure give the 95% confidence interval).
6.6 Summary

The impact of the indoor UWB channels with BSE on the QoS provisioning of WPANs has been investigated in this chapter, which have not been studied by previous works. We have quantified the PLR of IPTV traffic based on the channel model proposed in Chapter 2, and the admission region has been obtained numerically. The network capacity analysis provides valuable guidelines to dimension IPTV in-home distribution systems in reality. The results shown in this chapter beckon for further cross-layer design solutions, e.g., how to improve the UWB PHY systems and networking protocols to better support multimedia applications over UWB shadowing channels.

6.7 Symbol List

\begin{itemize}
  \item \( A \) \hspace{0.5cm} \text{data rate of each mini source in “ON” state (bps)}
  \item \( B \) \hspace{0.5cm} \text{buffer size (packets)}
  \item \( C \) \hspace{0.5cm} \text{number of channel states}
  \item \( K \) \hspace{0.5cm} \text{number of mini sources in the traffic model of one video source}
  \item \( M \) \hspace{0.5cm} \text{number of video sources}
  \item \( p_i \) \hspace{0.5cm} \text{probability that i mini sources are “ON”}
  \item \( P_{L \, (c)} \) \hspace{0.5cm} \text{PLR when the link transmission rate is } R_c
  \item \( \bar{P}_L \) \hspace{0.5cm} \text{average PLR}
  \item \( P_o \) \hspace{0.5cm} \text{packet loss rate in overloaded state}
  \item \( P_u \) \hspace{0.5cm} \text{packet loss rate in underloaded state}
  \item \( r \) \hspace{0.5cm} \text{buffer filling ratio}
  \item \( R_c \) \hspace{0.5cm} \text{UWB link transmission rates for channel state } S_c \ (c = 1, 2, \cdots, C)
  \item \( S \) \hspace{0.5cm} \text{average data rate of one video stream (bps)}
  \item \( S_c \) \hspace{0.5cm} \text{the } c\text{-th channel state } (c = 1, 2, \cdots, C)
  \item \( T_{ACK} \) \hspace{0.5cm} \text{transmission time of an ACK frame}
  \item \( T_C \) \hspace{0.5cm} \text{channel time allocated to one user by the piconet coordinator}
  \item \( T_F \) \hspace{0.5cm} \text{transmission time of a data frame}
  \item \( T_{SF} \) \hspace{0.5cm} \text{duration of one superframe}
  \item \( 1/\alpha \) \hspace{0.5cm} \text{average residence time in “OFF” state}
  \item \( 1/\beta \) \hspace{0.5cm} \text{average residence time in “ON” state}
  \item \( \Lambda \) \hspace{0.5cm} \text{data rate of each mini source in “ON” state (packets/superframe)}
  \item \( \bar{\lambda} \) \hspace{0.5cm} \text{average data rate of one video stream (packets/superframe)}
\end{itemize}
$\Lambda_M$ maximal data rate of leaky bucket (packets/superframe)

$\bar{\Lambda}$ average data rate of $M$ multiplexing streams

$\pi_c$ probability of the link with data rate $R_c$
Chapter 7

Conclusions and Future Work

7.1 Conclusions

In this thesis, we have tackled the three fundamental but critical problems in the wireless networking: (1) the error-prone and time-varying (fading) wireless channel which make the information transmission with QoS guarantee a very challenging task, (2) the delivery of multimedia services with high-rate, considerably bursty traffic and stringent QoS requirement, and (3) the multiuser access by which the limited resources should be shared efficiently and fairly. The following outlines the contributions achieved.

1. We have derived the APSD of the indoor UWB channel in closed-form and estimated the shadowing effect analytically. Then we have built a packet-level channel model using a FSMC for the time-varying shadowing channel.

2. We have investigated the multi-carrier communication systems over frequency-selective Nakagami-$m$ fading channels. The LCR and a novel FSMC for the variation of the subchannel SNR in the frequency domain have been obtained. Finally, a packet-level model for the multi-carrier system has been developed.

3. We have derived the higher-order statistics of the channel frequency response for OFDM systems in the mobile propagation environments, and proposed FSMC-based packet-level model, considering the unique modulation technologies of OFDM.

4. We have proposed a general analytical framework to study the wireless link performance, considering the correlated channel fading, error-control schemes
Chapter 7. Conclusions and Future Work

and pre-reserved access scheduling. In addition, by optimizing the AMC and packet fragmentation, a joint-adaptation mechanism with low implementation complexity has been proposed and analyzed.

5. We have derived the PLR of IPTV streams over the UWB shadowing channel and a low-complexity admission control method has been obtained.

7.2 Future Work

The channel models and the cross-layer designs presented in this thesis are ready to be extended to other networks. Some of the further research issues are listed as follows.

1. In Chapter 2, we have proposed the packet-level channel model for UWB systems where the transceivers both use single antenna. Multiple antennas can be used to effectively mitigate the channel fading and increase the system throughput by spatial diversity, which is a promising technology to be used in practical systems. Therefore, our future work will further analyze the BSE with multiple input and/or output antennas. The work will provide in-depth insight of and helpful guidance to improve the multiple-antenna technology, especially in indoor environments.

2. The cooperative and relay are newly emerging technologies to effectively enhance the communication reliability and capacity over fading or obstructed channels, which have gained a lot of attention in both academia and industry. To extend the proposed packet-level channel models for cooperative or relay systems is of great interest, which will become the important tools to analyze the new wireless networks using these technologies.

3. In this dissertation, we have analyzed the performance of reservation-based MAC over fading channels. In our future work, we will further investigate the performance of contention-based MAC protocols (e.g., the Prioritized Contention Access protocol defined in ECMA-368 [2]) based on the proposed packet-level channel models. How to fine-tune the contention parameter to improve the network throughput and optimize the error-control mechanisms with the contention-based MAC jointly will be further studied.
4. The OFDM-based technologies have been adopted by IEEE 802.16 WiMAX and the 4G cellular networks, which are supposed to provide multimedia service (like streamed video) to users in mobile environments. We can use the proposed packet-level channel models for multi-carrier and OFDM systems to develop the analytical model and also conduct simulations for these networks. Thus, we can analyze and optimize the networking process to improve the performance and QoS provisioning.
Appendix A

Derivation of Eq. (2.7) and (2.8)

A.1 Derivation of Eq. (2.7)

From (2.5), we have:

\[
\begin{align*}
\mathbb{P}(\theta) &= \sum_{k_0}^{\lfloor \tau_m \lambda \rfloor} E[P_{k_0}] + \sum_{l=1}^{\infty} \sum_{k=1}^{\lfloor \tau_m \lambda \rfloor} E[P_{k,l}] \\
&= \frac{\tau_m \Omega_0}{2\pi} \sum_{k_0}^{\lfloor \tau_m \lambda \rfloor} E\left[\frac{1}{t_{k,0}} e^{-\frac{t_{k,0}}{\gamma}}\right] + \frac{\Omega_0}{2\pi} \sum_{l=1}^{\infty} \sum_{k=1}^{\lfloor \tau_m \lambda \rfloor} E\left[e^{-\frac{t_{k,0}}{\gamma}}\right] + \frac{\Omega_0}{2\pi} \sum_{l=1}^{\infty} \sum_{k=1}^{\infty} E\left[e^{-\frac{\tau l}{\tau_m \lambda}} e^{-\frac{t_{k,l}}{\gamma}}\right].
\end{align*}
\]

(A.1)

Because \( t_{k,0} \) has the distribution of Gamma\((k, \lambda)\), the probability density function is

\[ f_{t_{k,0}}(x) = \frac{\lambda^k}{\Gamma(k)} x^{k-1} e^{-\lambda x} \] where \( \Gamma(k) = (k-1)! \). The expectation in term \( \bar{A} \) in (A.1) can be evaluated as

\[
E\left[\frac{1}{t_{k,0}} e^{-\frac{t_{k,0}}{\gamma}}\right] = \int_{0}^{\infty} \frac{1}{x} e^{-\frac{\lambda x}{\gamma}} \frac{\lambda^k}{\Gamma(k)} x^{k-1} e^{-\lambda x} dx = \frac{\lambda^k}{\Gamma(k)} \int_{0}^{\infty} x^{k-2} e^{-(\frac{\lambda}{\gamma}+\lambda)x} dx
\]

\[
= \frac{\lambda^k (k-2)!}{\Gamma(k) (\frac{\lambda}{\gamma}+\lambda)^{k-1}} = \frac{\lambda}{k-1} \rho^{k-1}, \quad (A.2)
\]

where \( \rho = \frac{\lambda}{1+\lambda \gamma} \). Because \( k_0 \geq 2 \) in (A.1), \( k \geq 2 \) and the convergence of the integral is guaranteed. Then, plug (A.2) into (A.1) and term \( \bar{A} \) in (2.7) is obtained.
Appendix A. Derivation of Eq. (2.7) and (2.8)

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Similar to (A.2), we can obtain

\[
E \left[ e^{-\frac{t_{k,0}}{\tau}} \right] = \int_0^{\infty} e^{-\frac{x}{\tau}} \frac{\lambda^k}{\Gamma(k)} x^{k-1} e^{-\lambda x} dx = \left( \frac{\lambda \gamma}{1 + \lambda \gamma} \right)^k = \rho^k, \quad (A.3)
\]

where \( k \geq 1 \). Thus, term \( \bar{B} \) in (A.1) can be obtained as

\[
\bar{B} = \frac{\Omega_0}{2\pi} \sum_{l=0}^{\infty} \sum_{k=1}^{\infty} \rho^k = \frac{\Omega_0 \rho^{[\tau_m \lambda]}}{2\pi \left( 1 - \rho \right)} . \quad (A.4)
\]

Because the random cluster delay \( T_l \) and ray delay \( t_{k,l} \) are independent and have the distribution of Gamma\((l, \Lambda)\) and Gamma\((k, \lambda)\), respectively, using (A.3), term \( \bar{C} \) in (A.1) is derived as:

\[
\bar{C} = \frac{\Omega_0}{2\pi} \sum_{l=1}^{\infty} \sum_{k=1}^{\infty} E \left[ e^{-\frac{T_l}{\tau}} \right] E \left[ e^{-\frac{t_{k,l}}{\tau}} \right] = \frac{\Omega_0}{2\pi} \sum_{l=1}^{\infty} \sum_{k=1}^{\infty} \left( \frac{\Gamma \Lambda}{1 + \Gamma \Lambda} \right)^l \left( \frac{\lambda \gamma}{1 + \lambda \gamma} \right)^k = \frac{\Omega_0}{2\pi} (\Gamma \Lambda) (\gamma \lambda) . \quad (A.5)
\]

Combining (A.2), (A.4) and (A.5) gives (2.7).

A.2 Derivation of Eq.(2.8)

The average power of each ray conditioned on the cluster delay and ray delay is given in (2.2). The delay for the first cluster is \( T_0 = 0 \). Using (A.3), the expectation of the total power of the CIR can be evaluated as

\[
E_t = E \left[ \sum_{l=0}^{\infty} \sum_{k=1}^{\infty} E[|a_{k,l}|^2] \right] = \Omega_0 \sum_{l=0}^{\infty} \sum_{k=1}^{\infty} E \left[ e^{-\frac{T_l}{\tau}} e^{-\frac{t_{k,l}}{\tau}} \right]
\]

\[
= \Omega_0 \sum_{l=0}^{\infty} \left( \frac{\Gamma \Lambda}{1 + \Gamma \Lambda} \right)^l \sum_{k=1}^{\infty} \left( \frac{\lambda \gamma}{1 + \lambda \gamma} \right)^k = \Omega_0 (1 + \Gamma \Lambda) (\gamma \lambda) . \quad (A.6)
\]

Here, \( E \left[ e^{-\frac{T_0}{\tau}} \right] = 1 = \left( \frac{\Gamma \Lambda}{1 + \Gamma \Lambda} \right)^0 \). To normalize the total power of the multipath components, set \( E_t = 1 \) and we obtain (2.8).
Appendix B

Proof of Proposition 2 in Section 4.4.2

According to [53], the Nakagami-\( m \) fading amplitude of the \( l \)th tap of the time-domain CIR is obtained by:

\[
r_{Nak,l} = |h_l(t)| = F_{Nak}^{-1} \left[ F_{Ray} (r_{Ray,l}) \right] = \Psi (r_{Ray,l}), \tag{B.1}
\]

where \( F_{Ray} \) is the CDF of Rayleigh distribution and the subsequent transformation \( F_{Nak}^{-1} \) is the inverse function of the CDF of the Nakagami-\( m \) distribution. The amplitude of Rayleigh fading, \( r_{Ray,l} \), can be generated by the well-known Jakes model [49]. Then, the inphase and quadrature components of \( h_l(t) \) are obtained by \( I_{Nak,l}(t) = r_{Nak,l}(t) \cos \theta_l(t) \) and \( Q_{Nak,l}(t) = r_{Nak,l}(t) \sin \theta_l(t) \), respectively.

We denote \( X_k \) and \( Y_k \) the real and imaginary parts of \( H_k(t) \), respectively. Thus, \( R_k(t) = |H_k(t)| = \sqrt{X_k^2(t) + Y_k^2(t)} \), and the derivative of \( R_k(t) \) with respect to time is:

\[
\dot{R}_k(t) = \frac{X_k(t) \dot{X}_k(t) + Y_k(t) \dot{Y}_k(t)}{R_k(t)}. \tag{B.2}
\]

From (4.1), we can get the expression of \( X_k(t) \) and \( Y_k(t) \) and their derivatives with respect to time. For brevity, only the results of \( X_k(t) \) are presented:

\[
\dot{X}_k(t) = \sum_{l=0}^{L-1} \left[ \dot{I}_{Nak,l}(t) \cos \left( 2\pi \frac{l_k}{N} \right) + \dot{Q}_{Nak,l}(t) \sin \left( 2\pi \frac{l_k}{N} \right) \right]. \tag{B.3}
\]

where \( \dot{I}_{Nak,l}(t) \) and \( \dot{Q}_{Nak,l}(t) \) are the derivatives of \( I_{Nak,l}(t) \) and \( Q_{Nak,l}(t) \) with respect
Appendix B. Proof of Proposition 2 in Section 4.4.2

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to time, respectively, and
\[ \dot{I}_{Nak,l}(t) = \cos \theta_l(t) \dot{r}_{Nak,l}(t) - \sin \theta_l(t) r_{Nak,l}(t) \dot{\theta}_l(t). \]  

(B.4)

From (B.1), the derivative \( \dot{r}_{Nak,l}(t) \) is:
\[ \dot{r}_{Nak,l} = \Psi (r_{Ray,l}) \dot{r}_{Ray,l}(t). \]  

(B.5)

Based on the Jakes model, \( \dot{r}_{Ray,l}(t) \), given the in-phase and quadrature components of the Rayleigh fading, is a Gaussian RV as \( \dot{r}_{Ray,l} \sim N(0, \pi^2 f_d^2 \Omega_{Ray,l}) \), where \( \Omega_{Ray,l} \) is the average power [49].

The function of \( \Psi (r_{Ray,l}) \) is plotted in Fig. B.1 for various values of \( m \). It can be seen that the function \( \Psi (r_{Ray,l}) \) is a straight line at most of the values of \( r_{Ray,l} \). For example, the probability of \( r_{Ray,l} < 0.3 \) is only 0.04 where the function is a curve. Thus, for tractability, the derivative \( \dot{\Psi (r_{Ray,l})} \) is approximated as a constant of
\[ \dot{\Psi (r_{Ray,l})} \approx E[r_{Nak,l}] E[r_{Ray,l}] = \sqrt{m}. \]  

(B.6)

This approximation is only violated with very small probability. Consequently, we also have \( r_{Nak,l}^2 \approx mr_{Ray,l}^2 \).

Therefore, from (B.5) and (B.6), \( \dot{r}_{Nak,l}(t) \) is a Gaussian RV with zero-mean and the variance of:
\[ \sigma_{\dot{r}_{Nak,l}}^2 = m \pi^2 f_d^2 \Omega_{Ray,l} = \pi^2 f_d^2 \Omega_{Nak,l} \]  

(B.7)

For the derivative \( \dot{\theta}_l(t) \), as an example, we consider the case of \( \theta_l(t) \) being in the first quadrant and thus \( \theta_l(t) = \arctan \left( \frac{Q_{Ray,l}(t)}{I_{Ray,l}(t)} \right) \). The derivative is:
\[ \dot{\theta}_l(t) = \frac{I_{Ray,l}(t)}{r_{Ray,l}(t)} Q_{Ray,l}(t) - \frac{Q_{Ray,l}(t)}{r_{Ray,l}(t)} I_{Ray,l}(t). \]  

(B.8)

\( \dot{Q}_{Ray,l}(t) \) and \( \dot{I}_{Ray,l}(t) \) both have the Gaussian distributions of \( N(0, \pi^2 f_d^2 \Omega_{Ray,l}) \) [49].

Due to the linearity of (B.8), \( \dot{\theta}_l(t) \) is a Gaussian RV with the variance of:
\[ \sigma_{\dot{\theta}_l}^2 = \frac{\pi^2 f_d^2 \Omega_{Ray,l}}{r_{Ray,l}^2} \]  

(B.9)

Thus, from (B.4), (B.7) and (B.9), \( \dot{I}_{Nak,l}(t) \) is a Gaussian RV with zero-mean and
Figure B.1: Function of $\Psi (r_{Ray,l}) (\Omega_{Ray} = 1)$
the variance of:

\[ \sigma^2_{I_{Nak,l}} = \cos^2 \theta_l(t) \cdot \pi^2 f_d^2 \Omega_{Nak,l} + \sin^2 \theta_l(t) \cdot r_{Nak,l}^2 \cdot \frac{\pi^2 f_d^2 \Omega_{Ray,l}}{r_{Ray}^2} \approx \pi^2 f_d^2 \Omega_{Nak,l}. \]  

(B.10)

Similarly, we can derive that the derivative \( \dot{Q}_{Nak,l}(t) \) is also a Gaussian RV as \( \dot{Q}_{Nak,l}(t) \sim N(0, \pi^2 f_d^2 \Omega_{Nak,l}) \).

Due to the linearity of (B.3), \( \dot{X}_k(t) \) is a Gaussian RV with zero-mean and the variance of:

\[ \sigma^2_{\dot{X}_k} = \pi^2 f_d^2 \sum_{l=0}^{L-1} \Omega_{Nak,l} = \pi^2 f_d^2 \tilde{\Omega}. \]  

(B.11)

Using similar approach, we can derive that the derivative \( \dot{Y}_k(t) \) has the same Gaussian distribution of \( N \left( 0, \pi^2 f_d^2 \tilde{\Omega} \right) \).

Finally, from (B.2), given \( I_{Nak,l}(t) \) and \( Q_{Nak,l}(t) \), \( \dot{R}_k(t) \) is a Gaussian RV with zero-mean and variance of:

\[ \sigma^2_{\dot{R}_k} = \frac{X_k^2(t)}{R_k^2(t)} \pi^2 f_d^2 \tilde{\Omega} + \frac{Y_k^2(t)}{R_k^2(t)} \pi^2 f_d^2 \tilde{\Omega} = \pi^2 f_d^2 \tilde{\Omega}. \]  

(B.12)

We can get the LCR of the amplitude of the channel frequency response taps by:

\[ \Lambda_R = \int_0^\infty \dot{R}_k P(\dot{R}_k, R_k = R) d\dot{R}_k = P(R_k = R) \int_0^\infty \dot{R}_k P(\dot{R}_k) d\dot{R}_k = \sqrt{2\pi} f_d R \frac{\tilde{\Omega}}{\sqrt{\tilde{\Omega}}} e^{-\frac{R^2}{\tilde{\Omega}}} \].  

(B.13)

Because the SNR is \( \gamma_k(t) = \frac{R_k^2(t)}{N_0} \), using variable substitution, we can obtain (4.6).
Bibliography


