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**Environment Models for Realistic Simulation
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Abstract

Wireless research and development requires effective and efficient simulation and emulation tools to validate and evaluate wireless designs. Wireless channel models are used in the tools to simulate signal propagation properties in the real physical world. However, due to practical issues, these models are often too generalized and simplified in large scale experiments, and they only provide limited realism.

In this thesis, a novel world model is proposed for simulation and emulation of wireless networks. The proposed model includes the design and implementation of a variety of environment models that enhance realism in simulation. These models capture realistic signal propagation properties across multiple connections, and over time: first, the impact of realistic physical world features, such as channel dynamics and cross link correlation are characterized at different time scales; then, both geometrical and statistical simulation models are developed to recreate desired channel dynamics among wireless network links efficiently.

Three major components of the proposed design are described in this thesis: 1) a flexible channel simulation model, 2) improvement of parameter accuracy in geometric channel models, and 3) wireless link correlation models with a case study in vehicular networks. The flexible channel simulation model supports fast generation of channel updates for complicated channel models, including small-scale fast fading, large-scale path loss and multi-path delay and attenuation. To achieve high realism, a variety of techniques are developed to obtain high parameter accuracy in geographic channel models. Link correlation models are developed for simulating wireless channels within a network context, where adjacent wireless links share the same propagation medium. The wireless link correlation model handles both temporal and spatial correlations, to reflect properties at different time scales and location-based similarities.

A case study in vehicular networks illustrates the effectiveness of using the proposed environment model to improve the realism of wireless simulation and emulation platforms. Simulation results from implemented models are compared against

the measurement data from physical world vehicle-to-vehicle channels, and show good approximation to reality. The evaluation results of correlated channel models show improved realism in channel properties and corresponding impact on the performance of a gossip protocol.

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Chapter 1

Introduction

The development of wireless technologies has significantly changed our way of communicating and sharing information. Easy access to networks is available at any time, and at any location, as long as we can build wireless connections among devices that are capable of transmitting and receiving signals in the open air. Wireless devices are usually allowed to move, while wireless connections can still be set up and maintained. Movement of devices and other objects in the propagation medium introduces dynamics in the connection quality of a wireless network. The connectivity may vary over time due to change of device location, moving speed, or time-varying interference in the area, etc.

The wireless dynamics challenge both wireless protocol design and evaluation. To build and maintain network connectivity on unreliable and hard-to-control wireless connections, protocols need to estimate, predict, and adapt to variations. On the other hand, performing controlled and realistic evaluation is also challenging because the wireless environment changes unpredictably and uncontrollably over time in the wild test-beds, while physical world properties are usually not reproduced accurately in simulation and emulation platforms. We will briefly describe challenges in wireless protocol design, followed by an analysis of physical world features that have impact on wireless channel properties. Then, we will address challenges in wireless channel simulation and emulation.

1.1 Challenges in Wireless Protocol Design

Many wireless protocol designs handle variations of connections by constant estimation and prediction of connection quality, allowing them to adapt to the dynamics over time. These protocols adapt to their environment to optimize performance, and increasingly the adaptation is ‘cognitive’ in the sense that the protocols collect information about the environment and make explicit decisions about how to best adapt.

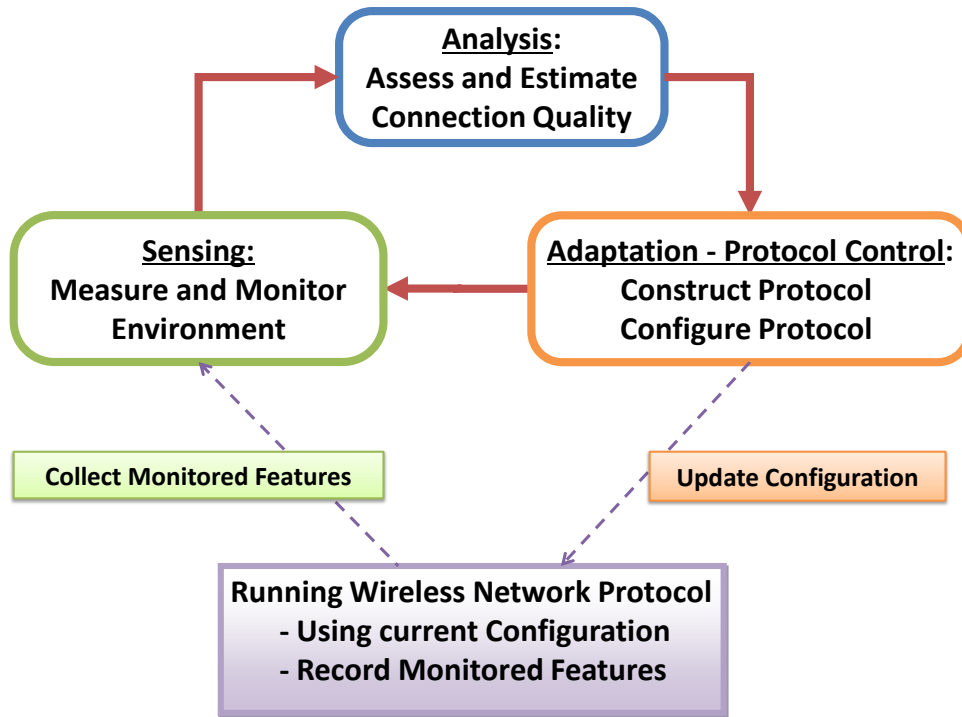


Figure 1.1: Wireless Protocol Control Mechanisms

Mechanism in Wireless Network Protocol Design

Cognitive protocols typically have three key components, similar to autonomic systems: sensing, analysis, and adaptation. Sensing means that the protocol measures its environment (*e.g.* channel properties) and its performance (*e.g.* throughput in bits/second). The analysis phase evaluates how well the protocol is doing, given current conditions, and determines how performance can be further improved, if needed. This analysis is typically based on a model of how protocol performance depends on both the environment and protocol configuration. Finally,

the adaptation phase adapts the protocol implementation. Figure 1.1 shows this three-phase control flow. We now elaborate on these three phases.

Adaptation: protocol control - Based on the result from the analysis phase, the *Adaptation* phase makes decisions and configures parameters to achieve a high level of performance.

For example, opportunistic routing protocols [12, 34] adapt the candidate routing path by updating the list of forwarding candidates, based on the measurement of the transmission time of a batch of packets during the sensing phase. Rate adaptation protocols, such as SampleRate [11], collect information on the packet delivery rate on a one-hop link. They use collected information to estimate the link quality, and then update the transmit rate accordingly.

Sensing - The *Sensing* phase measures link qualities, and monitors network performance, such as network connectivity, or end to end throughput.

Current sensing technologies include both active sensing and passive sensing. Active sensing is usually performed by active probing. For example, the IEEE 802.11 standards [1] allow a station to send *probe request* frames to request information from another station. A *probe response* frame will be sent by *APs* (access points) that receive the probe message. Passive listening is another sensing method, which is also an effective way to acquire connectivity information, since received messages from other wireless devices may be used to infer the link quality between the sender and the receiver. In the IEEE 802.11 standards, a new client may scan all channels to look for *APs*, and respond to beacons sent from *APs*. Passive listening is more common in protocol design, because it does not require additional message exchanges (less overhead traffic), which is especially useful when there is adequate traffic to obtain information about wireless stations.

Dynamics in wireless connectivity requires any information to be updated regularly, to maintain up-to-date knowledge of the network connectivity status. Some wireless protocols rely on observed variation/fluctuations in wireless link properties to trigger an analysis event, followed by a reconfiguration of the protocol. Ideally, the sensing frequency is determined by the rate at which the environment changes. A higher update frequency helps to more accurately reflect the status of the wireless network connection, but incurs higher system overhead due to monitoring and reconfiguration.

When more detailed information is available, such as direct measurements of the link quality,

the sensing phase can help in calibration as well. For example, when the noise level is higher in a crowded wireless environment, the transmit power thresholds needs to be adjusted to the current environment.

Analysis - The *Analysis* phase utilizes the information gathered during the sensing phase, and uses models to find the best configuration to optimize performance.

Various models have been developed to analyze the sensing information, and to determine the optimized configuration of the network. For example, the received *SINR* (Signal to Interference and Noise Ratio) model is used to measure the link quality between a pair of wireless devices, while *BER* (Bit Error Rate), *PER* (Packet Error Rate), and *ETX* (Expected Transmission Count [27]) characterize similar features at a higher level of abstraction. To model contention between links, conflict graphs are usually applied to explicitly identify the interference between links. For all links that are logically related, network topology is used to characterize connectivity between wireless devices.

Using these models, the analysis phase then estimates the expected performance for each configuration, and selects the one that optimizes the performance. For example, gossiping protocols [87] actively monitor signals from neighboring nodes and analyze connections to these nodes. This helps a gossiping node to identify sets of neighboring nodes with different levels of connectivities.

1.2 Features of the Physical World

Wireless protocols are challenged in real environments since wireless propagation features vary across space and time. Measurements have been conducted to understand and characterize features that impact wireless connections. For example, the distance between a pair of wireless transmitter (*Tx*) and receiver (*Rx*) plays a critical role in received signal strength. When we consider the simplest case where there is no other object around a pair of stationary *Tx* and *Rx*, the farther the wireless *Tx* and *Rx* are apart, the weaker the received signal will be.

In more realistic cases, there exist multiple mobile devices with a set of wireless connections among these devices. The wireless connectivity between these devices may vary similarly when

they move or interference sources appear or disappear. The variation in each wireless connection not only shows a temporal pattern related to movement, but also shows a spatial correlation among adjacent wireless connections.

In this section, we will review and identify major physical world features that can impact wireless propagation, as listed in Table 1.1. A bottom-up approach is used here to illustrate simple cases first and complicated scenarios later.

The Network	Spatial Correlation (network topology)	Temporal Correlation (source of impact)
A Single Wireless Link	<i>Static Features</i> Location, Distance Obstacles Ambient Noise	<i>Dynamic Features</i> Device Mobility (Scattering) Movement of Obstacles Varying Traffic (Noise, Interference)

Table 1.1: Physical World Impacts on Wireless Propagation

1.2.1 A Single Wireless Link

The propagation properties of a wireless link connecting two wireless devices (Tx/Rx) are determined by the relative location of the devices, as well as surrounding objects.

Static Features

Wireless signal strength decreases as the electromagnetic wave travels through the medium. The location of a pair of Tx and Rx , along with the distance and existence of obstacles blocking *LOS* (Line Of Sight) between them, determines the dominant propagation path. Moreover, there may exist obstacles around that introduce additional signal path from a Tx to an Rx , due to reflection or diffraction. As a result, the received signal at Rx usually consists of multiple copies of the transmitted signal, with different attenuation and distortion, along with other interfering signals. The combination of several copies of attenuated signal results in a distorted received signal.

The signal attenuation is usually modeled by a path-loss model, such as the log-distance based

model and the two-ray ground reflection model [57, 70, 71], and shadowing models. The quality of a received signal is also affected by the ambient noise level. Higher noise usually comes from heavy background wireless traffic that shares the same space and frequency. In addition, strong signals from adjacent transceivers add interference to the received signal.

Dynamic Features

The movement of wireless devices and other objects introduces dynamics in the wireless property and complicates the distortion of wireless signals. Mobility of wireless devices introduces variation to the relative speed and location of Tx and Rx , resulting in changes in the path loss. In addition, movement creates time-varying scattering effects, which are denoted as small-scale fading effects.

Temporal Correlation

Since the dynamics in wireless signals are caused by physical world mobility, the actual variation of a wireless link is correlated over time due to the continuity in physical world changes. Although complicated time-varying properties can be approximated using statistical models with randomness, the variation by nature is not completely random and does have temporal correlation properties underneath.

1.2.2 The Network

Wireless links connect adjacent wireless devices within communication range, creating a wireless network that provides connectivity among participating nodes. The desired network topology, such as a star or mesh topology regulates how wireless connections interact with each other. Although network conflict graphs are developed to model relations in on/off among wireless links status, the propagation features of each link is often individually modeled. In reality, the wireless properties of these links are usually not independent, because nearby objects, along with their activities, may have correlated impact on adjacent links.

1.2.3 Spatial Correlation

Adjacent wireless links in a network show correlated temporal changes, when these links experience similar changes in the environment. This is because the cause of the change usually comes from the same source, such as obstacles blocking the direct wireless path, or increasing noise/interference due to a crowded wireless spectrum.

Often, the same change in environment may affect a set of wireless links in the same vicinity, at roughly the same time. As a result, wireless links that are located near each other would experience similar improvement or degeneration at the same time. On the other hand, any localized impact would only affect a subset of the links, which leads to diversity in the network. We will refer to these correlations among nearby links as spatial correlations. Spatial correlation among wireless links are prevailing in various environments.

1.2.4 Impact on Wireless Protocols

Both static and dynamic features of the physical world affect wireless link properties and challenge wireless protocols' ability to understand, predict and adapt to such features, on multiple time scales. In addition, protocols are challenged by environment-specific patterns in wireless properties introduced by temporal correlation of channel properties as well as cross-link correlation among multiple connections. Moreover, the channel variation can require adaptation by the protocols at all layers of the protocol stack.

Impact at Multiple Time Scales

Mobility in the environment introduces dynamics of channel properties at different time scales, such as changes in fading, path loss and multiple path features. Small-scale fading is the result of a combination of multi-path and movement and can happen on time scales ranging from μs to tens of μs , depending on the speed of movement. Path loss depends on the distance between the transmitter and receiver as well as line-of-sight properties, and loss changes on the order of seconds and higher. On an even longer time scale, devices may move between very different environments (e.g., urban canyon to flat rural area into mountains) that have different types of

reflectors and multi-path.

Impact of Correlated Wireless Properties

Correlation of wireless properties over time and space introduces dependency in channel properties. This challenges wireless protocols to estimate and predict correlated channel properties. For example, protocols utilizing spatial diversity need to predict channel independency accurately to achieve desired diversity among multiple links.

Protocol Adaptation at Different Layers

Wireless protocols adapt to channel dynamics at multiple layers in the protocol stack. Examples include changes in coding and modulation at the physical layer; different routing, coding, and retransmission strategies at the MAC and network layer; different congestion control solutions at the transport layer; and application level strategies to adapt to available bandwidth.

1.3 Wireless Channel Simulation and Emulation Challenges

Simulation and emulation platforms are widely used for evaluation of wireless designs. The ability to control the wireless propagation environment and reproduce the same environment through configuration makes simulation and emulation systems [41, 57, 59] popular in wireless research. We identify several challenges associated with flexibility, realism and efficiency in the control of network simulation and emulation.

1.3.1 Flexible Control of Complex Channel Models

Wireless channels in the physical world show complicated time-varying properties caused by all kinds of dynamics in the environment. For example, fast movement of surrounding objects introduces time-varying reflected signals, which are usually modeled as small (time) scale fading effects. A lot of other environment dynamics contribute to the channel's time-varying features at different time scales: signals received by a mobile attenuate dramatically when the mobile moves

away from the transmitter; background noise level evolves as the overall wireless traffic pattern varies at different times of the day, etc.

Different wireless channel models have been developed to represent variation of channel properties at different time scales. When simulating wireless channels, multiple channel models need to be combined to represent realistic temporal variation of a wireless link over different time scales.

Dynamics in wireless channel properties requires simulated channels to be updated frequently with up-to-date knowledge of channel properties. When using channel models with corresponding parameters to represent channel quality, not only model parameters need to be updated, the exact model suitable for the simulated scenario may also need to be updated. This demands high flexibility in channel update implementation in simulation regarding model updates as well as parameter updates.

Complex models are often required in realistic channel simulation to represent a large set of physical world channel properties. This requires specific combination of multiple complicated channel models with each containing multiple configurable parameters. Flexible control of complex channel models at run time is desired to approximate specific dynamics in simulated wireless environment.

1.3.2 High Dynamics

High dynamics in channel properties are observed in environments with high-speed mobiles. To simulate such high dynamics, channel models and parameters need to be updated frequently to reflect the dynamics. As a result, calculation of channel updates could be computationally expensive, especially for complex channel models which represents complex environments. High efficiency model implementations are desired to simulate such environments with high accuracy.

1.3.3 Network-Scale Simulation

While obtaining accurate and realistic parameter values for one wireless channel configuration may be challenging, configuration of multiple wireless channel for complex environment is even

more challenging, especially for environments with high dynamics.

Network-scale wireless simulation requires high efficiency simulation process to support a large-scale networks. The simulation complexity increases dramatically with regard to the size of the simulated network N as well as the size of the simulated area: objects in the area must be modeled accurately, or sophisticated models need to be applied to represent realistic spatial correlation among multiple simulated links. It is even more critical for wireless emulation where all calculation must meet real-time requirement.

In addition, correlation among multiple links should be carefully represented in network-scale simulation to represent the spatial correlation among those links.

1.4 Proposed Solution

A novel wireless simulation architecture design, the ‘World Model’, is proposed for emulating a broader class of channel conditions, including indoor channels and mobile-to-mobile channels at vehicular speeds at a network scale, in real time.

The proposed design includes three major components: 1) a flexible channel simulation model, 2) wireless models with realistic temporal correlation, and 3) cross-link correlated models among multiple wireless links.

1.4.1 A Flexible Channel Simulation Model

The flexible channel simulation model is a framework for signal-level real-time simulation and emulation of propagation effects over generalized fading channels, at the scale of entire networks. As in previous work, the channel response is modeled in the time domain using a tapped delay line model. The proposed design generalizes the tap weight generation process to accommodate a broad class of channel conditions, including indoor channels and mobile-to-mobile channels at vehicular speeds. High efficiency at run-time is achieved by optimization of the tap weight generation process giving model parameters with high dynamics. This flexible model can be utilized to implement a wide range of channel models for a variety of realistic wireless environments. In this thesis, the discussion will focus on vehicle-to-vehicle wireless channels, which have high

dynamics, and are among the most challenging cases.

1.4.2 Temporal Correlation Models

Temporal correlation models are designed to specifically handle challenges in modeling realistic link dynamics in wireless networks, considering temporal features. There exist two major types of models capturing temporal correlation: 1) direct modeling of dimensions and mobility in physical world, and 2) stochastic models approximating temporal dynamics. While approach 1) is effective to reflect correlated time-varying features of a channel with high realism, it is often impractical to gather the information required for simulation.

A novel systematic approach is proposed for directly modeling environment-specific channels. The discussion in this thesis focuses on small-scale fading effects in vehicular channels modeling. The proposed design utilizes realistic (and complicated) geometric models along with land cover information derived from aerial maps. In order to approximate parameter values at high resolution, additional geometric information is required as well as a complete analysis of the simulated area before executing the experiments. Automated pre-processing along with fast run-time calculation makes this solution suitable for simulation or emulation. The proposed solution is efficient enough for real-time channel emulation, at the scale of entire networks.

1.4.3 Cross-Link Correlation Models

Wireless channels are sensitive to mobility of objects in the surrounding environment. The impact from these movements may affect multiple adjacent channels at the same time or location, which introduces correlated channel properties over time and space. Current simulation platforms often do not explicitly modeling these correlated time-varying channel features in wireless networks.

Our spatial correlation study proposes practical solutions to identify and compensate for the missing correlated properties in statistical models. The proposed solution introduces cross-link correlation among multiple adjacent links which have independent statistical properties (models or parameters).

1.5 Related Work

We provide an overview of most relevant works regarding simulation and emulation of wireless channels here.

1.5.1 Wireless Channel Models

The wireless propagation between two moving objects is generally modeled as a mobile-to-mobile communication channel, including large-scale path loss models, and small-scale fading models.

Large-scale path loss (and shadowing) models have been developed to represent path loss caused by loss of direct Line-Of-Sight (LOS) and slow variation of such effects over time. Sample geometric models includes Log-Distance path loss model, two-ray path loss model, and these models require exact information of transceivers and reflectors. Stochastic models, such as two-state Markov shadowing model [74], have been developed and stochastic processes are utilized to create dynamics in channel properties. These models approximate overall statistic properties of each single channel, but the exact dynamics over time could be off of reality, especially for multiple correlated channels.

Small-scale fading models are usually derived from stochastic models with specific assumptions on scatterer distribution pattern, such as ring models [5, 66], an elliptical scattering model, or a circular scattering model [28] that are suitable for stationary-to-mobile channels, but not mobile-to-mobile scenarios where scatterers do not follow the ring pattern around transmitters or receivers. Geometrical scattering models for mobile-to-mobile channels [6, 22] have also been developed. To model the impact of surrounding objects accurately, these model often requires detailed information about objects in the environment, which is challenging to obtain for large-scale simulation in diverse environment.

We studied popular channel models in existing research work, especially the stochastic shadowing models and geometric scattering models for mobile-to-mobile scenarios. We add new elements to the models to achieve high realism in dynamics for network-scale simulation.

1.5.2 Simulation and Emulation Platforms

Science and engineering rely heavily on the ability to perform controlled, repeatable experiments. Channel simulation and emulation tools are meant to bring some of this ability to wireless research. Traditionally, wireless *communication* researchers have used high-fidelity small-scale models, while wireless *networking* researchers have considered larger-scale systems, but with much less detailed channel models. Network emulation bridges that gap by providing real-time emulated channels between a reasonable number of interacting nodes.

Simulation and emulation platforms for wireless environments have been developed to evaluate wireless designs, and to examine how wireless protocols handle wireless environments and react to dynamics.

Current state-of-the-art channel emulators [7, 18] can simulate advanced point-to-point channel models with high simulation realism and accuracy. In addition, these emulators usually support complex models for *MIMO* channels with tight spatial correlations comparable to the carrier wavelength. However, these point-to-point channel emulators often target at one specific environment without large-scale temporal variation due to mobility which is common in network-scale simulation scenarios. In addition, these channel emulators rarely scale to support multiple wireless channels in wireless networks.

On the other hand, wireless network simulators [33, 47, 57, 58, 59, 70, 79, 80] are widely available for large-scale experiments. In these simulators, several distance-based path loss models [57, 71] and small-scale fading models [56, 69, 71] have been developed to simulate a limited range of time-varying channel properties directly and indirectly. In addition, simulation platforms implementing these models often do not help in picking parameters, which becomes an extra challenge left to users.

Network-level emulators have been developed for large-scale emulation with high realism, such as the CMU Wireless Network Emulator [41], ATEMU [68] and commercial platform RFnest [92]. The CMU Emulator provides flexible control of channel models, implemented as Java software on a general-purpose computer. We utilize the Emulator platform to prototype flexible channel control module, and high efficiency realistic simulation models.

In current simulation and emulation platforms, channels are modeled independently, and

the spatial correlations among adjacent wireless links are not explicitly addressed. When using stochastic models, configurations are independently for each channel, thus spatial correlation is often neglected in simulation. This results in under-estimation of spatial correlation among channels that are close by. To improve the consistency over time and space represented in simulation, we propose simulation models addressing correlation and implemented on simulation platform ns3 [57] as a proof of concept improvement.

1.5.3 Vehicular Networks

Vehicular networks are a group of challenging mobile-to-mobile wireless networks. Measurement studies of vehicular channels have been performed in various locations across the world [19, 21, 61, 82], which provide a set of traces for model evaluation and validation. In addition to the fading effects, the role of the *LOS* component in *DSRC* (Dedicated Short Range Communications) is also examined [14, 53]. These measurement studies requires tremendous effort to be executed, and provide valuable physical wireless environment facts at a specific time for a specific area.

Simulation of wireless vehicular networks consists of modeling vehicles moving at wide speed range on a road network based on traffic constrains, as well as simulating propagation channels among vehicles. SUMO [8] is a widely recognized simulation platform for large-scale simulation of vehicular networks in urban area. While SUMO supports large-scale simulation of vehicular mobility and achieves high realism in vehicle traffic simulation, the platform does not address wireless communication among vehicles. Researchers have attempted to use SUMO's realistic mobility trace as mobility input for wireless network simulation.

Similarly, we utilize SUMO to generate realistic vehicle movements based on the realistic traffic models, and implement realistic shadowing and fading models separately to represent channel dynamics.

1.5.4 Mobility Models

Vehicle mobility has special patterns due to traffic regulations. Research in network-wide simulation has contributed several traffic simulators, which generate realistic vehicular traffic, such as SUMO [8] and GrooveNet [52]. In addition, mobility models have been developed to reflect vehicle behavior and traffic status in the real world [46, 55, 88]. Simulated traces generated from these traffic simulators are more realistic, compared to other general mobility models [9, 39]. We utilize SUMO [8] with its mobility model extensions [46] to generate realistic vehicle traces for a given road topology, which are later used in ns-3 as input of node movements.

1.5.5 Network Correlations

The correlation cross multiple wireless links has been studied at different time-scales.

The spatial correlation of shadowing property among adjacent links have been frequently observed in wireless networks. Some measurement study specifically quantified the level of correlation versus distance in urban and suburban area [60], while others studies the correlated shadowing effects in multi-hop networks [4] and vehicular network [16]. These measurement studies provide physical world evidence of cross-link correlation.

Studies have shown the correlation in shadowing effects has significant impact on wireless protocol performance [81], specifically in vehicular networks [14]. Moreover, such correlation can even be utilized in discovery [49] and geographic mapping [67].

Therefore, when evaluating protocols using simulation, it is critical to reflect realistic correlation properties.

The spatial correlation can be presented by either detailed geometric channel models with accurate parameters or stochastic correlated models. While obtaining detailed geometric information of all objects is often impractical, correlation models are needed to represent such properties. Unfortunately, current simulation platforms do not provide options of using correlated channel models. We proposed a stochastic correlation model for NLOS shadowing effects as an example that helps to represent spatial correlation among multiple adjacent links. We utilize correlation measurement results mentioned above to parameterize models parameters.

1.5.6 Protocol Evaluation in Simulation

Wireless protocols are designed to provide network connectivity on unreliable and dynamic wireless connections. Protocols, such as rate adaptation protocols [11], handle variations in link quality explicitly. Protocols may even perform better in the presence of spatial and temporal diversity [45, 72]. For example, opportunistic routing protocols [12, 34, 50] leverages spatial diversity explicitly to find alternative paths for improved performance.

However, current simulation platforms usually lack models for simulating realistic high dynamics and correlation properties in real time. As a result, evaluating the performance of wireless protocol designs on such platforms may not reflect the performance that is representative for the physical world where rich variations and correlations exist. Using the realistic environment simulation models presented later in this thesis, we were able to compare protocol performances in such environment with high dynamics and different levels of correlation.

1.6 Thesis Statement

Simulating realistic wireless environments at network-scale requires accurate modeling and parametrization and efficient run-time implementation. The proposed ‘World Model’ simulation architecture is an effective and practical design for high-realism network-scale wireless simulation. The proposed temporal and cross-link correlation models significantly improve modeling realism as well as parameter accuracy. These simulation models are highly automated and can be applied to existing simulation platforms to enhance channel model realism. This solution significantly improves simulation and emulation realism for large-scale wireless networks.

1.7 Contributions

The major contributions of this thesis are:

A complete system design for realistic network-scale wireless simulation and emulation platform: Major design components and configuration considerations are discussed for this design. By identifying channel dynamics across different time scales, corresponding channel

simulation models are suggested and combined together to represent a realistic, complex, and practical simulation model for a broad range of environment of a wireless network.

A single fast channel update solution for a wide range of wireless channel models: Flexible channel control model combines channel updates efficiently for complicated channel models, and supports high frequency of channel updates while remains flexible for model updates. Channel updates can be generated efficiently for a wide variety of indoor and outdoor wireless propagation models using a tapped delay line with multiple fading tables.

A systematic approach to estimate location-specific object distribution: Using aerial photography and land cover image processing techniques, a fully automated pre-processing method is developed to estimate roadside scatterer density over an area of interest. High accuracy and low run-time computation makes this solution effective and practical.

A distance-based cross-link correlation model for shadowing properties: Cross-link correlation among multiple links are represented using stochastic models with additional components, the correlation models, designed to approximate spatially correlated channel properties among nearby links. An example of LOS/NLOS shadowing properties is illustrated in the design. Generalization of the distance-based correlation model is discussed for typical wireless environments.

A flexible, practical and reliable platform for vehicular wireless network research: A vehicular network simulation example is implemented in ns-3. The example supports spatial correlation channel models for shadowing properties. We study the impact of the correlation model on the performance of a basic gossip protocol. Complexity analysis of different modeling options provides guidelines for selecting the most appropriate model.

1.8 Thesis Organization

The rest of the thesis is organized as follows:

Chapter 2 presents system design of the ‘World Model’ simulation architecture, where high-level description of major components and configuration details are discussed.

Chapter 3-5 present design, implementation, and evaluation of three major components in

the ‘World Model’: Chapter 3 focuses on the flexible channel simulation model for fast run-time implementation of signal-level changes. Chapter 4 focuses on improving simulation realism for temporal correlated models. Chapter 5 focuses on compensating lost cross-link correlation properties in statistical models.

Finally, Chapter 6 summarizes the thesis, including the conclusions drawn from the research, and a discussion on future work.

Chapter 2

System Design

Simulation and emulation platforms are widely used for evaluation of wireless designs. The ability to control the wireless propagation environment and reproduce the same environment through configuration makes simulation and/or emulation popular in wireless research.

Here we first present our proposed system design of a wireless simulation platform, followed by a detailed discussion of the necessary models needed to achieve realism.

2.1 System Design Overview

As described in Chapter 1, the physical world has a significant impact on wireless signal propagation. To reflect this impact in wireless simulation/emulation platforms, we apply multiple modules in the system to model and represent these features. There exist a number of channel models that represent specific point-to-point link properties. However, proper selection and configuration of these models requires information about the physical environment in which the network is deployed. Our proposed system design provides a flexible configuration of realistic wireless environment, and is capable of modeling the physical world impacts described in Chapter 1.2 from the experiment configuration.

The system design consists of four major components: 1) a **World Model** that contains models of objects and events that reflects physical world objects and activities; 2) a **Wireless Feature Analysis** module that extracts relevant wireless link related features from the world

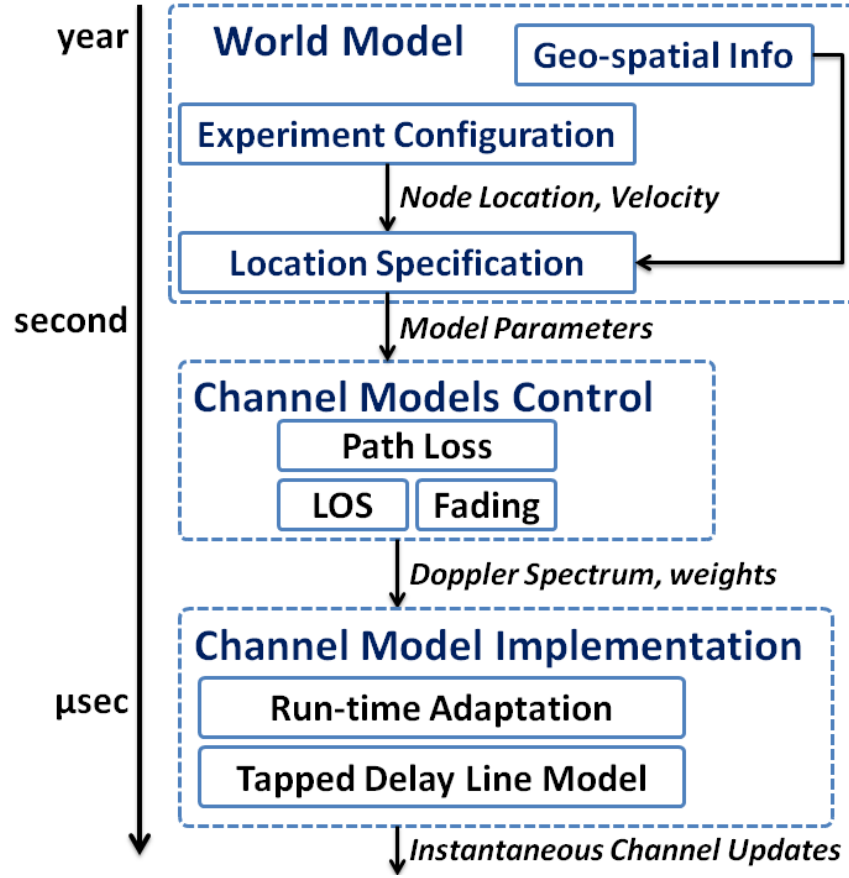


Figure 2.1: Proposed System Design

model events, and performs spatial and temporal analysis to select propagation models; 3) a **Channel Model** module that configures path models and updates parameters to reflect channel dynamics as desired; and 4) a **Configuration** module that users can use to define the type of environment they want to use in their experiments. It includes an input interface to enforce user-specified feature in the simulation.

2.2 World Model

The *World Model* component represents objects and associated activities and events during the simulation. For a given wireless environment, a set of objects and associated activity (events) are modeled depends on the specific physical environment. The object models can be created with desired properties, such as location and object mobility (speed, routes etc.)

While some object mobility events can be created explicitly from user input, other events should be derived using mobility models and other behavior-based collective models. For example, given the average speed and variation of moving vehicles in the environment, the movement of a group of vehicle objects can be implemented to reflect the desired statistical properties.

Objects in the world model all have an initial state, and changes in the state during the simulation will be regarded as update events. The initial states of objects and update events will thus represent a concrete instance of object behavior.

At each simulated step, events occurring at that moment introduce changes in object location and speed, which is updated accordingly. The changes are then passed on to the feature analysis component for further analysis.

2.3 Wireless Feature Analysis and Channel Control

The wireless channel characteristics are determined by objects in the environment as well as associated behaviors, such as location and mobility which are represented as world model states and update events. A *wireless feature analysis* model is designed to analyze the impact of these world model behaviors on wireless propagation.

Most simulation platforms use single-link channel models. For each link, there is a large set of possible configurations. When emulating the wireless propagation of a link, a most suitable channel model is selected, unless it is specified by the user explicitly. In addition, parameters in the selected channel model must be configured to represent specific link properties.

While wireless networks comprised of adjacent wireless links are modeled by a simple combination of isolated single link models, we find that behavior of these links is not necessarily independent in the physical world. More specifically, there exists both spatial and temporal correlations among adjacent links.

The *wireless feature analysis* component will interpret network state and updates from the World Model component, so that network-wide (cross-link) correlation property will be discovered. Chapter 4 and Chapter 5 will focus on design elements and consideration for the Temporal Correlation Analysis module and Spatial Correlation Analysis module, respectively.

After analysis of all network state updates, only updates affecting wireless properties are then passed on to the *Channel Model Control* module. Initially, a most suitable channel simulation model, selected by user or determined from current channel features, is applied to each wireless channel. The *Channel Model Control* is responsible for generating channel updates at desired frequency to approximate dynamics in channel properties. In addition, channel models should also be updated when significant channel feature changes are observed and a better channel model selection is available. Channel model updates and channel updates are constantly passed on to the *Flexible Channel Simulation* module where real-time updates are applied to each propagation paths.

2.4 Flexible Channel Simulation

Many point-to-point channel models have been developed [76, 83, 93] to characterize physical layer impacts that introduce attenuation and distortion of the propagated wireless signals. However, only a small set of these channel models has been implemented in network simulation/emulation platforms [33, 47, 57, 70, 80]. These platforms support several basic and simple channel models, while others [18] developed a limited number of complicated ones and require advanced understanding of the model to pre-configure the model and parameters properly. In Chapter 3, we will discuss our preliminary result on a *flexible channel simulation* model implementation that can produce a wide range of channel dynamics at a network scale, .

2.5 Configuration

Wireless experiments are designed and configured by users. In practice, most users adopt default parameter values for channel models in network experiments. There are two major reasons:

1. Users do not always know how to configure every single parameter in the models;
2. There are too many independent parameters in large-scale experiments.
3. It is difficult to update many parameters over time in a way that properly reflect both channel dynamics on multiple time scales and spatial correlation between nearby channels.

The *Configuration* component in the system is designed to help normal users to configure their experiment efficiently.

Wireless protocols are often designed for specific types of wireless deployments, and the simulation environment should be adapted to reflect the wireless properties of that desired physical world. The first step in configuration is to classify the wireless environment at a high level, such as indoor/office, outdoor/urban, etc.. With proper characterization of the type of wireless environment, a more suitable set of parameters can be obtained. This configuration module is also flexible in combining and switching between model inputs and user inputs, *e.g.*, allow overwriting of default configurations or providing a detailed and specific configuration of an object, a series of events, a particular channel model, or a parameter in the model.

The design and implementation of a wireless simulation/emulation platform as described in this section requires several critical design challenges to be addressed. We will organize the presentation of our solutions for addressing these challenges in the following chapters in a bottom-up order: starting with our preliminary result on the flexible channel update implementation in Chapter 3, and discuss spatial and temporal correlation models in Chapter 4 and Chapter 5. Example platform setup for wireless vehicular network are also discussed in each chapter for the corresponding component.

Chapter 3

Flexible Channel Simulation

Wireless network emulation enables controlled repeatable experimentation with reasonable-sized wireless networks. The combination of real radio hardware and signal-level emulation provides a level of realism significantly greater than that of network simulators, while the scale allows network-wide issues such as routing, forwarding, and resource management to be studied. Dynamics of wireless channel properties are simulated using channel models to approximate realistic variations.

Different channel models represent a large variety of link propagation features in the real physical world. Wireless channel dynamics means that any propagation feature of a link may change over time. Therefore, fast (and real time) configuration of such time varying features is necessary during wireless simulation and emulation.

In this chapter, we present a software and hardware architecture for emulating a broad class of channel conditions, including indoor channels and mobile-to-mobile channels at vehicular speeds, in real time.

3.1 Background

Prior work simulates Rayleigh and Rician fading at stationary-to-pedestrian speeds, but cannot support more general wireless channels [17, 42]. Recent work on FPGA-based emulation of vehicular channels [31] was able to provide configurable and flexible emulation. However, the

proposed solution only support emulation between one pair of transceivers.

The CMU Wireless Network Emulator introduced the ability to do signal-level emulation for up to 15 nodes for general wireless channels. In that approach, for n nodes, all $n(n-1)$ channels between them are modeled using a tapped delay line approach.

As in previous work, channel response is modeled in the time domain using a tapped delay line model, illustrated in Figure 3.1. Each tap effectively represents a resolvable propagation path, and the evolution of tap weights provides a statistical approximation of Doppler spreading and non-resolvable multipath effects. Time-varying tap weights must be generated to reflect desired large scale attenuation and small scale fading characteristics. The delay between taps and their relative magnitude determine the *frequency selectivity* of the channel and the degree of *inter-symbol interference* experienced. The rate at which tap weights change and the patterns of those changes determine *coherence time*, the (simulated) *Doppler spreading*, and higher-order statistics such as the *average fade duration*. In this chapter, the design and implementation of a flexible fading simulator is presented. The proposed solution is capable of producing a wide variety of weight sequences at each tap in real time.

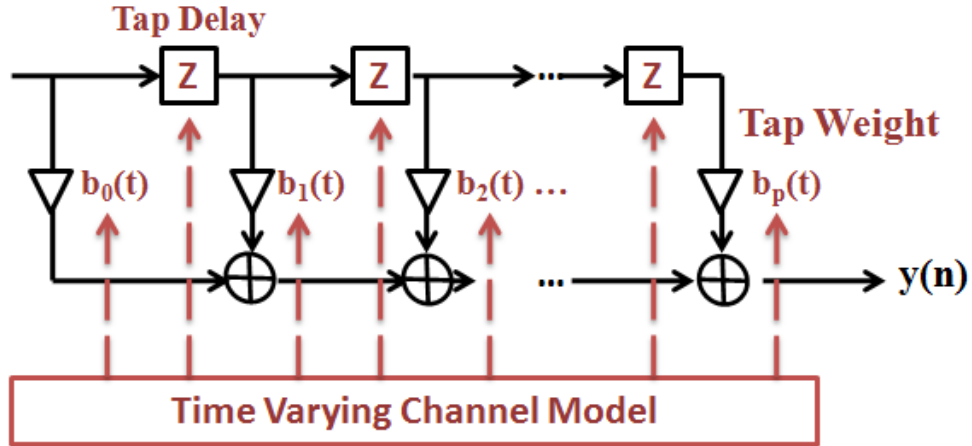


Figure 3.1: Tapped delay line model of an emulated signal path.

Two example channel definitions from GSM 3GPP [29] are shown in Figure 3.2. The rural area channel (RAx) is defined by four taps with a maximum excess delay of $0.5 \mu\text{s}$; the first has a Jakes Doppler spectrum with a line-of-sight (*LOS*) component and the remaining are classical (Jakes). The hilly terrain (HTx) channel is defined by twelve taps with a maximum excess delay

of 20 μs ; all taps have a classical Doppler spectrum. Reference channels for wideband mobile-to-mobile communication are not similarly standardized, however theoretical models and recent measurements suggest an Akki spectrum like those shown in Figure 3.7, and terrain-dependent delay spreads ranging from 0.3 to 5 μs [5, 62, 63, 82, 94].

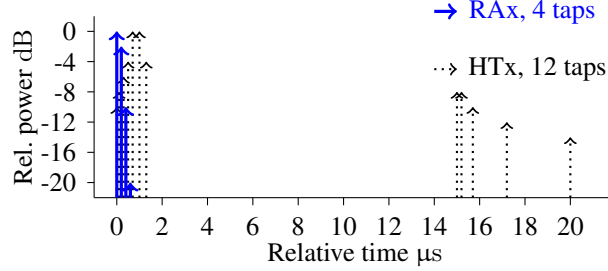


Figure 3.2: Tapped delay line models for reference channels from 3GPP TS 05.05. 4-tap RAx in solid blue, 12-tap HTx in dotted black.

A prototype of a channel simulation model is developed on the CMU Wireless Emulator platform [41] that is capable of switching in real time among multiple mobile-to-mobile and mobile-to-stationary fading channels. Several fading channel models have been implemented, representing different Doppler power spectra and a *LOS* component. For wireless experiments, channel updates are calculated frequently to reflect dynamics. The channel update rate is limited by system-wide hardware/software resources. Although techniques have been developed to utilize precomputed components for fast run-time adaptation, complex channel models usually require more computational resources to model and update at run time. The simulated network size is therefore limited by the number of channels that can be simulated at real time. Our design and implementation of a flexible simulation model is based on this Emulator platform and its tapped delay line implementation.

3.2 Tap Fading Spectra Simulation

Viewed in the frequency domain, the important properties of a tap weight sequence are captured by the Doppler power spectral density (Doppler spectrum) it produces. We therefore describe tap weight generation process in terms of the *fading spectrum* at each tap. The architecture described

below can produce the dramatically varying tap fading spectra associated with a wide range of wireless channels.

3.2.1 Principle of Operation

For each tap, weights with the desired characteristics are computed as illustrated in Figure 3.3. The desired spectrum is defined as a weighted sum of simpler spectra, and is produced at run time by combining samples drawn from its components. An attractive feature of this design is that a modest number of component spectra suffices to generate a broad range of channels (including most of the models discussed here, except for the geometric scattering model), and the computational work of generating samples for those spectra can be done off-line. This leaves only light-weight sampling and summing operations to be done in real time when there are no significant parameter changes. This process is described in more detail below:

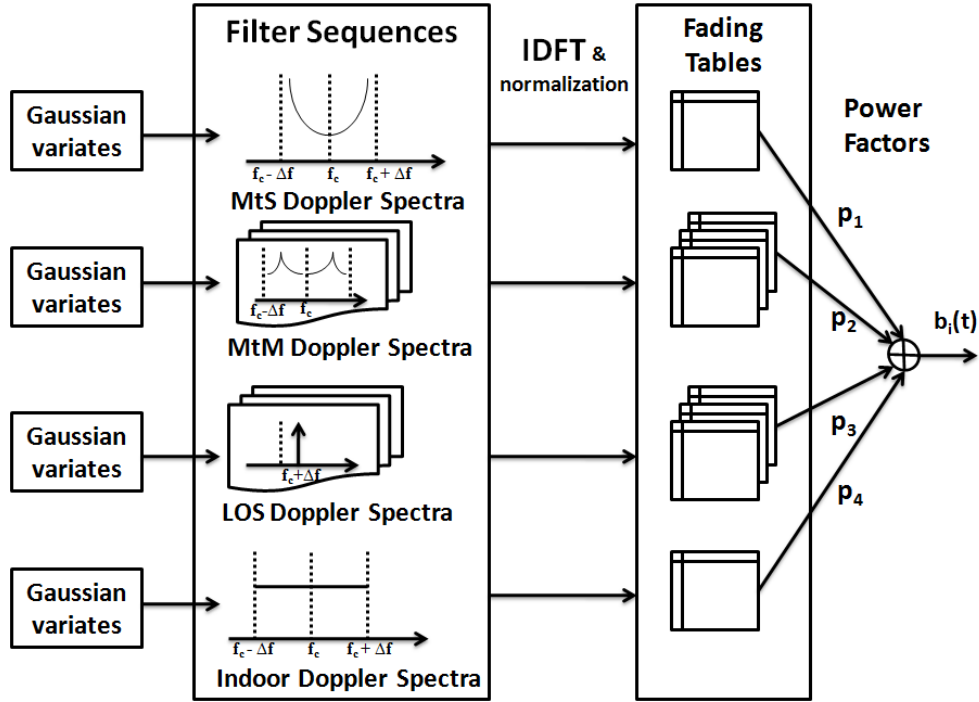


Figure 3.3: Tap weight generation process.

For each component Doppler spectrum, a frequency-domain channel response is generated as sequence of zero-mean i.i.d. Gaussian random numbers. Each sequence is filtered with the

appropriate Doppler spectrum [77]. Each spectrum represents one type of Doppler shifting or spreading of the propagated signal, for example the classic mobile-to-stationary (*MtS*) channel corresponds to the U-shaped Jakes Doppler spectrum.

After filtering, each sequence is then converted to a time domain sequence, normalized, and stored in a lookup table which we refer to as a *fading table*. Each fading table represents not just a single Doppler spectrum but a *family* of spectra, because different levels of Doppler shifting can be produced by iterating through the same table in larger or smaller steps. Additionally, many uncorrelated sequences can be drawn from the same table using different starting indices¹. Therefore, a single fading table can represent *all* Jakes spectra, while the Akki spectra require a separate table for each value of a , but not for each f_{m_1} in Eq. (3.3). The Doppler spectrum for geometric scattering models are time-variant. However, if we consider the contribution of each frequency component as one Doppler spectra contributor, the variation is essentially the change of power contribution of each frequency component. In this case, the overall spectra is a collection of these contributors. Since each contributor is associated with one frequency shift, as well as its corresponding weight (the contribution). Therefore, one fading table needs to be generated for each spectra contributor. At run time, the power contribution determines the weight $p_{j,k}$ for each spectra contributor k .

For any given tap i , at each time t , the tap weight $b_i(t)$ is produced by taking the “next” value from every fading table, and combining these values using the (possibly 0) weights $p_j(t)$. Therefore, each tap’s fading spectrum can be any of the component spectra, or a combined spectrum representing multiple fading effects. For example a Rayleigh-distributed classical Doppler spectrum combined with a line-of-sight factor produces a Rician distribution. For time-varying Doppler spectra, the combination of all related fading tables is required. Several of the important component Doppler spectra are described in the following sections.

3.2.2 The Mobile-to-X Channel Models

The mobile-to-stationary (*MtS*) scattering channel, as modeled by [24], assumes a ring of scatterers around the receiver producing a uniformly distributed angle of arrival. The Doppler power

¹Multiple tables may optionally be used if the possibility of a spaced-time correlation must be avoided.

spectrum $S(f)$ of *MtS* fading channels can be described as Eq. (3.1):

$$S(f) = \begin{cases} \frac{1}{4\pi f_m} \frac{1}{\sqrt{1 - \frac{(f-f_c)^2}{f_m^2}}}, & |f - f_c| \leq f_m \\ 0, & otherwise \end{cases} \quad (3.1)$$

where f_c is the center frequency, and f_m is the maximum Doppler shift, defined as:

$$f_m = \frac{V}{c} f_c \quad (3.2)$$

In Eq. (3.2), V is the speed of the mobile and c is the speed of light. A filter sequence generated for f_{max} can be used for any $f_m \in (0, f_{max}]$ by stepping through the sequence at a lower speed. f_m and f_{max} correspond directly to V and some V_{max} , which is the greatest (physical) speed for which the sequence can be used.

The mobile-to-mobile (*MtM*) scattering channel, as modeled by [5], considers independent double-ring scattering (that is, at both transmitter and receiver). Let the speed of the first mobile be V_1 , and the speed of the second be V_2 (without loss of generality $V_1 \geq V_2$). The corresponding maximum Doppler shifts are f_{m1} and f_{m2} respectively. The Doppler power spectrum $S(f)$ of *MtM* fading channel is described by Eq. (3.3):

$$S(f) = \begin{cases} \frac{1}{\pi^2 f_{m1} \sqrt{a}} Re(K[\frac{(1+a)}{2\sqrt{a}} \sqrt{1 - (\frac{f-f_c}{(1+a)f_{m1}})^2}]), & \\ \quad when & |f - f_c| \leq (1+a)f_{m1} \\ 0, & otherwise \end{cases} \quad (3.3)$$

where $K(\cdot)$ is the complete elliptic integral of the first kind, and a is the speed ratio, defined as: $a = V_2/V_1$, ($0 < a \leq 1$).

For any given a , a single fading table can be generated to produce tap sequences for any V_1 up to a predefined maximum, as with the *MtS* channel. At any time t , $V_1(t)$ determines the rate at which new values are read from the table.

Setting $a = 0$ causes the mobile-to-mobile channel to approximately reduce to the classical mobile-to-stationary channel: The *MtM* model still considers a ring of scatters around each mobile, but the effect of scatterers around the stationary device is negligible. Although the fading sequences generated using Eq. (3.1) (Rayleigh distribution) are not exactly the same as the

sequences generated using Eq. (3.3) (double-Rayleigh distribution) when $a = 0$, the results are very close in most cases, and can be used as a reasonable approximation.

The mobile-to-mobile scattering channel for vehicular networks, as proposed by [22], attempts to capture the small-scale fading effects from reflections off roadside objects.

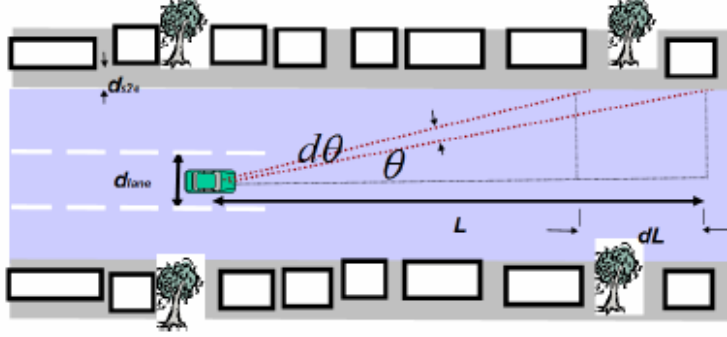


Figure 3.4: Geometrical Model for V2V Channel [22]

This fading model is a geometric model that uses location and density of roadside objects (buildings and trees) to estimate the reflections and their impact on fading, as shown in Figure 3.4. The assumption of scatterer location (arranged along both sides of the road) in this model is a close approximation of the reality in vehicular networks, thus we adopt this model as an example of geometry-based fading models for stationary scatterers.

In this model, the roadside objects are divided into small *cones* by the angle of arrival of the reflected path. The fading Doppler spectrum is then computed by aggregating frequency response from scatterers within each small cone.

$$S(f)df = G(\theta)p(\theta)f(\theta)d\theta. \quad (3.4)$$

Where

$p(\theta)$ is the probability distribution of θ ;

$f(\theta)$ is the response from scatterers observed at angle θ ;

$G(\theta)$ is antenna gain in the direction θ ;

and $S(f)$ is received power density at frequency f .

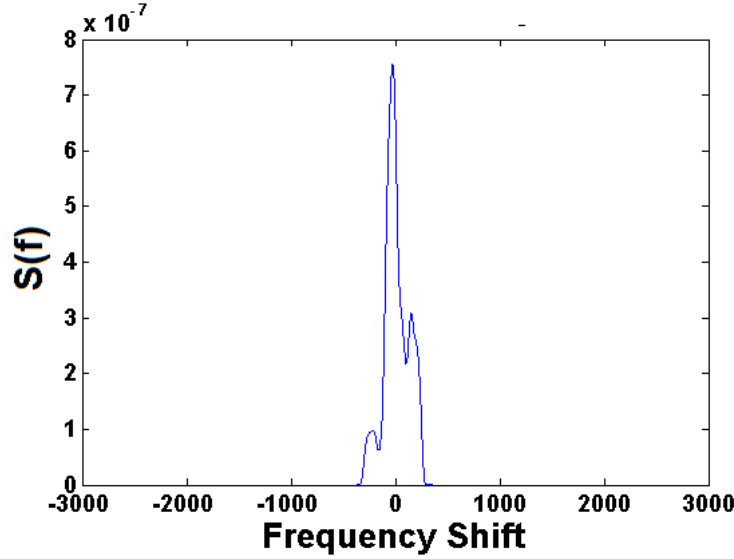


Figure 3.5: Doppler spectrum generated by Geometrical Model

A sample Doppler spectrum generated using this model is shown in Figure 3.5 and Figure 4.1(a) shows it combined with the LOS component. More details can be found in the paper [22].

Finer Granularity Fading (Spectrum De-smoothing)

When we compare the modeled Doppler spectrum in Figure 4.1(a), the measured spectrum in Figure 4.1(d) is jagged. This is a direct result of our methodology.

The geometry-based model described above calculates the Doppler spectrum for fading caused by reflections off large objects. A key parameter is the estimated density of scatterers. As we discuss in more detail later, our methodology for estimating this density based on aerial photography results in a fairly coarse estimate for the density. Specifically, we present result for density estimate on a 10 meter grid. While it is sufficient to capture building and large trees or groups of trees, it is not sufficient to capture the impact of individual scattering features on these objects, or to capture the impact of small scatterers. As a result, we should view the Doppler spectrum envelop as an average fading Doppler spectrum envelope for the large objects in the environment, which explains why it is smooth.

The many small “peaks” in the measured Doppler spectrum in Figure 4.1(d) are a result of

the small scatterers in the environment, including small features on large objects. Since we lack ground truth for the small scatterers, we do not try to develop a detailed model for them, as we do for large objects. Instead, we model their impact by filtering the spectrum used in simulation with a random variable, as suggested in [66], to approach actual randomness in scatterer density at a finer granularity.

In addition, the Doppler effect on a line of sight signal between two (possibly) mobile stations is a simple frequency shift: If θ_{Tx} (θ_{Rx}) is the angle between the transmitter's (receiver's) velocity vector $\vec{v}_{Tx}$ ($\vec{v}_{Rx}$) and the direction of wave propagation, the Doppler shift f_d is given by:

$$\frac{f_d}{f_0} = \frac{|\vec{v}_{Tx}|}{c} \cos(\theta_{Tx}) + \frac{|\vec{v}_{Rx}|}{c} \cos(\theta_{Rx})$$

The Doppler spectrum for this signal is an impulse at f_d .

3.2.3 The Indoor Channel

Another Doppler spectrum of interest is an indoor scattering spectrum. Indoor channels are generally distinguished by relatively low velocities and a rich three-dimensional scattering environment. Both measurement studies and theoretical models suggest that this combination leads to a “flat” Doppler spectrum [25, 86, 95]. The flat spectrum is not a special case of the mobile-to-mobile channel described above, but can still be simulated using the general procedure from § 3.2.1.

3.2.4 General Wireless Channel Model

As described in § 3.2.1, multiple fading models can be combined to represent an aggregate fading spectrum. This allows for combinations beyond the specific models discussed in this section, for example, [84] improves the *MtM* scattering model by combining multiple Doppler spectra with an LOS component. Near-arbitrary user-defined component spectra can be included, as long as they are known in advance.

3.3 Fading Tap Implementation and Validation

This section discusses the implementation and validation of the tap fading spectrum generation process described in the preceding section. Our prototype is implemented on the CMU Wireless Network Emulator [17] for the 2.4 GHz ISM band. The architecture is shown in Figure 3.6: A control computer generates tap configuration values in real time using the process described here, and the weight and delay values are sent to the signal processing FPGA. Both the mobile-to-x and indoor fading models are implemented on this platform. Discussion will be focused on the mobile-to-x case.

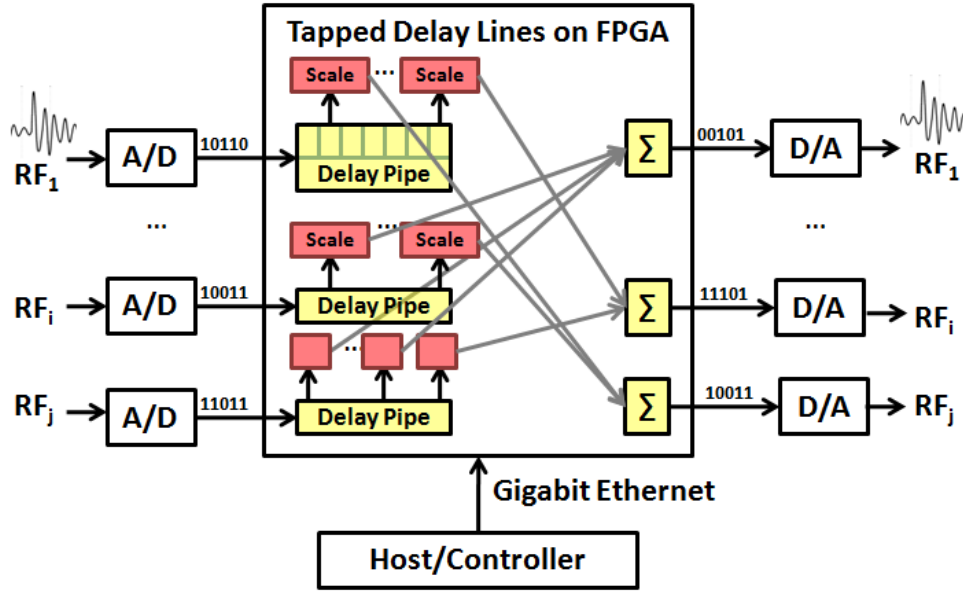


Figure 3.6: System Architecture

3.3.1 Generating Fading Tables

Tap weights are generated using the process in Figure 3.3. A long sequence of frequency sampling points is created to represent one Doppler spectrum. We choose a maximum speed $V_{max} = 70$ m/s (≈ 156 mile/h). Relative to a center frequency f_c of 2.437 GHz, the maximum Doppler shift is $f_{max} = \frac{V_{max}}{c} f_c \approx 600$ Hz. This requires a sampling frequency $f_s \geq 1.2$ kHz to smoothly simulate spectra for Doppler shifts up to f_{max} . We select f_s to be 1.2 kHz. As a result, the time between data points in the time-domain fading tables is $\frac{1}{f_s} \approx 0.42$ μ s. The more

sampling points used for a given frequency range, the longer the resulting time-domain fading table can be. We choose a sequence length of 65536, which implies a time-domain fading table covering ≈ 30 seconds at V_{max} . This means that the small-scale fading process is periodic, but we consider the period to be acceptably long.

The prototype generates sequences for the following component Doppler spectra:

- A normalized Jakes' spectrum (Eq. (3.1)) to represent the *MtS* Doppler power spectrum.
- A *set* of Akki spectra (Eq. (3.3)) for the *MtM* Doppler power spectra for different (binned) speed ratios. The $K(\cdot)$ values in Eq. (3.3) are static, and thus generated off-line.
- A normalized “flat” indoor Doppler power spectrum.
- Two LOS spectra with a spike at $f_{LOS} = \pm \frac{V}{c} f_c$.

Figure 3.7 shows two examples of the Akki spectrum filter generated for the *MtM* Doppler power spectrum, with speed ratios $a = 0.5$ and 1, with no LOS component. Figure 3.8 shows a corresponding sequence of time domain fading samples generated for $a = 1$.

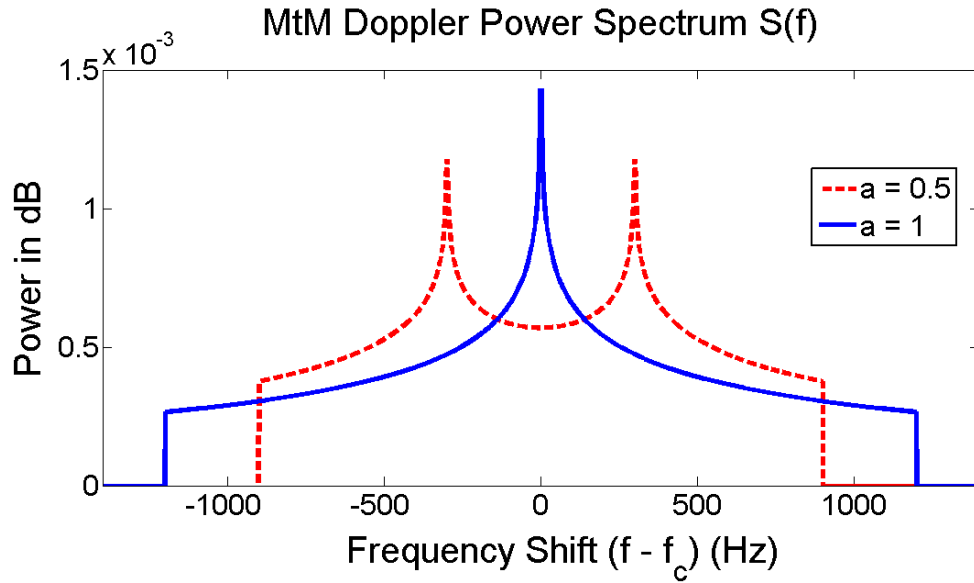


Figure 3.7: Akki (MtM) filter spectra for speed ratios $a = 0.5$ and $a = 1$.

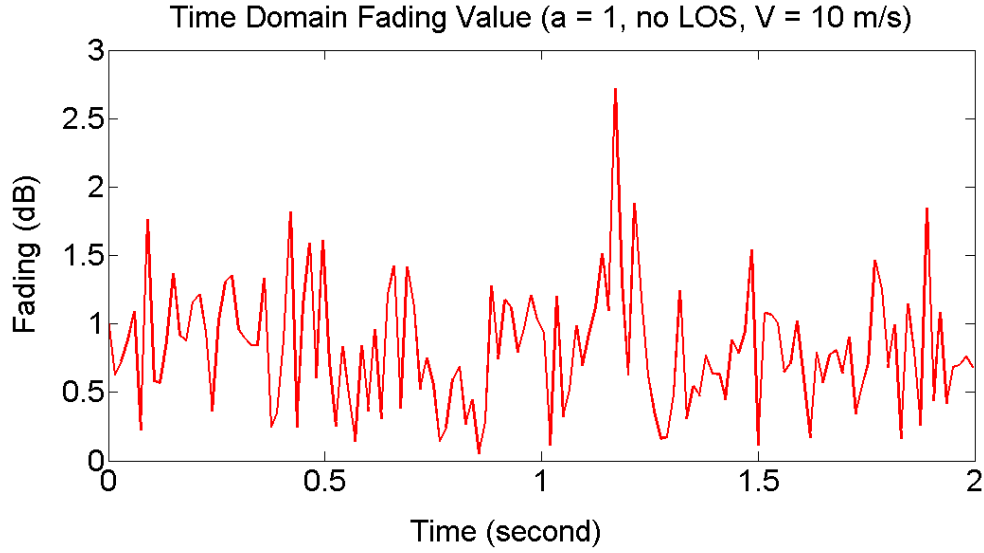


Figure 3.8: MtM channel time domain samples.

3.3.2 Run Time Simulation

At run time, the control software selects fading tables and assigns power factors to each fading table. For example, when both nodes are moving, an *MtM* fading table is selected: the current speed ratio $a = \frac{V_2}{V_1}$ determines which *MtM* Doppler power spectrum is applied. The power factors can be either configured by the user, or set to default values for typical channels. For example, when there is a direct LOS between sender and receiver, the LOS components will be included with higher power factors. The run-time software infers channel requirements from higher-layer environment models, switching fading tables and changing power factors when necessary.

3.3.3 Verification

This section presents a qualitative statistical evaluation of the samples produced by our prototype implementation. Figure 3.9 shows an averaged frequency domain view of a large number of (time domain) fading sequences for the MtM channel with $a = 0.5$. The result shows random variation around the filter spectrum shape.

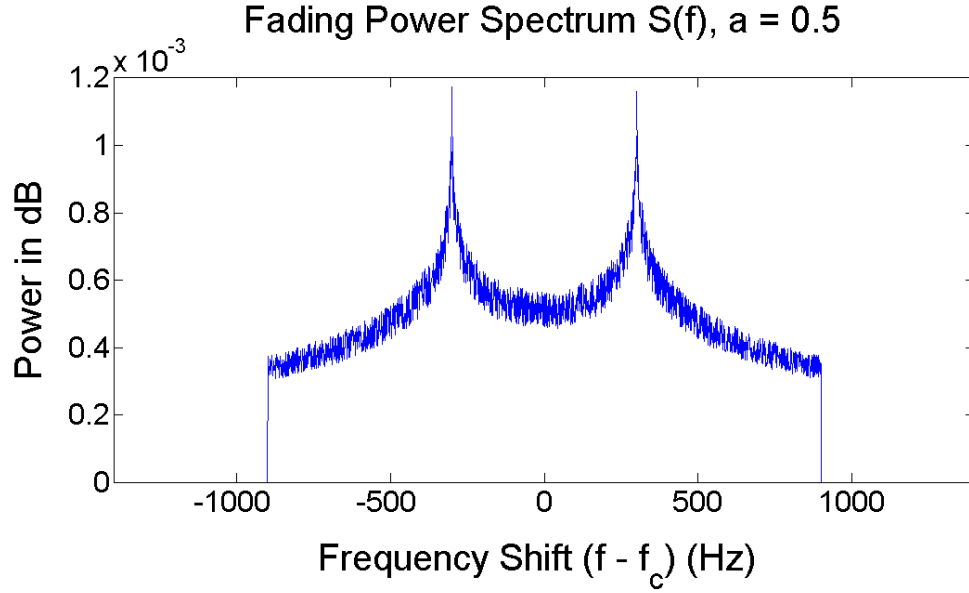


Figure 3.9: Generated MtM channel spectrum: $a = 0.5$, no LOS.

We also evaluate the distribution of the filtered samples. Theoretically, linear transformation of Gaussian random vectors result in Gaussian random vectors. Because the filtering process and IDFT in Figure 3.3 are both linear, the resulting fading are expected to be Gaussian variables. Figure 3.10 shows a Q-Q plot of normalized fading table values against a zero-mean Gaussian distribution with standard deviation of 1.0. The straight-line fit suggests that the Gaussian distribution is maintained.

3.4 Simulation Resource Analysis

3.4.1 System Model

The architecture considered here is based on the current CMU Wireless Network Emulator [17], and is shown in Figure 3.6. Signal processing, which must be fast and synchronous, is performed in a central FPGA. Channel (and higher-level environmental) modeling, which is more complicated and less timing-sensitive, is performed on a general-purpose computer. The two systems are linked by a serial channel. In this architecture, FPGA resources limit operations on the signal path, host CPU resources limit channel modeling, and the bandwidth of the host-FPGA link

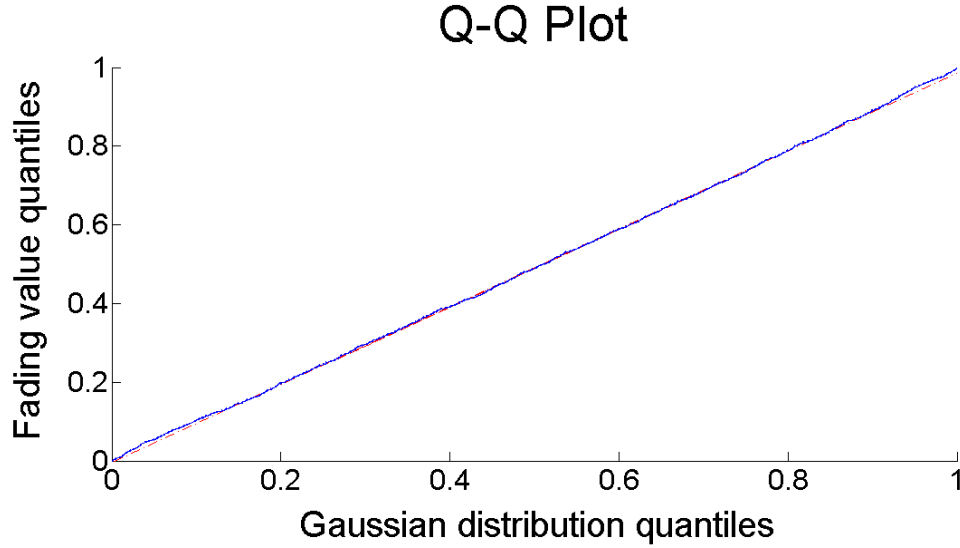


Figure 3.10: Q-Q plot: MtM channel tap weights vs. Gaussian

limits updates to the signal path. Timing precision on the host is a cross-cutting issue. The techniques discussed in this section are applicable to other architectures, but we will use this as a reference point in considering the resource costs of various simulation options.

Variables having a significant impact on resource use are shown in Table 3.1. Any given resource limit will allow trade-offs over these variables; specifics are discussed below.

3.4.2 Resource Limits and Feasible Ranges

For the sake of simplicity, we consider only homogeneous designs in which every node, channel, and path gets the same level of resources as every other. A well-chosen inhomogeneous configuration might be more useful, however the homogeneous case serves to illustrate general limits.

Some preliminary definitions are shown in Table 3.2:

Variable	Design Points
Bandwidth	5 MHz (min. IMT-Advanced channel) 22 MHz (one 802.11 channel) 83.5 MHz (2.4 GHz ISM band) 84 MHz (upper UHF TV bands)
Channels	2 (single bi-directional link) 18 (3x3 MIMO, bi-directional) 760 (20 node SISO network) 3420 (20 node 3x3 MIMO)
Taps per channel	1 (minimum) 2 (TS 05.05 indoor model) 6 (TS 05.05 rural and reduced models) 12 (All TS 05.05 models)
Maximum excess delay	$\approx 0.4 \mu\text{s}$ (802.11 card equalizer) $0.4\text{-}0.6 \mu\text{s}$ (rural, indoor models) $5.0 \mu\text{s}$ (urban model) $20.0 \mu\text{s}$ (hilly terrain model)
Minimum coherence time	$23 \mu\text{s}$ (v2v worst-case 300 km/h, 5.9 GHz) $50 \mu\text{s}$ (v2v, worst-case 300 km/h, 2.4 GHz) $260 \mu\text{s}$ (v2v worst measured, 5.9 GHz)

Table 3.1: Wireless network emulator design space variables

Variable		Definition
n		number of nodes
A		number of antennas per node
p		number of taps per channel
τ		maximum excess delay
N	$= A^2 n(n-1) p$	total number of taps (paths)
f_m	$= \frac{v}{\lambda}$	maximum Doppler spread
T_C	$\approx \frac{.25}{f_m}$	minimum coherence time
B		bandwidth
f_{samp}	$\geq 2B$	sampling rate
d		dynamic range (dB)
s	$\geq \frac{d}{6.02}$	sample size (bits)

Table 3.2: Variable Definition

FPGA Multipliers Blocks

The main limiting operation in the tapped delay line channel model is the signal multiplication for each tap. These are implemented using dedicated multiplier components in the FPGA fabric. Our reference FPGA, the Virtex-6 XC6VS475T, contains $\approx 2,000$ multipliers with a maximum operational rate of 600 MHz [91]. This gives a limit of $f_{mult} \lesssim 1.2 * 10^{12}$ multiplications per second. Each tap requires one multiplication for every sample processed. The number of distinct paths is therefore bounded by Eq. (3.5):

$$N \leq \frac{f_{mult}}{f_{samp}} \leq \frac{f_{mult}}{2B} \quad (3.5)$$

If $B = 100$ MHz ($\approx$ the 2.4 GHz ISM band or upper (ch. 38 – 51) UHF TV band), this gives $N \leq 6000$. This allows, for example, a 22-node SISO network with 12 taps per channel, or a 15-node 3x3 MIMO network with 3 taps. Referring to Table 3.2, the multiplier cost is $O(n)$ in bandwidth and taps per channel, but $O(n^2)$ in nodes or antennas per node.

Block RAM

Delay on the simulated signal paths is implemented using on-chip block RAM. The memory required depends on the sample size (which depends on the required dynamic range), the sample rate, and the duration for which a sample must remain in RAM, which is the channel delay spread. Define the duration of data that can be stored as:

$$S_{max} \leq \frac{\text{RAM}}{sf_{smp}} \quad (3.6)$$

Our reference FPGA has a $3.6 * 10^7$ bits of block RAM. Considering $B = 100$ MHz, and an 18-bit sample size ($d = 108$ dB), $S_{max} \leq 1$ S. The delay spread is bound by Eq. (3.7). The number of taps is not a factor, as each sample needs to be held until the final tap, regardless of the total number.

$$\tau \leq \frac{S_{max}}{A^2 n(n-1)} \quad (3.7)$$

For any of the channels discussed in Table 3.1, multipliers will be the limiting factor on our FPGA: Considering the limiting 15-node 3x3 MIMO network from above, $\tau \leq 530$ μ s.

Host-FPGA Communication

If tap weights are computed on the host, and evolve according to a random process, they must be sent to the FPGA at an interval of k times the tap's coherence time. The k will depend on the sophistication of on-FPGA interpolation, but by definition the value cannot be accurately forecast beyond the duration for which there is significant correlation. Let s_t be the size of a tap weight, in bits. The (worst case) data rate r will be bound by Eq. (3.8):

$$\frac{s_t N}{k T_c} \leq r \leq \text{host-fpga bandwidth} \quad (3.8)$$

Consider as a design point $k = 1$, $s_t = 24$ bits, and 1 Gb/s of bandwidth. This gives the following relation: $N \lesssim 4 * 10^7 T_c$. This is in fact limiting for vehicular coherence time estimates: For our worst-case coherence time of $T_c = 23$ μ s, this allows about 960 taps, enough for a 9-node (SISO) network with 12-tap channels, or a 15 nodes with 4-tap channels. On the other hand, the worst *observed* value $T_c = 260$ μ s allows 30 nodes with 12-tap channels. The number of possible taps is $O(n)$ in the minimum coherence time, and in the available bandwidth. The number of taps required scales as described in § 3.4.2.

3.5 Summary

Network emulation enables research into network-scale systems – which would otherwise be limited to low-fidelity network simulators and one-off field experiments – to use real radio hardware and realistic channel models.

In this chapter, we present a framework for signal-level emulation of propagation effects over generalized fading channels, at the scale of entire networks. In §3.2 we described our architecture for generating appropriate tap weights. Our hardware and software architecture goes beyond previous work in that it supports real-time emulation of a very general and parametric class of channels, which includes vehicular (broadband mobile-to-mobile) and indoor channels, in addition to classical stationary-to-mobile and stationary-to-stationary channels.

In §3.3, we presented our implementation of the tap weight generation process and verification. Lastly, we discussed the resources required to effectively implement various channel models in § 3.4.

Given the ability to implement a wide range of channel models, the next challenge is determining which models to use for each channel – and for inter-channel interactions – given arbitrary and dynamic user-specified environments, which is presented in Chapter 4 and Chapter 5.

Chapter 4

Temporal Correlation Models and Parameters

In this Chapter, we presents a general framework for modeling and reproducing environment-specific channel properties with high accuracy.

Complex geometric channel models have been developed to represent wireless properties and dynamics at high level of details. However, the problem of what parameters to use for a specific environment is less well studied, although parameter configuration in these models has a big impact on modeling accuracy. We studied a geometric model for channel scattering features, and a systematic approach is presented in this chapter to estimate location-specific scattering properties using aerial photography. We first describe the proposed framework in detail and then validate it for fading and line-of-sight effects in vehicle-to-vehicle channels. We show that it is practical to estimate *localized* environment information, and that adding such information to state-of-the art channel models significantly increases their accuracy.

4.1 Background

Areas with high speed mobiles are considered to be the most challenging environments when simulating dynamics. This is because of the swift changes occurs in a relative short period of time due to the high mobility. A typical representative of wireless network exhibiting such high

dynamics are vehicular networks. Therefore, we will focus our discussion on vehicular networks in this chapter.

The properties of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless channels are highly variable and difficult to estimate. Vehicles can travel through very different environments, producing distinctly different channels, *e.g.*, in urban environments, on rural roads, and on multi-lane highways. Even within a given area, the location and density of surrounding objects varies dramatically, leading to varying impact on reflected signals.

Realistic vehicular channel models provide a basis for analysis and evaluation of wireless vehicular networks by allowing flexible, controllable, repeatable experimentation. While general mobile-to-mobile channel models are currently supported in some wireless network simulation and emulation systems [57, 70, 89], those models do not capture the unique, environment-specific and highly dynamic properties of vehicular channels.

The differences between V2V-specific channels and the ‘general mobile-to-mobile model’ are largely the result of differences in technological assumptions: In contrast to cellular, technologies like DSRC and Wi-Fi have relatively short communication ranges (tens to hundreds of meters) which makes *local* conditions and geometry very important, and reduces the usefulness of wide-area averages. This limitation crops up in two significant ways: First “averaged geometries,” such as an infinite uniformly-distributed field of scatterers, are less valid. Second “averaged parameters,” such as a uniform density of road-side objects, are less predictive. One especially pernicious local effect is “line of sight” (LOS) obstruction by moving vehicles. Recent studies show a 10dB to 30dB LOS effect on received signal strength [54]. While this is conceptually just a special case of shadowing, it is caused by small fast obstacles with highly-patterned movement, while typical shadowing effects are caused by the terminals’ positions relative to large stationary terrain features. These processes produce substantially different dynamics.

Fading effects caused by scatterers in the environment, are location-specific in the vehicular network. Classical fading models assume a uniform “ring” distribution [5] [66] of scatterers around the transmitter and/or receiver, however V2V channel measurements [20, 61] suggest that the geometry of scatterers in vehicular networks is irregular and environment specific.

Several recent models have attempted to capture the “local geometry” of vehicular environ-

ments [22, 44, 96]. These consider factors such as the width of roads, cars’ positions within a road, the presence of intersections, and the type and density of scattering objects along roads. Models parameterized by such information achieve greater accuracy, but introduce the new challenge of discovering or estimating these parameters: Accurate, point-by-point values are impractical to obtain for any reasonably large area, and when “ground truth” parameter values are not available, the accuracy of the channel model will be limited by how well those parameters can be estimated.

We present a realistic vehicular channel simulation model that captures the unique channel features in V2V communication. The models are implemented in a real-time emulation platform, and evaluation results shows significant improvement in modeling accuracy, and achievements of high resource efficiency.

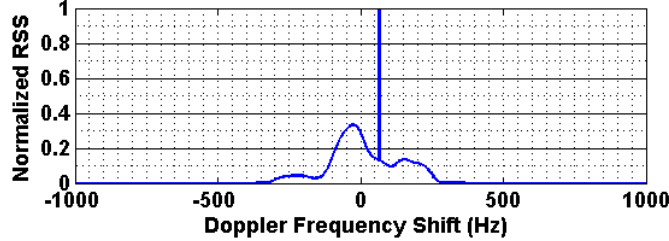
4.2 A Realistic V2V Simulation Model

In this section, we describe a realistic model for environment-sensitive channel simulation. We utilize the general architecture for wireless channel simulation and emulation described in Section 2.1 and Figure 2.1. We will describe the functionality of each component, with special focus on models for V2V channels.

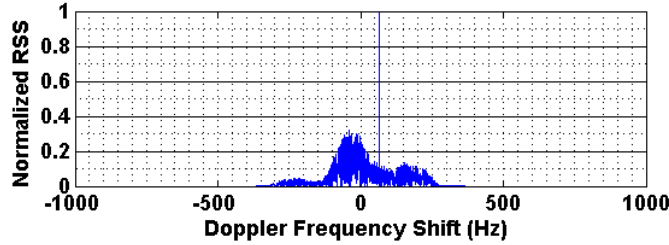
4.2.1 Channel Model Control in Vehicular Channels

We now discuss the vehicular channel model that we will use throughout this section. The model is suitable for vehicle-to-vehicle communication in an urban/suburban environment, although the methodology we present in the next section is more general, *i.e.* it can be used for other vehicular models and outdoor environments as well.

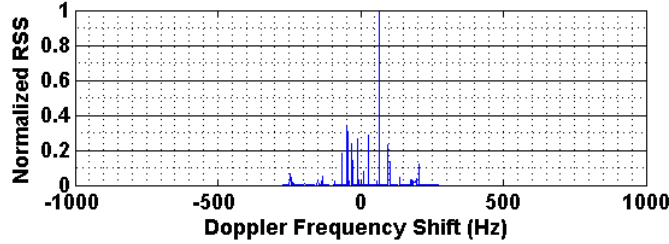
The specific environment we focus on is an urban/suburban environment with buildings, trees and mobile vehicles on the road. We chose this particular environment because there is growing interest in vehicular networking and it is also a challenging channel model because of the complexity of the environment, and rapid variation in channel conditions.



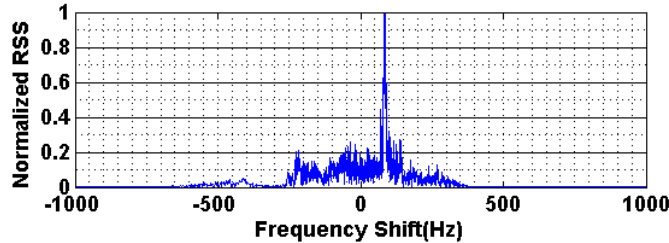
(a) LOS and Fading Envelope



(b) Filtered with Gaussian variates



(c) Filtered with Realistic Fading Scatterer



(d) Doppler Spectrum Measurement from Trace # 100

Figure 4.1: Generate Channel Doppler Spectrum

We will distinguish between two types of reflectors. We observed that in a typical urban/suburban vehicular network, the two primary paths are line of sight (LOS) and reflections off buildings and possibly other objects (*e.g.* trees) lining the street. We will refer to these objects as *large scatterers*. While there may be many other potential large scatterers in the area, their contributions will be minimal since they are effectively hidden behind the buildings lining the

street. Besides large reflectors, urban and suburban environments also have many smaller objects visible from the road that can reflect and scatter RF signals, thus contributing to fading. These include smaller structural elements associated with buildings and trees (e.g., balconies, branches, etc.), moving and parked cars, and traffic signs. We will call these objects *small scatterers*.

Since the differences in lengths between the LOS and various reflected paths are relatively small, we only need to model a single resolvable path. This path uses two Doppler spectra: one representing the contribution from LOS, and the other fading from reflections. The Doppler spectrum representing fading needs to model the effects of both large and small scatterers. We will use (a) a geometry-based fading model for large scatterers; and (b) a stochastic fine grained fading model for small scatterers.

To represent the path loss, LOS and fading effects mentioned above, our V2V channel model includes three major components, as shown in the *Channel Model Control* box in Figure 2.1: (a) a large-scale *path loss model*; (b) a V2V *LOS model*; and (c) a small-scale *fading model* that represents time-varying reflection and scattering effects of both large and small scatterers. The output of the LOS model determines the relative contribution (“power factor”) of the LOS Doppler spectrum in Figure 3.3, and the combined tap weight is scaled by the path loss value.

We now elaborate on how we model the different components of the channel. We use a standard log-distance model for part (a), large-scale path loss. This model obtains distance information from the World Model in Figure 2.1. In this section, we focus on the accurate modeling of dynamics in the environment and the development of appropriate models for (b) and (c). To illustrate the contribution of the different components to the Doppler spectrum we will use Figure 4.1, which was generated using our implementation (see Section 4.6 for more details). The Doppler spectrum in Figure 4.1(d) is derived from a trace collected in an urban environment, which we use as ground truth [20]. The Doppler spectra in Figures 4.1(a)-(c) were generated using our model, with incrementally more features enabled.

V2V Line-of-Sight

Line-of-sight is more than a specialized case of shadowing: When present, it is manifested as an impulse in the Doppler power spectrum. In a V2V environment, the LOS component exists as a

dominant received signal when there are no other objects between communicating vehicles. The V2V LOS model decides whether there exists a LOS component between transmitting vehicle and receiving vehicle. If it exists, a corresponding Doppler spectrum component is included in the simulated channel. The Doppler spectrum for the LOS component is then determined by the relative velocity of the transmitting and receiving vehicles. We can clearly see a LOS component in Figure 4.1(a).

Geometry-Based Fading Models for Stationary Scatterers

We extend the model proposed in [22], which attempts to capture the small-scale fading effects from reflections off roadside objects. We believe this theoretical model is a suitable fading model for realistic V2V simulation.

4.2.2 A Realistic V2V World Model

In the simulation architecture, the *World Model* is a coarse representation of the physical world properties, and a set of rules for translating this information into channel model parameters. Then, time-varying vehicular channels can be created in simulation with parameters inputs that represent desired channel properties.

Vehicular channel models (*e.g.* [22, 44, 96]) require significant information about the environment, much of it specific to the exact locations of the communicating devices. In examining V2V channel measurements, we find that not only do the observed channel conditions vary significantly within the same general environment, but a model using area-averaged parameter values performs significantly worse than the same model with best-estimated location specific values. It therefore does not suffice to have a good vehicular channel model: One must also have good knowledge of the environment, or sophisticated approach to generating synthetic environments, to derive realistic channel conditions. This requires accurate estimation of geometry-based model parameters that are location-specific and hard to obtain, especially for large area covered by a vehicular network. We discuss parameter estimation next.

4.3 Parameter Analysis

In this section, we focus on how to achieve high accuracy in estimating parameter values for the vehicular channel models described in the previous section.

4.3.1 Types of Parameters

	Physical World	Signal Propagation Abstraction
Specific	Topography Structures Location of mobiles Velocity of mobiles	Path loss exponent Clear line of sight (LOS)
Statistical	Vegetation density Traffic on roads Building density Terrain type	Rician k-factor Scatterer distribution

Table 4.1: Examples of environment attributes / model parameters

The precision with which a channel model models a particular environment depends not only on the sophistication of the model but also on the information of the parameters it uses and the accuracy of the parameters used during the experiment. Generally, channel model parameters can be divided into two major categories: **physical world** parameters that directly represent physical world features, and **signal propagation abstraction** parameters that capture some effect of the

physical world without representing the details that give rise to it. For physical world parameters are used, it is up to the model to determine how they impact RF signal propagation, while signal propagation parameters can be applied directly.

Either type can in principle be treated either as **specific** values or **statistical** distributions. Specific values will either be based on observations and measurements of a target environment or will be an average value. A statistical distribution will try to represent the values typically found in a type of environment. Several example parameters are listed in Table 4.1. Which parameters are “best” depends on the goals. One would expect specific parameters to allow more precise control over the channel model than statistical distributions, but collecting the parameters can be expensive. Similarly, physical world parameters seem to provide a more direct way to build a channel model that reflects a specific environment, but many parameters are needed. The results presented later in this section are consistent with this trends.

Next, we describe the traces that we used and we then discuss the parameter set of each specific V2V channel model component, with focus on components highlighted in Figure 4.2.

4.3.2 Traces Used in Our Study

A recent measurement of signal-level vehicle-to-vehicle channel provides realistic signal level facts in a suburban area [20]. The measurement took snapshot of the propagation channels at high frequency and generated Doppler spectrum at high frequency. We studied the collected traces and derived parameter values for that environment. During evaluation, we also use the trace as “ground truth” to show how close we can approach the reality while applying improved parameter values in models.

4.3.3 Example Parameters in Vehicular Channel Models

There are three major sub-models to the vehicular channel model, as described in § 4.2.1: The line of sight model (§ 4.2.1), the geometry-based fading Model (§ 4.2.1), and the “de-smoothing” of the Doppler spectrum (§ 3.2.2). Each of these sub-models has controllable parameters that can be tuned to reflect the time- and location-specific effects within an environment. We will now

examine each sub-model in details and discuss the parameter set of each model. Additionally, the magnitude of each model's contribution is an environment-specific property which must be modeled as well (§ 4.3.3).

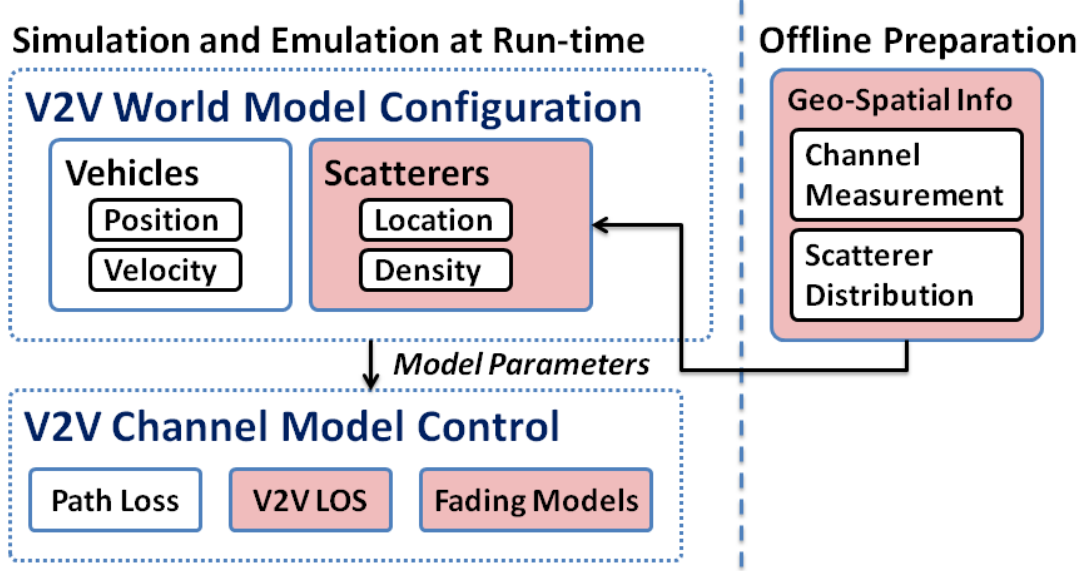


Figure 4.2: Determining parameter values for channel models

Line of Sight Doppler Shift

Assuming the vehicles' positions and velocities are being explicitly modeled, the necessary parameters in Equation 3.2.2 can be computed geometrically.

Parameter	Notation
Receiver position	P_{Rx}
Transmitter position	P_{Tx}
Receiver velocity	$\vec{v}_{Rx}$
Transmitter velocity	$\vec{v}_{Tx}$

Table 4.2: Parameters of Line of Sight Doppler Model

Geometry-based Fading Doppler Spread

The geometry-based fading Doppler spectrum describes the *aggregate* signal received by indirect paths reflected by objects in the environment. Here we consider the model described in [22] as an example. Fading effects from road-side scatterers are captured in this model, for two vehicles driving on a straight street, where scatters are road-side trees and buildings. The model’s parameters are given in Table 4.3. Other sophisticated V2V channel models such as [44] have very similar parameter sets.

Parameter	Notation
Transmitter (Tx) and receiver (Rx) velocity	$\vec{v}_{Tx}, \vec{v}_{Rx}$
Distance between Tx and Rx	d_{tr}
Density of road-side scatterers	ρ
(Mean) distance from road side to scatterers	d_{s2e}
Width of road lanes	d_{lane}
Number of lanes “above” (left of) Tx and Rx	N_a
Number of lanes “below” (right of) Tx and Rx	N_b

Table 4.3: Parameters of Geometrical V2V Model

Of these parameters, “ground truth” data is the least available for the scatterer density ρ . For a given drive (real or simulated), the other parameters can largely be derived from mobility data and street databases. In their evaluation, the authors of [22] were concerned with reproducing the *shape* of the measured Doppler spectrum, and used a scaling factor (which subsumes ρ) to match the model’s amplitude with the measured data. Their process to determine a location-specific scaling factor relies on manual editing (counting), which is not practical for areas with considerable size or variation. We estimate ρ – along with d_{s2e} – on a point-by-point basis by the *automated* processing of aerial photographs. This process, which will be described in detail in §4.4, is scalable for large area with variable ρ .

Model for Small Scatterers

In § 3.2.2 we observed that the measured Doppler spectrum is ragged while the Doppler spectrum generated by the geo-based fading model is smooth. Analysis of the non-smoothness showed that it is caused by many small “peaks” in the measured Doppler spectrum. The peaks represent strong reflections from small statics and mobile scatterers, i.e., objects with dimensions smaller than those modeled by the geo-based fading model. The spacing between peak locations indicates the spatial distribution pattern of scatterers along the road while their position and movement in the Doppler spectrum is determined by the speed of objects in the environment.

The best way to model the impact of these small scatterers is to develop an appropriate geo-based model that would use information about their positions to determine the number, location, and weight of the peaks at each time step. To do this correctly would require that the location, shape, and composition of scattering objects be known with extraordinary precision and accuracy. This is impractical for several reasons: First, many scatterers can and do move, meaning that site measurements become out of date almost immediately. Second, even for permanent stationary objects, the best publicly available maps and photographs have resolution and accuracy on the order of 5m, which is several orders of magnitude larger than the minimum relevant feature size.

The resolution of input data fundamentally limits that of the model output, which is therefore in effect a low-pass filtered average of what would be produced by the real environment. Example output is shown in Figure 4.1a. The measured values for the same location (shown in sub-figure 4.1d) show “spiky” variation corresponding to reflections from smaller features. We investigate two alternative methods for “de-smoothing” the envelope to reintroduce such small-scale variation. The first is to filter the spectrum with simple Gaussian noise: We define a random sequence $X \sim \mathcal{N}(0.5, 1)$, bounded to be between 0 and 1. For each frequency point f in the IDFT output, the original model output y_f is multiplied by X_f . Sub-figure 4.1b shows the effect of this approach.

We also define a new “energy-coalescing” de-smoothing function which attempts to replicate the underlying physical process: Intuitively, the model’s output over any small frequency range $[f_{low}, f_{high})$ represents the smoothed average of finer variation which ought to appear within

that range. We therefore generate a de-smoothed estimate by *reallocating* energy to peaks at randomly-chosen frequencies. The expected spacing between peaks δf_{peak} is a tunable parameter, which we estimate from the measured traces. The results of this process are shown in sub-figure c. Relevant parameters are shown in Table 4.4. Note that these approaches model the *observed* effect at the signal level; we have not yet developed *predictive* models for this variation.

Model	Parameter	Notation
Gaussian	Standard error	σ^2
Coalescing	Peak component spacing	δf_{peak}
Coalescing	Peak energy fraction	p_{peak}

Table 4.4: Parameters of Scattering Granularity Models

Component Contributions

The Doppler spreading spectra for both the line of sight and scattered signals contribute to the received signal. While total received power is determined by large-scale path loss, the relative weight (power contribution) among each component needs to be configured. The channel effects of each component – tap weight contributions in our realization – must be scaled to represent the magnitude of the channel gain (loss) for each. The range of relative weight can be obtained from measurements in specific environment, and then be applied to simulation of similar scenarios.

For the LOS component, we model these magnitudes as (1) an absolute path loss magnitude, and (2) a relative line-of-sight magnitude. We do not attempt to evaluate path loss models – we are using the same (measured) path loss value with both the modeled and measured fading processes in our evaluation. For fading components, we used the results in the trace study in [20] to determine the relative power ratio for specific vehicular environments. These measured values were then used in all evaluation scenarios.

In §4.4 and §4.5, we describe our novel geometry-based scatterer estimation and LOS status estimation, followed by an evaluation of the accuracy of the model in §4.6.

4.4 Geometry-based Scatterer Estimation

As discussed in §4.3, accuracy in density estimation is a critical set of parameters in the V2V fading model [22]. In this section, we will show how this estimation accuracy can be improved systematically.

Rather than use an area or environment-type average as in [22], we estimate point-by-point value along the route(s) of interest. Here we consider two types of scatterer: trees and man-made structures. Some propagation studies have attempted to identify and model every specific object in the region of interest, but this is impractical at the scale of a meaningful vehicular network. We are therefore interested in approximations that can be applied to large areas, using existing publicly-available data, in an automated way.

We explored several alternatives, and were able to achieve the best accuracy by extracting relevant features from aerial photographs. While the availability and quality of imagery varies by region, 1m x 1m *digital aerial orthophotography* is available for most of the United States [3]. Using established *spectral signature* criteria [13], the type of land cover in each pixel can be estimated.

4.4.1 Estimate Land Cover Type

Digital aerial image provides 3-channel(RGB) color reflection of a given area. Both pixel-based and object-based methodologies have been developed to estimate the type of land based on its digital aerial image. According to [13], pixel-based methods are applied first to distinguish lands covered with vegetation. Then, different object-based methods are utilized to identify objects and other constructions within each group. We'll briefly describe how we apply the process in our case.

Vegetation Type

In general, lands covered with vegetation show strong reflection in channel Green. Using the PCA analysis, a pixel is identified as type of vegetation based on relative value among the 3 channels: $(G^3 - R^3)^{1/3}$. For all pixels labeled as vegetation, we further distinguish tree pixels

from grass pixels. (This is because only trees are regarded as roadside scatterers in our estimation.) Since there exists higher fluctuation of reflection (in channel G) among adjacent tree pixels, using variation of channel-G response within a small window will help to differentiate tree pixels from grass pixels.

Road and Other Constructions

For pixels identified as non-vegetation, we use the object-based method described in [13] to distinguish roads and buildings. Since we only use the aerial image, elevation data is not considered in the process. The basic idea is to expand continuous pixels along the road, while building pixels have borders. We also assign an ‘other’ type for the rest pixels, which usually include land covered with water.

Figure 4.3 shows an example classification map generated for central Pittsburgh. The location and density of roadside scatterers and road (lane) dimensions can be estimated from the land cover classification results, combined with explicit road information from U.S. Census data [85]. For any given road segment, the scatterer distribution model calculates roadside scatterer (building and trees) density.

4.4.2 Calculate Scatterer Density

Roadside scatterer density is estimated by counting the density of tree pixels and building pixels along the road.

Identify roadside pixels

For pixels labeled as road, we generate a road buffer of 50m wide on both sides of the road. Only pixels fall in the road buffer are considered as road-side pixels.

Estimate roadside scatterer density

Among all road-side pixels, we only consider tree pixels and building pixels in scatterers estimation.

For the area we are studying, the best aerial maps available are from National Agricultural Imagery Program [3], The most recent photographs in this area are 4-band (RGB plus infrared), with an absolute position accuracy of $\pm 6\text{m}$. Therefore, we use a $10\text{m} \times 10\text{m}$ mask to estimate scatterer density for each position.

The accuracy of mapping is limited by image quality and classification algorithms. However, this general approach proves effective in practice, and accuracy can be improved with better inputs. Although the processing time for a large area is significant, it can be done off-line and needs to be performed only once.

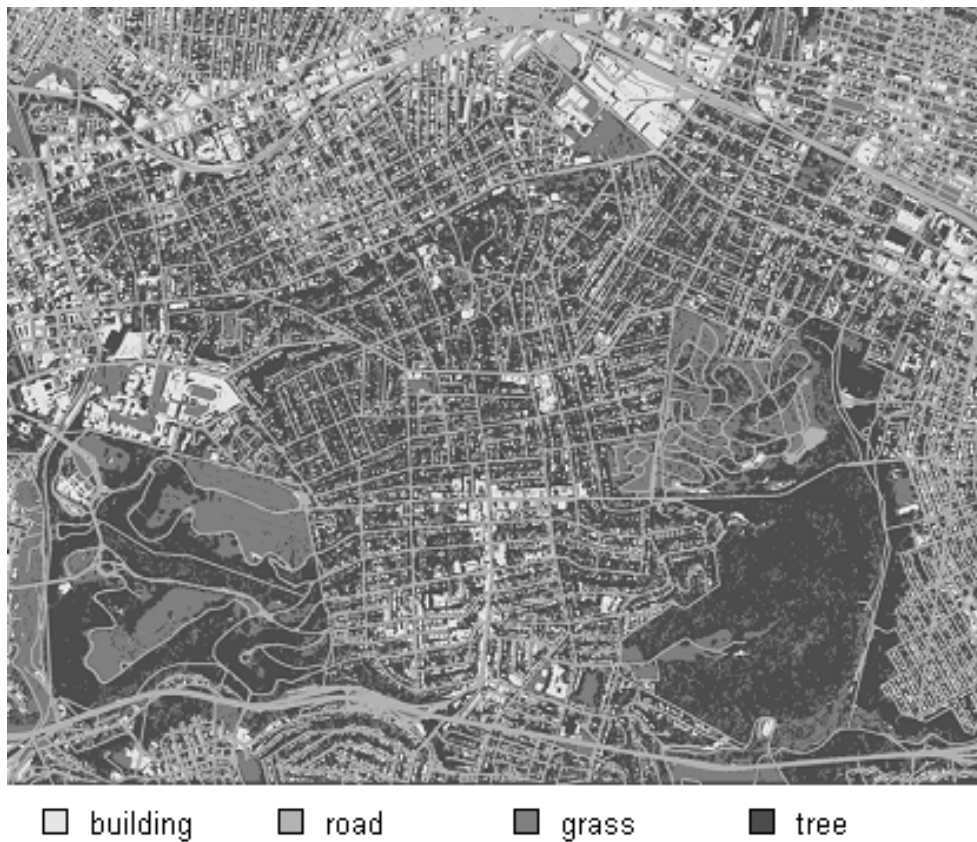


Figure 4.3: Classified Map

Considering the fact that locations of building and trees are stationary in general, the calculation is performed off-line for any given area of interest. At run time, exact scatterer density along the route (at given locations) can be obtained quickly by a simple table (map) lookup.

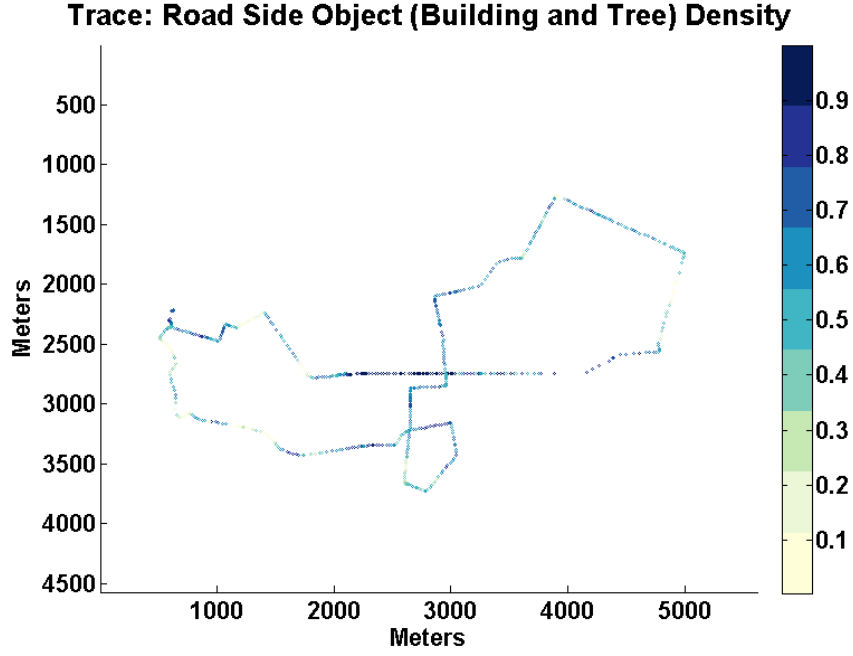


Figure 4.4: Roadside Scatterer Density

Figure 4.4 shows sample roadside scatterer densities generated for a given route. Using these estimates, fading models can generate more realistic location-specific Doppler spectrum. The benefits are shown in the evaluation part (§4.6), when comparing against fixed parameter values.

4.5 V2V Line-Of-Sight Estimation

In this section, we introduce a trace measurement-driven method of estimating V2V LOS status for the *V2V Line-Of-Sight module* (4.2.1).

The *Line-Of-Sight path* between two vehicles varies (appears or disappears) over time, especially when vehicles frequently switch lanes and/or merge lanes. In principle, the exact LOS status could be determined geometrically by modeling the dimensions and behavior of every object in the area that could block the LOS path. This explicit modeling approach will not be practical without adequate information of all objects in that area. Instead, we use a trace measurement-driven approach that can estimate the *LOS path status*.

We first studied the statistical pattern of LOS status in the channel measurement traces

from [20]. A trace (1.5s window) is labeled as LOS-evident if: (a) There exists one frequency component (or a small number of a frequency components) having dramatically greater magnitude than all other frequency components, and (b) there exists a single frequency component accounting for a large fraction of the total received power. Figure 4.5 shows that these criteria largely agree with each other.

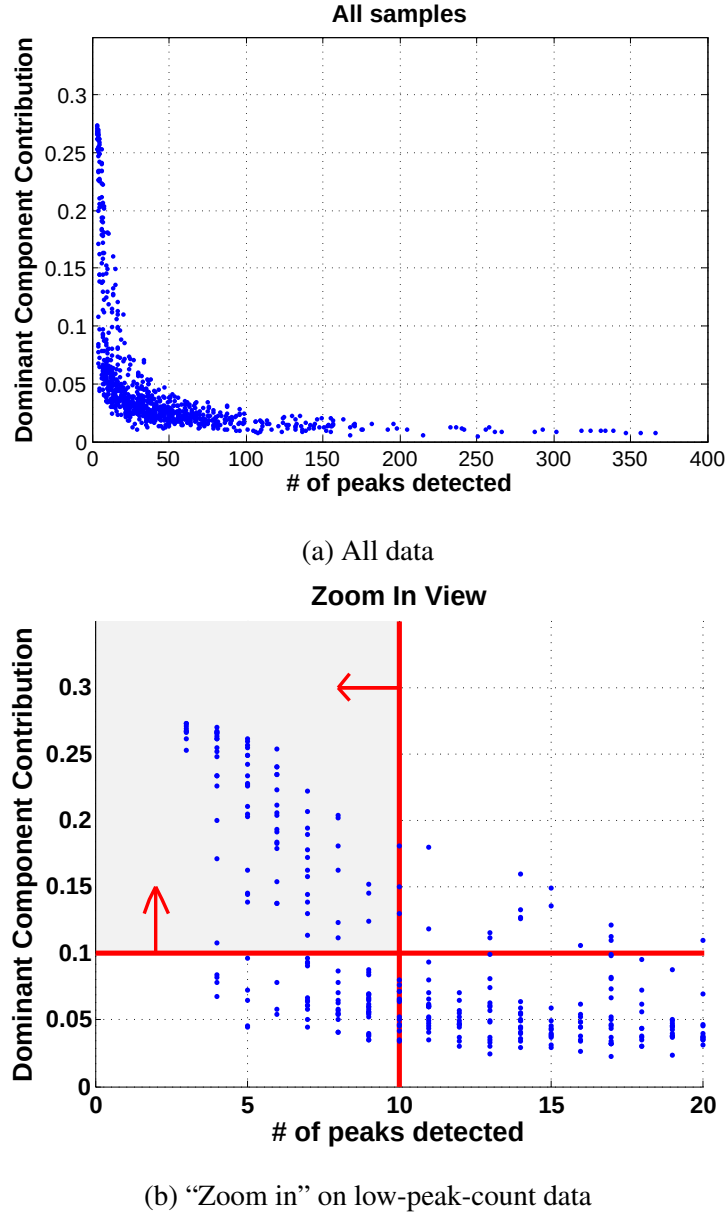


Figure 4.5: Detect Dominant Components (LOS)

Figure 4.5 shows the pattern extracted from traces, with each data point represents one trace. For each trace, we count the number of dominant frequency components (peak counts) as well as corresponding power contributed compared to total power (power ratio).

Notice that traces with high peak counts essentially have large numbers of comparable frequency components, which indicates no dominant components among all. The figure shows that: a) traces with high dominant power ratio have low peak counts (mostly fewer than 10); and b) traces with low peak counts have higher dominant power contribution (mostly higher than 0.1). This observation matches with properties of dominant components (LOS). Therefore, we use both power ratio and peak counts to label traces as LOS-evident as described above.

Following [2], the V2V LOS status can be modeled using a two-state Markov model. The LOS transition behavior is represented by two configurable parameters: 1) t_{NLOS} : the average duration of *NLOS* period; and 2) p_{block} : the probability of losing LOS per unit time. These are first estimated to fit the line-of-sight pattern identified in real traces, and then the Markov model transition probabilities are derived from those parameters.

From measurement traces, consecutive samples of LOS components represent a long LOS duration, with gaps in between indicating *NLOS* periods. We determine the typical value and range of t_{LOS} and t_{NLOS} by averaging the length of continuous LOS segments, and gaps between these segments. The probability of p_{block} is estimated by calculating the percentage of samples that are not labeled as LOS-evident.

Although the parameter values estimated from traces are specific this location and time, the same approach could be applied to measurements from other V2V or V2I environments. It possible that representative values exist for generally similar environments, but this has not been tested.

4.6 Evaluation

We evaluate the accuracy of our fading model at two different levels. First we evaluate how well the channel model matches the measured channel at the signal level. The signal-level channel “closeness” is measured by the Doppler spectrum similarity. Second we use 802.11 link-layer

measurements to compare the modeled and measured channel at the link level. Our metric is packet delivery ration (PDR). At the channel level, our proposed location-specific model has less than half the error of an area-average model. At the packet level, the location-specific model has less than $\frac{1}{4}$ the error.

4.6.1 Wireless Network Emulator

Our packet-level experiments are implemented on the next-generation prototype of the CMU Wireless Network Emulator [89] in the 2.4GHz ISM band. The architecture is shown in Figure 4.6: Each transmitter's signal is converted to baseband and digitized in the input side of the emulator. The digital signals are filtered through a tapped-delay line FIR filter to produce both attenuation and delay, including fading and resolvable multipath effects (see Figure 3.1). This real-time per-sample signal processing is performed in the FPGA. The number of taps, their weights, and the delays between taps are controlled by software running on a general-purpose computer (see Figure 3.3). In general, every attached radio is both a transmitter and receiver, and a distinct channel is emulated for every transmitter-receiver pair. For the purposes of these experiments, the emulator is configured with a single, unidirectional, one tap channel between the transmitter and the receiver.

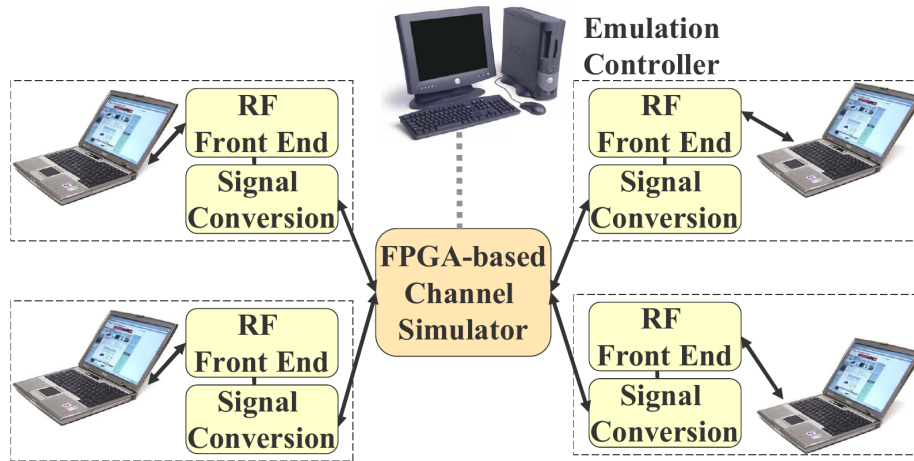


Figure 4.6: Overall Emulator Architecture

4.6.2 Doppler Spectrum Similarity

To evaluate the accuracy of our fading models and the impact of using detailed environment-specific parameters, we compare the difference between two modeled fading spectra and the real measured spectrum. We consider 889 measurements collected for [20], where each measurement includes GPS-derived position and velocity for the mobiles, and the Doppler spectrum for a 1.5s narrow-band continuous-wave measurement. We label these spectra M_i $i \in (1, 889)$. For each such point, two modeled Doppler spectra are computed: The first is a baseline estimate D_i , which uses the real (instantaneous, location-specific) values for position and velocity, but a fixed *area average* value for ρ . This essentially matches the model as described in [22]. We also compute a location-specific spectrum E_i , which again uses the real position and velocity information, but also incorporates the estimated point-specific ρ values. For other configurable parameters $d_{s2e}, d_{lane}, N_a, N_b$, we apply the same observed values in [20] because the road dimensions does not vary much within the area where the measurement data were collected.

For each i , the accuracy of D_i and E_i is computed as the *Kullback-Leibler divergence* [48] relative to M_i ¹. Note that K-L divergence was developed as a measure of similarity between probability density functions. We are applying the technique to the more general problem of comparing functions which are not probability densities; this approach was introduced by [32]. This use of the K-L divergence metric lacks the precise information-theoretic meaning of the original, but still provides an intuitively-reasonable measure of difference. For the K-L divergence to be well-defined, the two functions need to “look like” probability distributions. Therefore, if the frequency sample points are denoted as f_j , we normalize each Doppler spectrum *e.g.* E_i to $E'_i = \frac{E_i}{s}$ for $s = (\sum_{f_j} E_i(f_j))^{-1}$. This normalization discards the total received power s , leaving only the difference in shape. Finally, the K-L divergence of two spectra is then defined as:

$$d_{KL}(E_i || M_i) = \sum_j E'_i(f_j) \ln \frac{E'_i(f_j)}{M'_i(f_j)} \quad (4.1)$$

and $d_{KL}(D_i || M_i)$ is defined similarly. The K-L divergence is 0 when two (normalized) spectra

¹Notice that D_{1-889} and E_{1-889} are basic fading envelopes. Therefore, we applied a smoothing window of 100 Hz on the measured spectrum and use the result as the fading spectrum envelope M_{1-889} .

are identical, and increases as the point-wise values differ.

The spectrum similarities $d_{KL}(D_i||M_i)$ and $d_{KL}(E_i||M_i)$ along a measured route are shown in Figure 4.7. Figure 4.8 shows empirical CDF (cumulative distribution function) of the spectrum divergence for the two estimation methods.

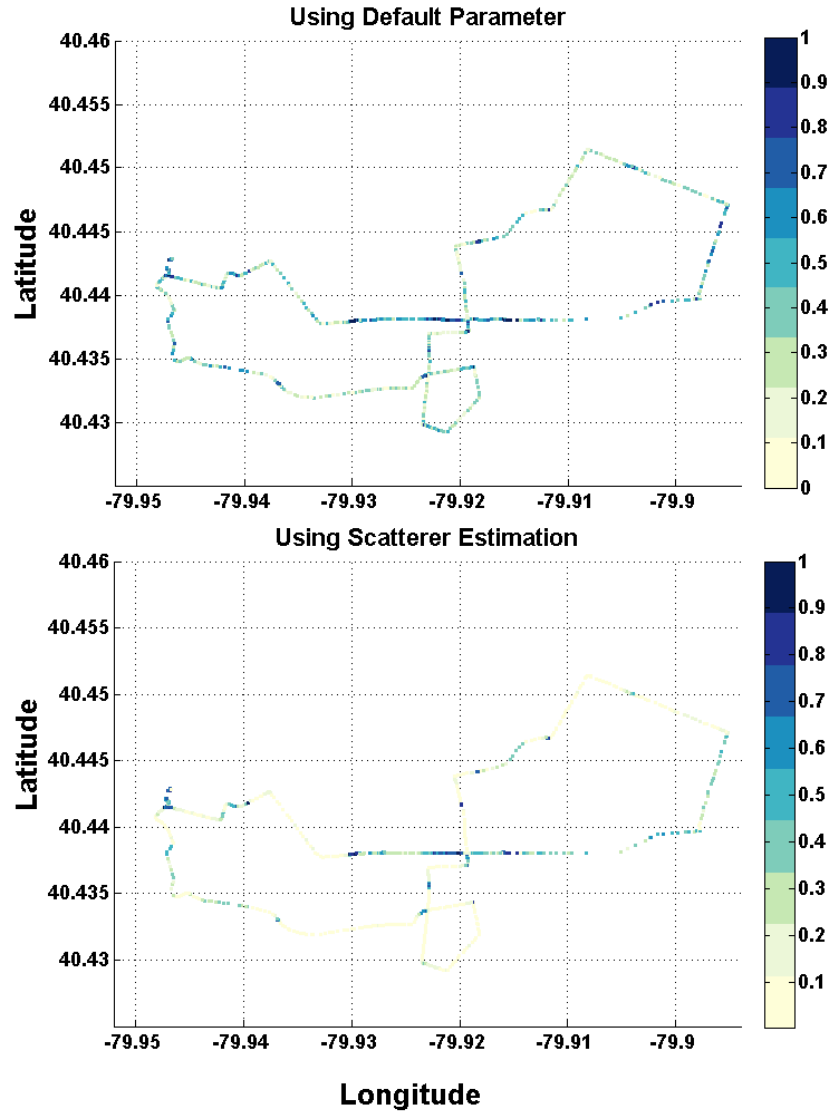


Figure 4.7: Spectrum Similarity Comparison on Map

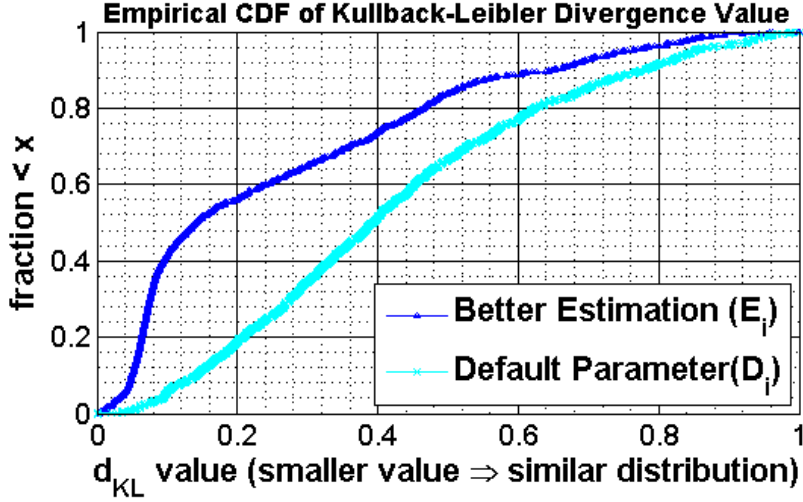


Figure 4.8: Spectrum Similarity Comparison (CDF)

The location-specific estimates are significantly better than the area-average: The median error (K-L divergence) of the E_i is **36%** that of the D_i (0.14 vs. 0.39). The E_i curve is always better (left of) the D_i curve, with a Kolmogorov-Smirnov statistic of 0.37.

4.6.3 Link Layer Comparison

While the Doppler spectrum is interesting in itself, for many purposes the pressing question is “how does this fading pattern impact communication?” We show that, for real 802.11a radios using **BPSK with half rate** over a range of path loss values, the location-specific fading model produces packet error rates (PER) significantly closer to reality than the area-average model.

This experiment was conducted as follows: Two 802.11a nodes were placed in RF-shielded test enclosures, with one antenna port on each node’s wireless NIC connected to the channel emulator described in § 4.6.1. A unidirectional channel was configured from the transmitter to the receiver. For each measurement point i , a large-scale *path loss model* generates its corresponding path loss value based on the Tx-Rx distance². The same path loss value (for measurement point i) was combined with each of the small-scale fading Doppler spectra M_i , D_i , and E_i , respectively.

²The channel measurements collected do not allow us to reconstruct the path loss at each measurement point. The path loss values used are therefore not necessarily correct, but they are credible and most importantly do not vary between Doppler spectra at each point.

For each spectrum, the resultant tap weights were used to produce a single-tap channel. For each point i and fading spectrum, the transmitter broadcast 2000 packets over a 20-second window, which were logged by the receiver. The PER was then calculated for each experiment.

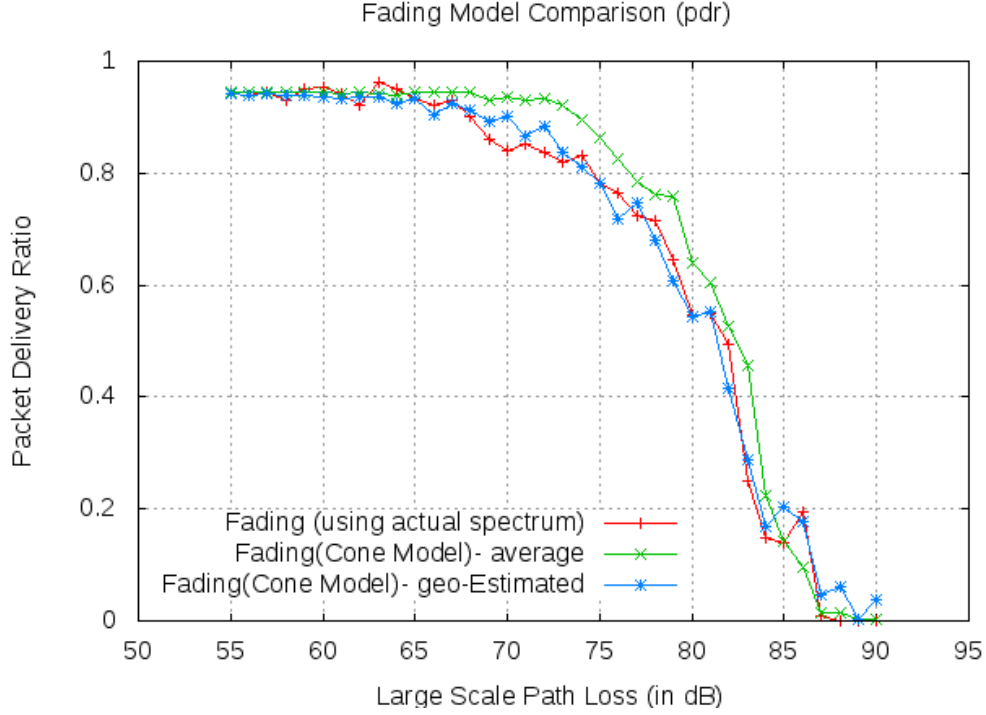


Figure 4.9: Link Level Comparison

The measured packet delivery ratio results is shown in Figure 4.9. The red (+) line in this figure is the reference data set: the PDR results using measured Doppler spectra M_i . The green (x) line shows the results using area-average ρ (spectra D_i), and the blue (*) line show the results using location-specific ρ (spectra E_i). We observe that path loss is the dominant factor in determining PDR, and that the location-specific fading channel approximates the measured values more closely than the area-average model. Over all points i , the location-specific model and area-average model have mean squared errors of **0.034** and **0.158**, respectively. The error of the improved model is less than $\frac{1}{4}$ that of the baseline.

4.7 Run-time Complexity

In this section, we first explain run-time challenges in simulating vehicular channels with high dynamics. Then, we introduce several optimizations that improve real-time simulation efficiency. A prototype of the simulation model from Figure 2.1 has been implemented on the Wireless Network Emulator [42]. The channel models are implemented as Java software on a general-purpose computer. The performance evaluation in this section is from this prototype.

4.7.1 Channel Updates Calculation

During simulated experiments, the dynamics of a given channel are implemented by changing the weights in a tapped delay line to represent its time-varying channel properties. These weight changes (channel updates) must be produced several times per channel coherence time. Rather than stepping a time-domain channel model in real time, we produce these update from pre-generated “fading tables” as described in [89]. There are therefore two computationally important tasks: Generating a channel update from given fading tables, and generating new fading tables. The first must happen very frequently ($O(1/T_c)$ for *every* channel) and must therefore be quite simple. The second is computationally much more expensive and must occur much less often; minimizing such computations is the subject of the rest of this section.

Fading tables are generated from frequency domain Doppler spectrum through IDFT computation. The Doppler spectrum of a realistic V2V channel is not static: when parameter value changes as vehicles move, the fading spectrum (and fading tables) needs to be re-computed to implement the changes. For example, in the geometry-based fading model [22], any change of status (parameters in 4.3) leads to a different spectrum. With high dynamics in V2V channels, constant re-calculation of spectrum and fading tables can exhaust the limited computational resources for real-time simulation.

To reduce run-time fading table calculation, we utilize the following observations:

1. If the same (or similar enough) sets of parameters occur regularly, fading tables can be cached for re-use (on-line solution).
2. If parameter values are available ahead of time, spectrum and fading tables can be gener-

ated beforehand (off-line solution).

Next, we describe our hybrid solution that combines both off-line preparation and run-time optimization. The following discussion are based on the fading model in §4.2.1.

4.7.2 Real-Time Constraint

The three primary timing constraints for real-time channel simulation and emulation are the sample time T_{samp} , the channel coherence time T_c , and the stationarity time T_{stat} : $T_{samp} \ll T_c \ll T_{stat}$. Typical values for these limits are shown in Table 4.5.

Time	Typical Value	Required Action
T_{samp}	5ns	Multiply samples by tap weights.
T_c	$\approx 50\mu\text{s}$	Update tap weights k times.
T_{stat}	$\approx 20\text{ms}$	Update channel model.

Table 4.5: Time constraints

T_{samp} is based on a 100MHz real baseband channel, sampled at the Nyquist rate. In our architecture, sample-rate processing is done on an FPGA [89]. Here we addresses only the software processing which is bound by T_c and T_{stat} . Updating tap weights in discrete steps means approximating the continuous smooth variation of the channel as a step function or linear interpolation. Numerical evaluation in [30] shows that a linear interpolation with time steps of $T_c/40$ is functionally indistinguishable from the smooth curve; we have used steps as slow as $T_c/4$ with no noticeable degradation.

Reasonable estimates of T_c range from a theoretical worst case of $23\mu\text{s}$ for vehicles at 300km/h and 5.9GHz to a least measured value of $260\mu\text{s}$ [82]. The term *stationarity time* and our estimated value come from [10]; their measured minimum value is 19.6ms, with 5% T_{stat} values ranging from 70ms to 924ms.

Producing tap weight updates from an *existing* fading table is a relatively light-weight operation. Our current, un-optimized implementation requires $\approx 3\mu\text{s}$ per tap on a single processor

core [89]. We would like to improve that in order to support larger networks with shorter coherence times, however that is orthogonal to the choice of channel model and will therefore not be considered further here. The geometrical V2V channel model we considered here differs from the ones considered in 3 in that it can produce a wide range of Doppler spectrum shapes, and no single fading table or small set of tables can represent all of them. It is therefore possible that a new fading table must be computed at run time. The remainder of this section addresses the computational cost of doing so.

4.7.3 Channel Model Update Cost

First, we consider the time required to update a single one-path channel. As mentioned in §4.7.1, the most time-consuming processes during channel updates are (a) generating the fading Doppler spectrum, and (b) performing an IDFT to obtain a fading table. Next, we analyze the computation complexity of (a) and (b), using the geometry-based fading model, followed by measurement results.

Frequency-Domain Spectrum Generation

In (a), the geometry-based fading model divides the whole space into N small cones (sections), where N is a design variable. For each cone, scatterer density is estimated, and corresponding Doppler spectrum component is calculated. The per-cone computation requires essentially constant time. Thus, the overall calculation complexity is $O(N)$. Note that the number of cones N is naturally related to the spatial resolution of the input data as small cones correspond to higher angular resolution.

IDFT

Frequency domain interpolation regulates the spectrum to include a fixed number of samples, equally spaced in the maximum Doppler shift range. In (b), a fixed-point IDFT translates the spectrum to a fading table. In this case, the time cost of IDFT is a fixed cost, and independent of N .

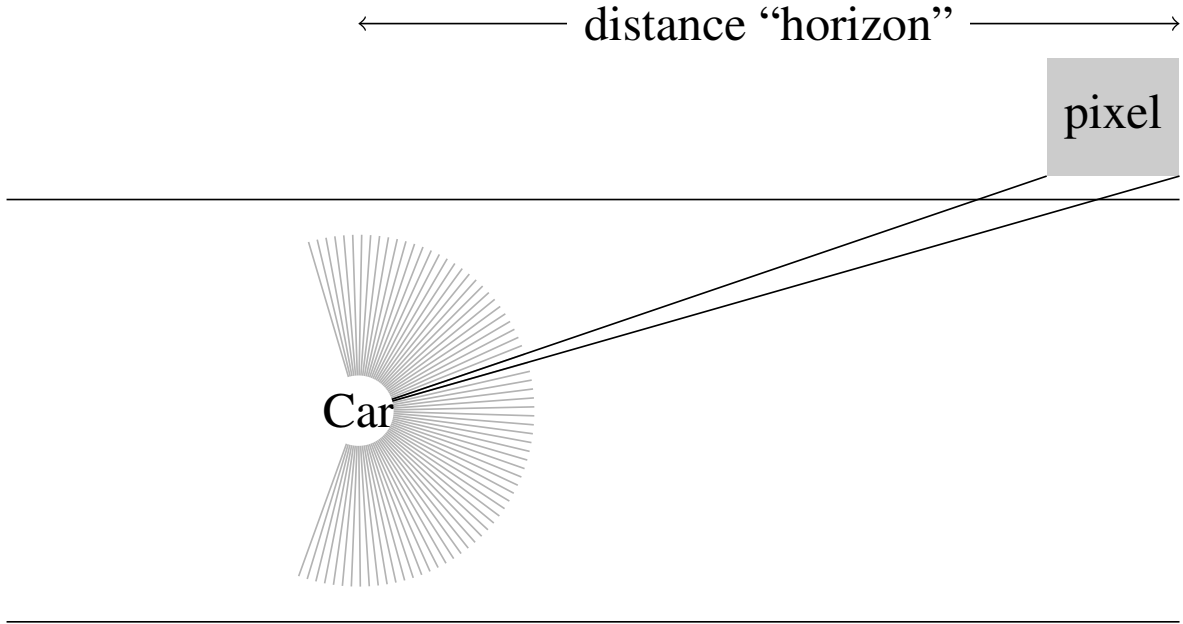


Figure 4.10: Finest reasonable angular resolution

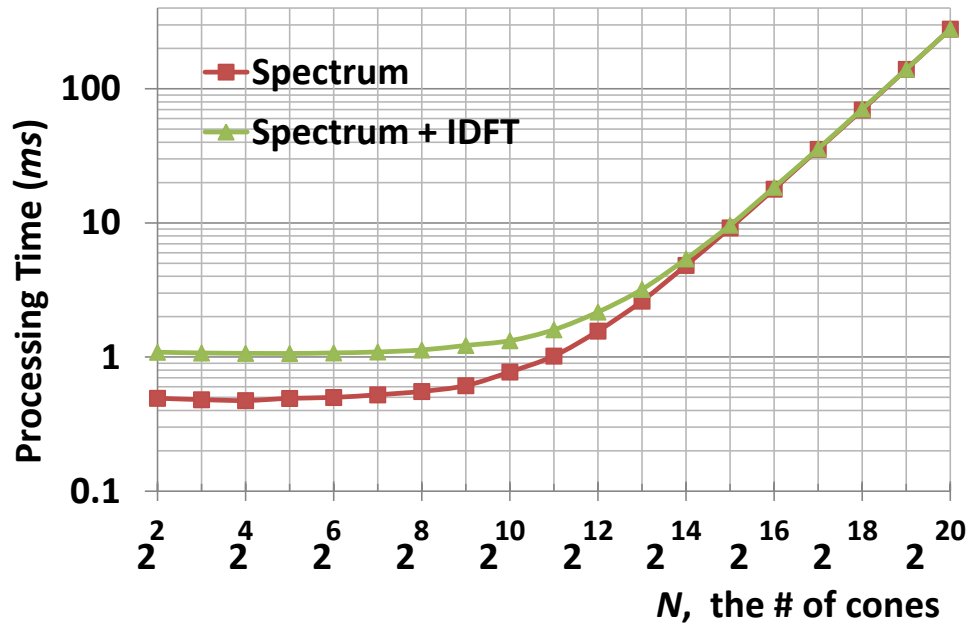


Figure 4.11: Time to generate an N -cone fading table.

We measured the time cost of step (a) and (a) + (b). The measurement was performed on a desktop computer, using one core of an Intel 3.80GHz Xeon processor. The time cost is averaged

over 1000 trials.

As shown in Figure 4.11, with a small number of cones ($N \leq 2^9$ or 512), the total time cost for spectrum calculation is relatively stable ($\approx 1\text{ms}$). In addition, the difference between two curves (with small N) confirms a stable time cost of IDFT operation (about 0.5ms). With large N , the overall cost trend is linear as dominated by $O(N)$.

For a single one-tap channel, the cost of computing a new fading table exceeds T_c , but is below the bound of T_{stat} . However, as network grows to n cars (or n antennas), the number of channels grows as $O(n^2)$. If a new fading table must be computed for every channel every T_{stat} , n is severely limited.

4.7.4 Re-usable Fading Table

Some simple Doppler spectra (*e.g.* Jakes') have the nice property that *all* spectra in the family can be generated from one another by scaling the amplitude and frequency [89]. This is unfortunately not true of the vehicular channel from §4.2.1. Table 4.6 classifies the fading model parameters by their effect on the Doppler spectrum and rate of change. Crucially, the parameters V_{Tx} and V_{Rx} are rapidly-varying and effect the shape of the Doppler spectrum.

Parameter	Variation	Scales Spectrum
v_{Tx}	slow - fast	×
v_{Rx}	slow - fast	×
ρ	static	×
v_{Tx}	slow - fast	✓
$\frac{v_{Rx}}{v_{Tx}}$	slow - fast	×
constant ρ	no change	✓
d_{s2e}, d_{lane}	slow	×
N_a, N_b	slow	×

Table 4.6: Scaling Factors in Parameters

The situation can be improved somewhat: The shape of the Doppler spectrum depends only on the *ratio* V_{Rx} and V_{Tx} , not on the *magnitude* of either velocity. Rewriting the Doppler spectrum model in terms of the ratio $\frac{v_{Rx}}{v_{Tx}}$ and one free magnitude (arbitrarily V_{Tx}) therefore eliminates one “shape-affecting” parameter.

In Table 4.6, parameters in the first group are original listed in [22]. The second group shows the situation after re-formulation. Parameters in the third group vary slowly over time and can be regarded as constant during a limited amount of time. As described in [89], a fading table can be re-used for different values of spectrum-scaling parameters so long as the shape-affecting ones remain the same.

4.7.5 Off-line Preparation

While re-usable tables help to improve run-time efficiency, calculation of new fading tables is unavoidable when shape-affecting parameters change. This may happen continuously when vehicles move.

The goal of off-line preparation is to avoid run-time calculation of new fading tables by pre-generation of various type of fading tables with given parameter values. We start with a fixed scatterer density of ρ , and handle spatial variation of ρ at the end of the section.

Although the exact value of a set of parameter are not available at any moment, one can estimate the range of each parameter in Table 4.6. For example, typical driving speed is between 20 mph to 30 mph in a suburban area. In most car-following scenario, speed ratio is often close to 1. The average distance of d_{e2s} is between 6 to 10m. Fading tables generated using these parameter values will be utilized with higher probability during run-time simulation.

Table 4.7 shows a set of typical values selected for typical suburban vehicular channels. The transmitter speed v_{Tx} and scatterer density ρ are applied at run-time to scale the spectrum (fading tables). The size of the parameter space is exponential in the number of parameters, but only $O(n^4)$ in the number of *discrete* values per parameter. It is therefore feasible to quantize these parameters and pre-compute Doppler spectra for all parameter combinations. For the discrete values in Table 4.7, there are 2,700 ($20 \times 5 \times 3 \times 9$) such combinations. The fading table representation of each Doppler spectrum requires $64kB$ memory, for a total of $172.8MB$. At run-

time, actual parameter values can be rounded to quantization points. As long as actual parameter values fall in the estimated range, no run-time fading table generation is required, at the cost of some quantization error.

Parameter	Min	Max	Values	# of Values
$\frac{v_{Rx}}{v_{Tx}}$	0.1	10	0, 0.1, ..., 0.9, 1, 2, ..., 10	20
d_{s2e} (m)	6	10	6, 7, 8, 9, 10	5
d_{lane} (m)	3	5	3,4,5	3
N_a, N_b (m)	0	2	0,1,2	$3 \times 3 = 9$

Table 4.7: Typical shape-affecting parameter values

Variable Scatterer Density: When ρ varies over space, similar approaches can be applied. The set of angular intervals $\{[\theta_i, \theta_i + d\theta) | i \in 1, \dots, N\}$ partitions space around the receiving vehicle into N cones. Crucially, the Doppler spectrum received over the entire set of cones is simply the sum of independently-computed responses for each cone [23, eqs. (7)–(11)]. We can therefore scale each cone’s spectrum by its ρ_i *before* summing the cones’ spectra. We fix $N = 2^9$ for our experiments, giving an angular resolution $d\theta = \frac{2\pi}{2^9}$. Increasing N improves spectrum accuracy up to the limit imposed by the spatial resolution of the input data, as described in § 4.7.3.

As discussed in [89], table-based off-line preparation is computationally efficient. Such preparation relies on prediction of vehicle behaviors and model/parameter. In simulation, some of these parameters are configured explicitly by users, while others are generated during simulation (*e.g.* from mobility model) and may not be available beforehand.

Therefore, a careful study of the simulated area and mobile behaviors is critical for real-time V2V channel simulation. During off-line preparation, we utilized aerial photos to examine scattering properties, and vehicle traces are studied to obtain speed and location information. For other environment/scenario, the same approach still applies in helping prediction of parameter ranges for off-line preparation.

4.8 Summary

Realistic simulation of high dynamic wireless channels requires not only realistic channel simulation models but accurate parameter values as well to approximate dynamics in surrounding environments with high realism.

In this chapter, we first introduced simulation channel model control for vehicular networks in §4.2. We narrowed down the discussion on the most challenge environments with high dynamics: the vehicle-to-vehicle fading channels and LOS components. We discussed parameters for simulation models in §4.3 and provide an example specifically for vehicular channels. Next, we described our novel scatterer estimation approach and V2V line-of-sight estimation process in §4.4 and §4.5. We introduced our practical and efficient way for extracting critical parameters from realistic environments.

§4.6 presents an evaluation of the accuracy of our channel modeling approach. We show that for a given channel model the use of area-average parameter values results in a significant loss of accuracy relative to point-by-point values. In addition, we show that by indirectly estimating those values from readily-available data, much of that accuracy can be regained.

Lastly, we presented the computational complexity of our models in §4.7.

4.8.1 Generalization of Approach

Our evaluation focuses on parameterizing the V2V fading model from [22], but the approach is meant to generalize to other channels and models which depend heavily on local features of the environment.

In any outdoor environment, the fading properties of wireless channels are strongly influenced by the stationary and mobile objects in the environment. When modeling such effects, accurate estimation of location, dimension, and density of such objects is needed to achieve high modeling accuracy. Geometric modeling of each object helps to provide an accurate description of each item. However, when modeling an environment with a huge number of objects, estimating densities is a more practical approach that suffices. Our approach of using imaging processing and additional road information would dramatically improve the accuracy and effi-

ciency in such estimation. Arial map and road information data could be used for rural and densely populated areas, while terrain data that includes elevation information would be needed for open areas with hills.

For indoor environments, the wireless channel dynamics is also affected by geometric distributions of objects in the surrounding area. Although arial maps are not applicable to indoor object identification, using corresponding information, in this case floor plans and room descriptions to infer furniture density and layout , would also help to improve estimation accuracy.

The generalization of our proposed solution is to utilize available information and perform efficient and systematic processing so that we can obtain higher level abstraction of detailed object density, location, and mobility information with high accuracy.

Chapter 5

Cross-Link (Spatial) Correlation Models

Wireless channels are defined by the presence and motion of objects between and around the communicating stations. As parts of the environment change, so do the channels experienced by nearby stations. The common models in current use often do not consider the spatial locality of most channel effects: Except for correlated fading in MIMO models for nearby antennas, it is typical to model channels or links with *mutually-independently* random processes.

In this chapter, we evaluate the effects of that assumption of independence in the context of vehicular multi-hop networks. We first look in depth at how to model spatial correlation for links for different types of channel properties and models, using vehicular channels as an example. Then we compare independent stochastic, locally cross-correlated stochastic, and explicitly geometric models in terms of the application-level performance they induce. Specifically, we present our evaluation of how the choice of model impacts the performance of a gossip protocol. In addition, we compare the complexity of the different modeling options. We show that while explicitly modeling correlation for stochastic channel properties can improve realism, the complexity increases quickly with modeling additional correlated properties.

5.1 Background

The properties of wireless links are highly dynamic because the signal propagation environment changes as a result of movement in the environment. The performance of many wireless network

protocols and applications is sensitive to changes in wireless channel (*e.g.*, signal strength) and consequently link (*e.g.*, packet delivery rates, bandwidth) properties. Examples are transmit rate adaptation, TCP window size, and video bit rate adaptation. In a mobile environment with multiple wireless links, the changes of nearby links are not independent for the simple reason that the links share the same physical environment. Movement by objects, for example, is likely to impact all nearby links, although the precise nature of the impact will differ. We will refer to this phenomenon as spatial correlation across wireless links.

Some protocols and applications are not only sensitive to changes in the properties of individual links, but also to how these changes are correlated across multiple links. Examples include routing protocols that adapt to quality of the links in multi-hop wireless network [27, 40] or protocols that rely on opportunistic overhearing of packets [50]. In order to evaluate these protocols, simulators not only need to accurately model the channel or link dynamics of individual links, but they also need to properly model the correlation of these properties across nearby links. When such correlation is not accounted for (as is typically the case), the diversity of adjacent links is often over-estimated, which can easily lead to incorrect results, *i.e.*, the benefits or drawbacks of specific techniques observed in simulation may differ significantly from those obtained in the real world.

Models for the properties of individual channels can be broadly classified in two categories. A first approach is to model relevant components of the physical space explicitly, and to directly derive the corresponding link properties. Examples include the ITS Irregular Terrain Model point-to-point mode for path loss [38] or computational electrodynamics for small-scale fading. The drawback of this approach is that the model inputs (and possibly the model itself) describe only a specific environment and that collecting the input for the model can be time consuming. As a result, people have develop stochastic models that directly generate the desired channel property, *e.g.* log-normal shadowing, Rayleigh, Rician and Nakagami fading. [56, 75]. Such models can often be used to represent many very different environments with a simple parameter change (*e.g.* a different K factor or maximum Doppler shift), or multiple instances of a similar environment with a change of random seed. However, precisely *because* they don't require a comprehensive description of the environment, the similarity (or dissimilarity) between channels

in the same environment tends not to be captured.

On the other hand, the spatial correlation of wireless properties among adjacent links have been frequently observed in wireless networks. Some measurement study specifically quantified the level of correlation versus distance in urban and suburban area [60], while others studies the correlated shadowing effects in multi-hop networks [4] and vehicular network [16]. Studies have shown the correlation in shadowing effects has significant impact on wireless protocol performance [81], specifically in vehicular networks [14]. Moreover, such correlation can even be utilized in discovery [49] and geographic gapping [67].

Although different types of stochastic correlated models [60] [37] have been proposed for wireless channels, these models are not present in most wireless simulation platforms such as [57] and [70]. When evaluating adaptive protocols (such as PRO[50]) that are sensitive to spatial correlation, the spatial diversity, which is essentially the opposite side of correlation, could be mis-represented.

5.2 Channel Dynamics and Network Adaptation

Channel dynamics on multiple time scales can result in radically different channels that may require adaptation by the protocols at all layers of the protocol stack. Examples include changes in coding and modulation at the physical layer; different routing, coding, and retransmission strategies at the MAC and network layer; different congestion control solutions at the transport layer; and application level strategies to optimize quality of experience given available bandwidth at the application layer. These protocols adapt to their environment to optimize performance, and increasingly the adaptation is ‘cognitive’ in the sense that the protocols collect information about the environment and make explicit decisions about how to best adapt, as discussed in Section § 1.1.

In wireless networks, most adaptive behavior targets the optimization of individual links, e.g., transmit rate adaptation. To properly evaluate such optimizations, it is sufficient that accurate channel models are used and that their inputs are set and changed in a way that reflects the target physical environment. However, for the evaluation of protocols that deal specifically with

topology (e.g., routing) or that try to leverage spatial diversity or correlation, simulators will have to accurately model the spatial properties affecting the protocols. We consider specific examples in the context of vehicular networks.

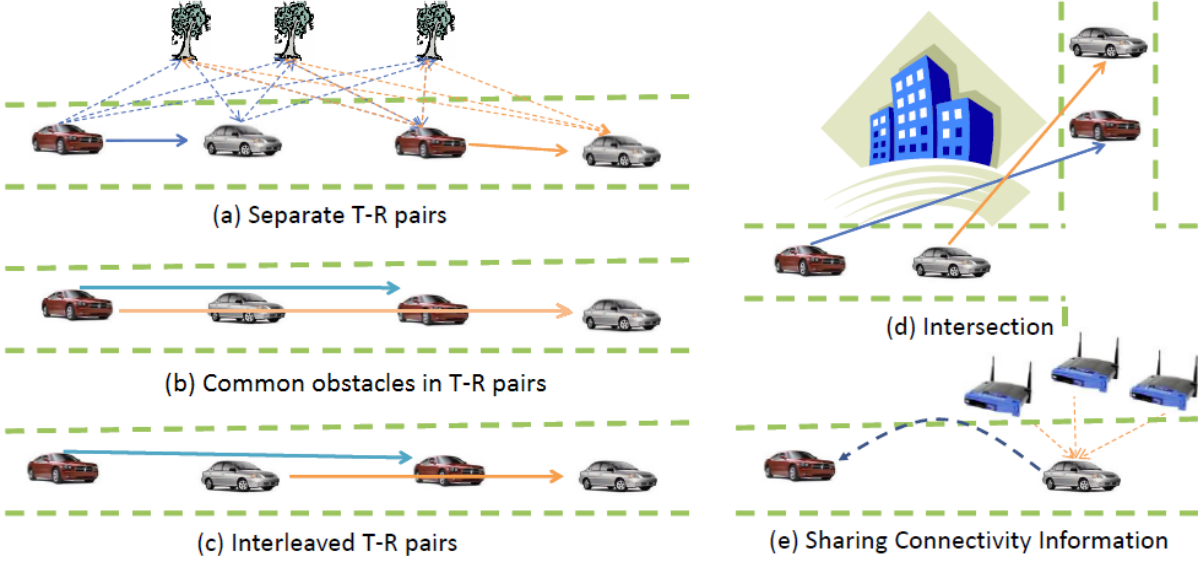


Figure 5.1: Examples of Spatial Correlation across Links

Challenges in Simulation Realism of Vehicular Networks

Vehicular networks are challenging because of the high degree of mobility and rich channel dynamics. We now look at some examples of spatial correlation between vehicular channels, considering fading, path loss, and line-of-sight (LOS) channel properties.

Figure 5.1(a) shows two wireless channels in close proximity on a road segment. Since the two channels are in the same environment, their properties are affected by similar reflectors and mobility effects, resulting in similar fading properties. Figures 5.1(b) and (c) are cases with channels partially overlapping. We again expect fading properties to be similar, but LOS properties are much more tightly coupled. Figure 5.1(d) shows an example of an intersection, where nearby channels may have similar LOS properties due to blockage by buildings.

It can be difficult to predict how specific types of spatial correlation affect various adaptive protocols, and it becomes more difficult as the protocol becomes more sophisticated and more links are involved. As a very simple example, let us consider PRO, a Protocol for Retransmitting

Opportunistically [50]. In PRO, if a transmission from a transmitter A to a receiver B fails, a relay node R can retransmit the packet on behalf of A, if it overheard the packet and has a better channel to B than A. This has been shown to offer the biggest benefit in environments with significant fading or shadowing, which is not surprising since PRO leverages spatial diversity between channels A-R and A-B.

Let us now consider how PRO may perform in some of the examples shown in Figure 5.1. Even if the three channels between A, B, and a potential relay R have LOS, we would expect PRO to benefits because of the high degree of fading. If relays experience LOS obstruction independent of (or negatively correlated with) the A-B link, the relative benefit of PRO should increase. However, if the same buildings (Figure 5.1(d)) or cars (Figure 5.1(b)) block both the A-B link and A-R links, the relays will be of little use and the benefit of PRO will be less.

5.3 Modeling Channel Dynamics

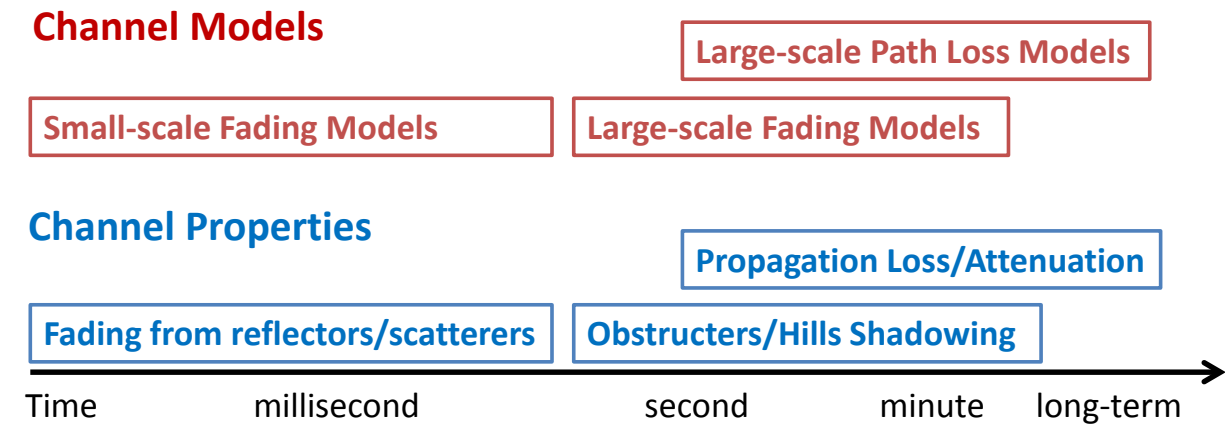


Figure 5.2: Channel Properties/Models at different time scales

This section presents an overview of the different types of models that can be used to model various channel properties. We also introduce an example stochastic channel model for LOS blocking.

5.3.1 Types of Channel Models

Both the instantaneous channel properties and the dynamics depend are determined by the presence and movement of the many objects in a typical environment, and it is generally not practically to exactly compute the instantaneous channel response, let alone its evolution over time. A common approach is therefore to maintain a simplified view of the objects in an environment, and then to introduce stochastic models for the effects which cannot be realistically computed from that view.

Channel model typically consists of multiple components that model different channel properties, often happening on different time scales. Figure 5.2 shows an example: properties include large-scale path-loss, shadowing due to objects in the line-of-sight, and small scale fading. These models can be classified according to a couple of properties.

First, the **model** can be completely generic, or be designed for a specific environment. Second, the inputs can be environment-specific or output-matched . Environment-specific inputs are based on observations or measurements of a specific (real or artificially generated) environment (e.g., density, location, and speed of objects). In contrast, output-matched parameters do not necessarily reflect a specific properties of an environment, but they are chosen so the model output will have the desired properties, i.e., it roughly matches channel measurements.

The third model property relates directly to how dynamics are models and it falls between two extremes. First, in a purely **deterministic** model (e.g. typical for path loss) the dynamics of the output (e.g. loss) follow directly from variation in the input (e.g. distance between transmitter and receiver), or else they are not captured at all.

In this case, obtaining realistic channel dynamics requires varying the input parameters, which typically implies having detailed environment-specific inputs. At the other end, dynamics can be entirely internal to the model (e.g. typical fading models): The model is a random process with prescribed temporal behavior (e.g. autocorrelation). The underlying physical events (the positions of the objects whose motion is causing the fading) are not represented, so spatial correlation will typically not be captured. Between the two extremes, a stochastic model may have some environment-specific inputs, and if those change together across “independent” channels, there may be some covariance.

These properties define a large design space. Models for properties that are coarse and change slowly, e.g., path loss, tend to use deterministic models with mostly environment-specific inputs. We will refer to these models as **geometric** models. Models for more fine-grain properties that can change quickly, e.g., fading, or are hard to model, e.g., large numbers of small objects, tend to use models that are inherently **stochastic**. Some properties can however modeled either way. Examples include LOS blocking (shadowing), random packet loss, etc.

As a concrete example, [43] describes a set of models for properties of vehicular channels. It uses a geometric model for path-loss, and stochastic models for LOS blocking and scattering by small objects. The model for fading caused by large objects is an environment-specific stochastic model with environment-specific inputs.

The focus of this section is on modeling link correlation for both geometric and stochastic channel properties. To make the discussion more specific, we will use models for LOS blocking as an example.

5.3.2 Modeling Shadowing and Line of Sight

Shadowing is reduction in signal strength caused by obstructions which absorb incident energy or reflect it away from the shadowed area. Shadowing occurs when obstructing objects – stationary or mobile – impinge significantly on the Fresnel zone around the dominant propagation path. Treating shadowing as a binary condition (Line-Of-Sight vs. Non-Line-Of-Sight) is a substantial simplification, but it’s probably not unreasonable at higher frequencies [53]. The LOS/NLOS status of a path can be estimated geometrically [15] or with measurement-driven stochastic models [2].

Here, we briefly introduce a typical stochastic shadowing model (2-state Markov shadowing model) based on [2], and shown in Figure 5.3. Two shadowing link states (*LOS* and *NLOS*) are considered in the model. The transition probabilities are p_1 and p_2 . At initialization, each link randomly selects a starting state. For each state, the probability distribution over possible subsequent states is realized as a discrete random variable. Because each state in this model has only two possible next states, the discrete “next state” distributions are implemented as random variables r with a continuous distribution and a cutoff threshold. For example, if

$current_state = LOS$, $next_state$ is $NLOS$ iff $r_i \leq p_1$.

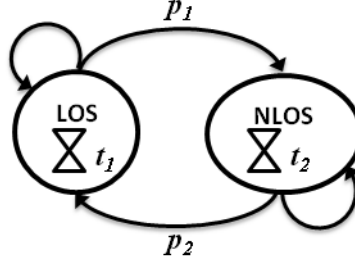


Figure 5.3: Two-state Markov Shadowing Model

5.4 Correlated Channel Models

In this section, we look at spatial correlation for channels that are modeled geometrically and stochastically. We will use the LOS property as a running example.

5.4.1 Geometric Models

For geometric models, the calculated channel properties are completely determined by input (environment details). Assuming consistent information about the environment is used to model all links in the simulation, spatial correlation between links will automatically be captured. In the LOS case, if the same information about the location and size of physical objects (cars, buildings) is used consistently throughout the simulation, all the different examples of spatial correlation shown in Figure 5.1 will be captured.

To validate this claim, we looked at the spatial correlation observed in a simulation using the geometric LOS model described in § 5.5.3. Figure 5.4 shows the *observed* agreement between links' LOS states as a function of the distance between them. These are calculated over 20 second intervals so that the two pairs of cars positions relative to each other do not change too much within a single data point. Short time spans mean that relatively few transitions occur on each link per interval, so the observed variance is relatively inaccurate. Consequently we use simple agreement (what fraction of the time both links have the same LOS status) rather than correlation as a similarity metric. Linear fits are plotted for three distance ranges: 0 to 50m, 0 to

100m, and 0 to 500m For the first two, there is a statistically-significant relationship ($p < 0.001$) with slopes of -0.004 ; $-0.0001/\text{m}$ respectively.

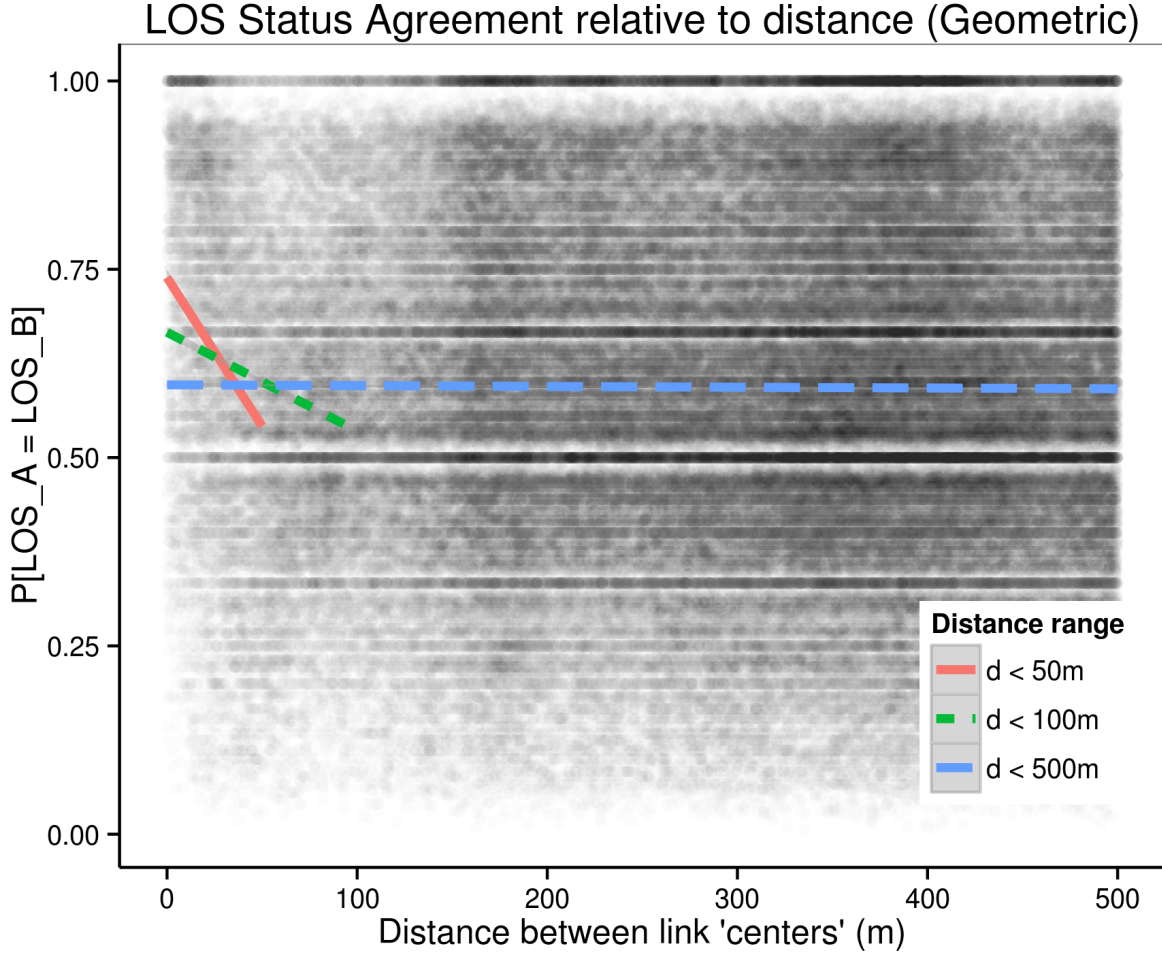


Figure 5.4: Probability of LOS state agreement as a function of distance, geometric model.

5.4.2 Statistical Models

For statistical models, there is no explicit information on correlated physical world impacts. In addition, the independent random process associated with each link introduces additional isolation among multiple channels. In order to have realistic inter-channel correlation, it must be modeled explicitly. This implies (a) determining the expected correlation properties among channels, and (b) applying this correlation to (time-series) models while maintaining their statistical

properties. The approach which we explore here is to enforce correlation across the random variables which are implicit *inputs* to stochastic models. The most straightforward stochastic models consist of a random variable which is filtered to produce the desired output distribution and autocorrelation; many fading model implementations work this way. In that case, the desired correlation of model *outputs* can be directly achieved by correlating the input random variables, possibly with some adjustment for the filtering. In this work, we do something similar, but with a discrete model that has a more complicated structure.

5.4.3 Example: Correlated Stochastic Shadowing Model

In the Markov two-state LOS/NLOS model described in § 5.3.2, each link is modeled independently with individual streams of random variables as input. The correlation among multiple links is missing in this modeling process. In this model, input random variables r determine the next transition out of each state. When modeled independently, the streams of random variables applied for each link are i.i.d.. To compensate for the correlation among physical events (LOS blockage and clearance) while maintaining the overall statistical property of each individual link, we introduce correlation among the streams of random variables of links that are close by, to simulate the correlation of physical events in the real world. To find the necessary *input* correlation among the random variables to produce a desired *output* correlation in the state, we solve for the stationary distribution of the Markov chain given p_1 and p_2 and numerically compute the input-output relation.

Suppose we have a network of n connected links that are simulated independently with random variable streams r_l $l \in [1, n)$, where each l represents one link. The desired correlation between input random streams of link l_1 and link l_2 is denoted as $\rho(l_1, l_2)$. The pair-wise correlation among n links can be presented in an n by n correlation matrix C :

$$\begin{pmatrix} c_{1,1} = 1 & \dots & c_{1,i} & \dots & c_{1,n} \\ & & \dots & & \\ c_{i,1} & \dots & c_{i,i} = 1 & \dots & c_{i,n} \\ & & \dots & & \\ c_{n,1} & \dots & c_{n,i} & \dots & c_{n,n} = 1 \end{pmatrix}$$

where

$$c_{i,j} = \rho(l_i, l_j) = \text{Corr}(\text{link}_i, \text{link}_j) \quad (5.1)$$

is the correlation coefficient between link l_i and link l_j .

Given i.i.d. random variables for all links $R = [r(l)]$, the original correlation among inputs is $RR^T = I$. The task is to find $R_{\text{corr}} = [r_{\text{corr}}(l)]$ such that

$$R_{\text{corr}} R_{\text{corr}}^T = C \quad (5.2)$$

As elements of matrix C are chosen individually, and there is no guarantee that C is a valid correlation matrix (C is symmetric, but not always positive-definite). A simple way to deal with this is to find the nearest correlation matrix C_{near} [36, 73] for C . Then, a corresponding R_{corr} can be found by computing an X through spectral decomposition of C_{near} such that

$$X^T X = C_{\text{near}} \quad (5.3)$$

The correlated input R_{corr} can then be derived by:

$$R_{\text{corr}} = RX \quad (5.4)$$

Each stream in $R_{\text{corr}} = [r_{\text{corr}}(l)]$ is now a linear combination of original n i.i.d. random inputs, and still preserves original statistics.

5.4.4 Determine Level of Correlation

The correlation coefficient $\rho(l_i, l_j)$ reflects the *desired* level of correlation in some property between the two links. In general, finding this is a significant modeling problem in its own right: It will depend on the property in question and may be very environment-specific. We do not attempt to solve this problem – neither in general nor for the LOS status model specifically – rather we are studying the options for *implementing* such correlation once the desired level is known. For this work, we use a very simple model, where $\rho(l_i, l_j)$ is a piecewise linear function of distance (measured from the “center point” of each link), ranging from $\rho = 0.9$ at 0m to 0.01 at 1500m. Distance-based correlation models (either auto- or cross-) have been successfully developed for small-scale fading [37], path loss [67], shadowing from stationary objects [60], and more.

When modeling wireless networks with high dynamics, the correlation property among adjacent links may change over time. For example, mobility of transceiver will change the distance between links. In this case, the correlation matrix needs to be updated to reflect the dynamics.

5.5 NS-3 Simulation Models

A prototype of the proposed stochastic shadowing model with correlation was implemented in ns-3. We utilize this simulation model to evaluate how the realism of shadowing simulation model impacts the performance of network protocols. Our simulation focuses on the performance of a gossiping protocol executing in a wireless vehicle-to-vehicle network deployed in a urban area. The simulation design utilizes realistic vehicle mobility and road topologies. The simulation results show significant differences in the performance of the gossiping protocol when different types of models are used for shadowing.

5.5.1 Gossiping Protocol

We envision an application similar to DSRC Basic Safety Messages, but in which some high-priority messages are rebroadcast to achieve wider geographic distribution and/or greater confidence that all nearby nodes will be informed. The protocol is as follows: Each vehicle broadcasts status packets with a fixed interval of 100ms. When a node wishes to retransmit a message it has overheard, that data is included in its next periodic packet. We implement a simple gossiping scheme: When a vehicle receives a new message in an incoming packet, it selectively rebroadcasts the new message with a certain probability (to avoid message flooding). Gradually, each message will spread throughout the network and, assuming a sufficiently dense vehicular network, it will eventually reach all vehicles in the area. (Any real protocol along these lines would need to bound messages' scopes, but we do not consider this.)

The primary performance metric for the gossip protocol is the delivery time of messages in the vehicular network, *i.e.*, how long it takes for vehicles to receive a new message. The delivery time is mostly determined by the topology of a vehicular network as well as the quality of the wireless links, which is influenced strongly by the surrounding physical environment. Our

interest is not in the actual performance of this (admittedly very simple) gossiping protocol. Rather, we are interested in understanding the relative difference in performance of the gossiping protocol, when different patterns or models of spatial correlation across links are used.

5.5.2 Simulation Setup

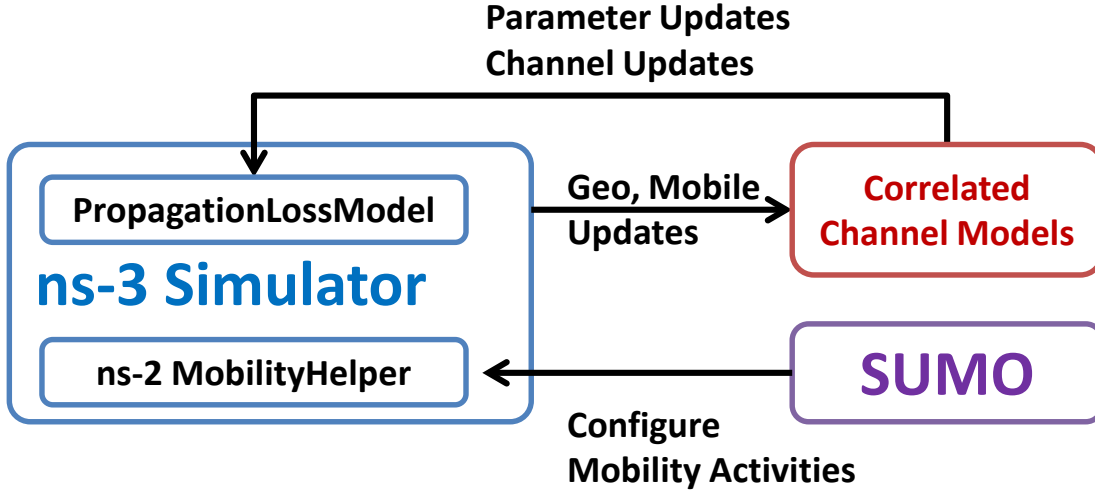


Figure 5.5: Simulation Platform Overview

To best approximate the described scenario above, we combined multiple simulation tools and platforms to generate realistic vehicle mobility scenarios as well as channel propagation properties. A road network map was generated for a roughly 1.5 km x 1.5 km semi-residential region of a major U.S. city. Vehicles move along roads following the true map, however the specific traffic load and vehicle routes are synthetically generated using MOVE [46] and SUMO [8]. Wireless channels and networking were simulated in ns-3 [57], which was extended with the shadowing channel models described in § 5.5.3. The channel, PHY and MAC layer were implemented as a `YansWifiChannel` model with log-distance large scale path loss (exponent = 3.0) and Rayleigh¹ fading, in addition to our shadowing models.

¹Note that ns-3 does not support Rician or more vehicular-specific fading models, unless one wishes to do symbol-by-symbol simulation with `PhySim-WiFi`.

5.5.3 Shadowing Models

We implemented both geometric shadowing models and stochastic shadowing models to be employed and compared in simulation. The output of a shadowing model is an additional attenuation that is added to the path loss. The loss is set to be 8dB for an NLOS (shadowed) link and 0dB for an LOS (un-shadowed) link. We use the following three shadowing models, and a baseline “No obstructions” case without shadowing.

Geometric

A simple geometric shadowing model is implemented with following features: Vehicles which are on the same road have an NLOS state if and only if another vehicle is on the same road between them.² Vehicles on different road segments but within 50m of each other (that is, roughly, vehicles within the same intersection for the road sizes in this neighborhood) have an unobstructed LOS. Vehicles on different road segments between 50m and 175m (that is, on intersecting roads) have NLOS. (NLOS propagation conditions near intersections are investigated in *e.g.* [65].) Vehicles on different road segments further than 175m apart are unable to communicate at all.

Stochastic (Independent)

In the stochastic model, links are modeled independently, so the shadowing properties of links are independent. The Markov two-state shadowing model described in § 5.3.2 is implemented, and each link is associated with one instance of this model. The transition probability parameters are fitted to match the behavior of the geometric model as closely as possible; this is described in more detail in § 5.5.4.

Stochastic (Correlated)

The stochastic LOS model is modified to enforce pairwise correlation as described in §5.4.3. The level of correlation between two links is determined using distance metrics. A basic piecewise

²This model does not consider which lane any given vehicle is in; it may therefore have false positives when the “intervening” vehicle is not actually physically between the communicating pair.

function is implemented in simulation:

$$\rho(d) = \begin{cases} 0 & d \geq d_{max} \\ \rho_1 \frac{d_{max}-d}{d_{max}-d_1} & d_1 \leq d < d_{max} \\ \rho_1 + (\rho_{max} - \rho_1) \frac{d_1-d}{d_1-d_0} & d_0 \leq d < d_1 \\ \rho_{max} & 0 \leq d < d_{min} \end{cases}$$

The exact parameter values are configured for desired simulated scenarios. An example set of values for suburban area is: $d_{min} = 10\text{m}$, $d_1 = 500\text{m}$, $d_{max} = 1500\text{m}$, $\rho_1 = 0.3$ and $\rho_{max} = 0.9$. The d_{max} reflects that links are independent when more than 1500m (≈ 1 mile) apart from each other. The d_1 reflects the length of one road segment, on the theory that links on the same road have higher similarity than those that are not.

5.5.4 Accuracy of Stochastic LOS Model

The uncorrelated stochastic line-of-sight model introduced in § 5.4.3 has two free parameters: p_1 and p_2 . They determine the expected duration of LOS and NLOS periods respectively:

$$E[T_{LOS}] = \frac{1-p_1}{p_1} \quad E[T_{NLOS}] = \frac{1-p_2}{p_2} \quad (5.5)$$

By extension $\frac{T_{LOS}}{T_{NLOS}}$ is the probability that any given link will be in an LOS state at any given time, which directly affects the link PDR (packet delivery ratio). The stochastic model parameters, p_1 and p_2 , could be determined independently from measured $E[T_{LOS}]$ and $E[T_{NLOS}]$ (as in [2, 90]). However, we hope to isolate the effect of spatial variation and correlation: That is, to the extent possible *average link performance is held constant across models*, leaving the spatial and temporal differences as determinants of application-layer performance. Therefore, we use an alternative approach to configure p_1 and p_2 . Since $\frac{p_1}{p_2}$ (equivalent to $\frac{T_{LOS}}{T_{NLOS}}$) largely determines link PDR, we select the $\frac{p_1}{p_2}$ ratio that produces a PDR which matches the actual link PDR property observed from geometric model from § 5.5.3.³ Next, the exact p_1 is calculated from $E[T_{LOS}]$ and p_2 value is determined afterwards.

³Note in Table 5.1 that the PDRs are not perfectly matched; a subset of the full experiment was used for fitting. This difference should bias the results toward the stochastic model producing *worse* overall performance. The actual results are the opposite, so we think it safe to conclude that the results are not an artifact of this bias.

Figure 5.6 shows the distributions of the duration of LOS and NLOS states for links across all models considered. The mean duration for each state is close across models (see Table 5.1). Note that this does not automatically follow from tuning the models to produce the same expected PDR; it is reassuring to see that fixing the models to produce the same output by one measure does in fact lead to them being similar by other measures. The distributions are not identical. Note also that the distributions for the independent and correlated variants of the stochastic model are almost identical: This confirms that the *average* link behavior is the same, only the inter-link correlation differs.

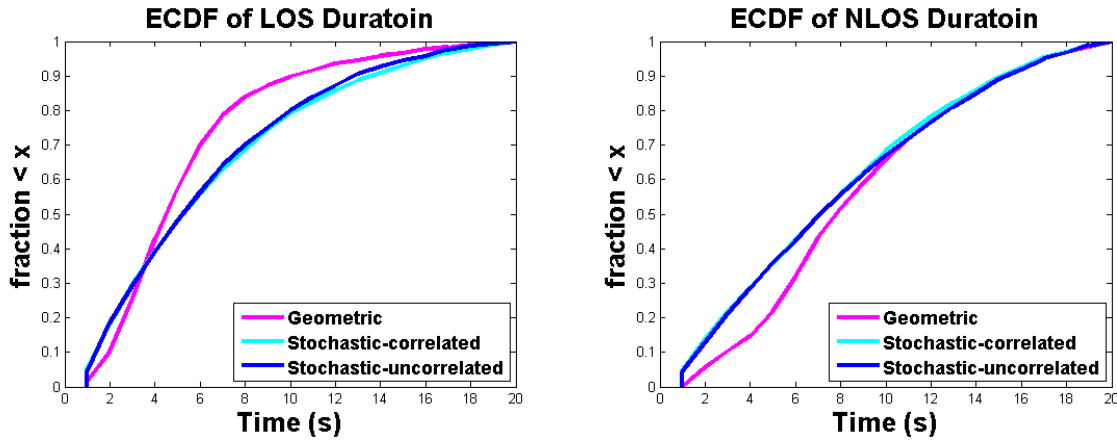


Figure 5.6: ECDF of LOS and NLOS durations.

	Geometric	Stochastic
Packet delivery ratio	0.28	0.23
LOS probability	0.89	0.73
E[LOS duration] (s)	5.87	6.75
E[NLOS duration] (s)	9.09	8.35

Table 5.1: Link-level Comparison of Shadowing Models.

5.5.5 Simulated Scenario

The simulated vehicular network has 300 vehicles, scattered across a 1 mile x 1 mile suburban area. The road network in this area consists of 5 east-west roads and 5 south-north roads. There are on average 5 cars on each road segment (between two intersections). One new emergency message is generated at time 0.01s at one single vehicle in the center. Each simulation runs for 20 seconds, during which time the new message was always distributed to all vehicles that are reachable in the network.

We do not have access to measured data sets that can be used as a ground truth for shadowing in urban areas. We expect that geometric models will generally give the most realistic results since they use the most detailed representation of the physical world, so our discussion will compare the results for other models with those for the geometric model. Geometric propagation models (*e.g.* the ITM point-to-point mode for natural terrain) are widely employed in software tools like [26, 51, 78].

5.6 Simulation Results

The simulation results address two basic questions:

1. *Do spatial patterns in link quality matter to application performance?*
2. *How well does a stochastic model with explicit spatial correlation approximate the effects of “real” spatial patterns?*

The next section (§ 5.7) considers the computational cost of such models.

We define application-layer performance as the time required for each participating node to receive the gossiped message. This section looks at both overall performance (the distribution of delivery time over all nodes) and delivery time relative to distance.

5.6.1 Overall Message Delivery Time

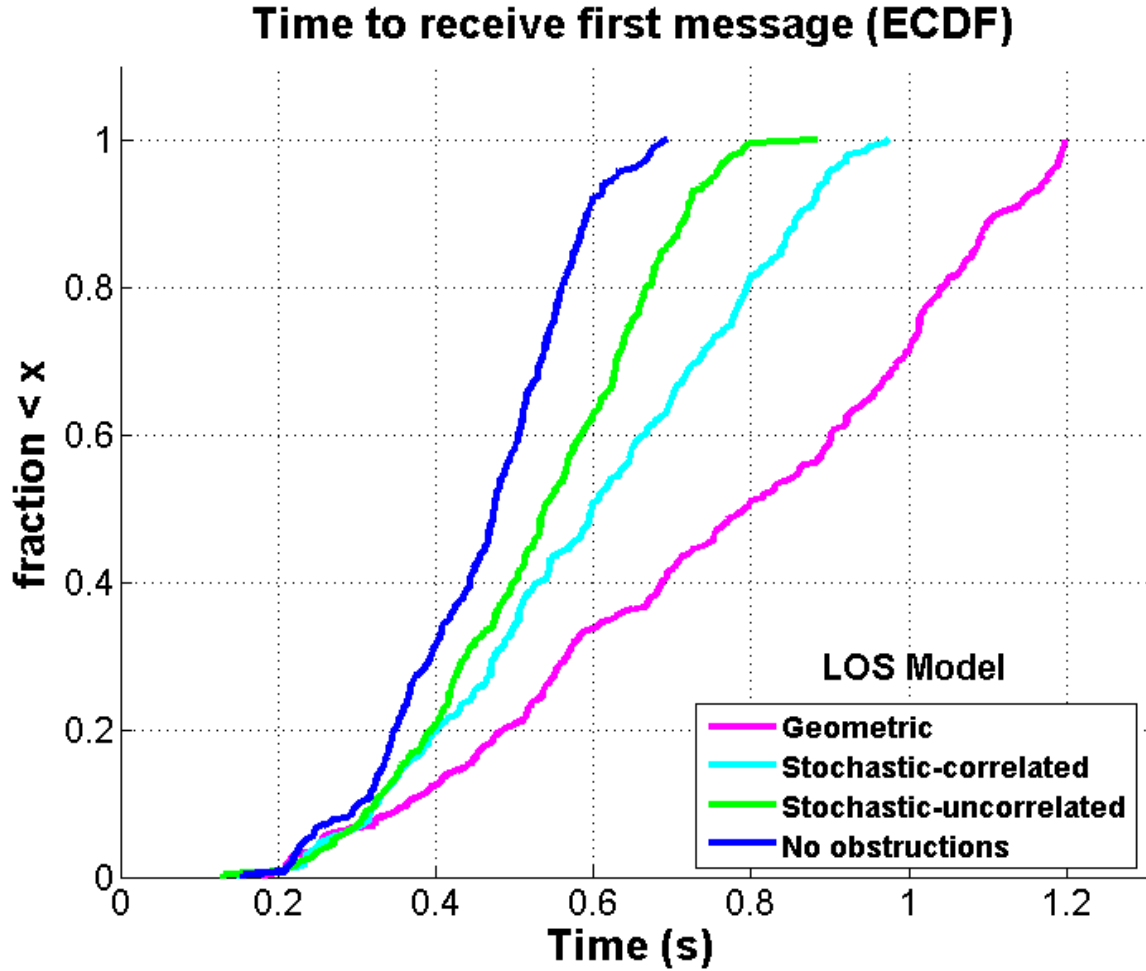


Figure 5.7: End-To-End Delay

Figure 5.7 shows the cumulative distribution function of the delivery times over all nodes in the simulation. In addition to the three shadowing models already discussed, a baseline *no obstructions* case is included for reference. This shows the performance without any shadowing effects.

We observe a substantial effect from spatial and temporal variation: The median packet delivery time is 0.52s for the independent model 0.82s for the geometric case; the Kolmogorov-Smirnoff (K-S) distance between the two distributions is 0.6. Recall that the probability of success for an arbitrary link at an arbitrary moment is **identical** across the geometric and both

stochastic models. The Markov model has similar (but not identical) time-series behavior to the geometric case (see § 5.5.4), suggesting spatial patterns as the primary difference.

We additionally note a significant difference between the correlated and independent stochastic model outputs: The K-S distance is 0.37. In this case, the degree of cross-correlation is the only difference between the models. The cross-correlated model is closer to the geometric model (in both median and variance) than the independent model is, but there is still a significant difference (K-S distance of 0.36).

5.6.2 Delivery Time Relative to Distance

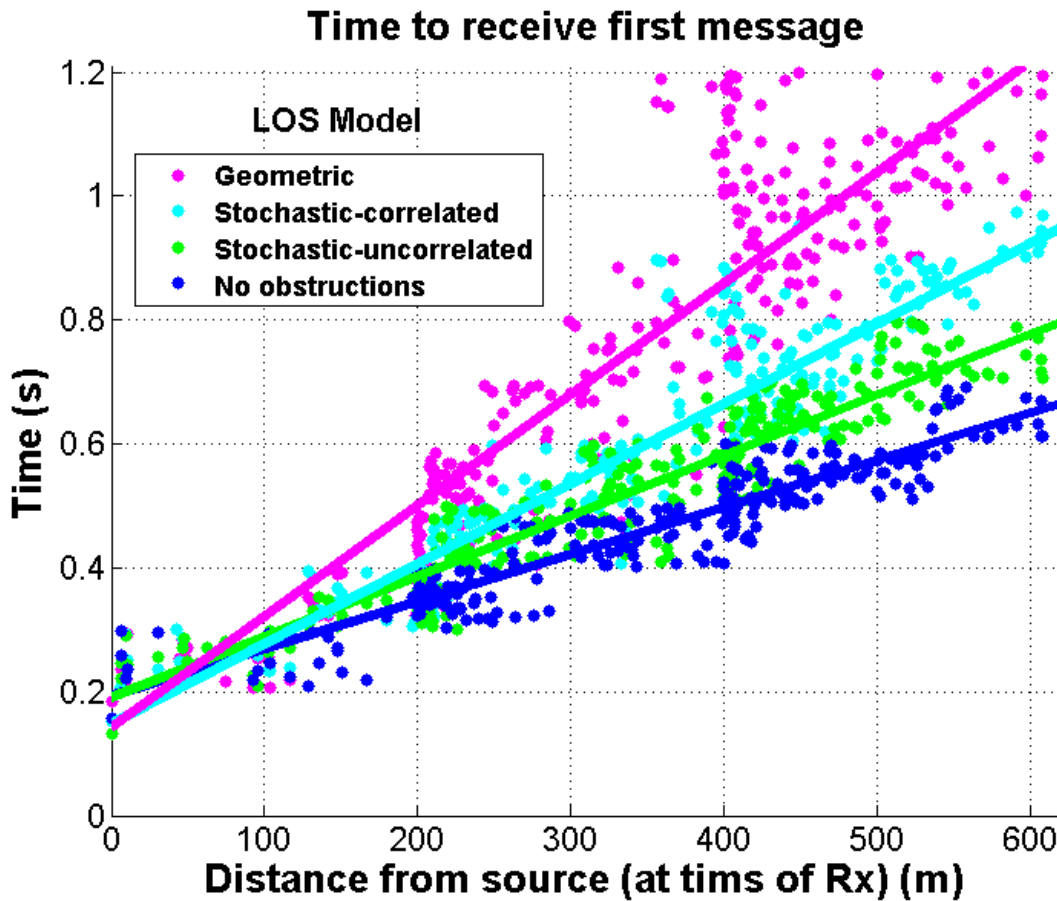


Figure 5.8: Message Delivery Time

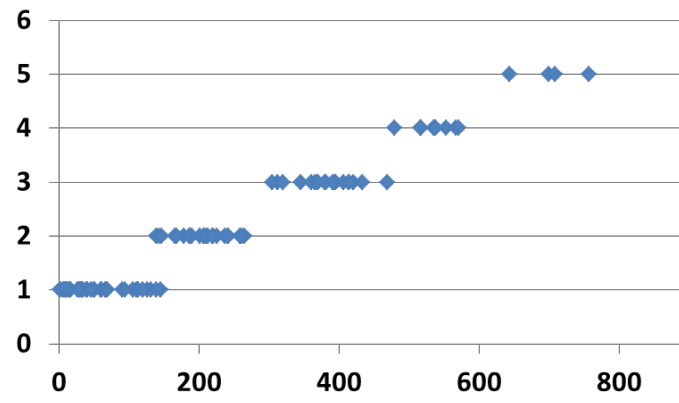
Figure 5.8 is a scatter plot of message delivery times (y-axis) as a function of the distance between the receiver and the vehicle that originated the message.

If we draw a line to approximate linear regression of the delivery time vs. distance, the slope is proportional to the number of hops for a given distance. Geometric models impose constraints on connectivity as a result of LOS blocking due to buildings and vehicles, and as a result, more hops are required on average compared to the empty world model that ignores shadowing. Using stochastic shadowing model improves the level of realism somewhat relative to the empty world model, while adding spatial correlation brings the results even closer to those obtained with the geometric model.

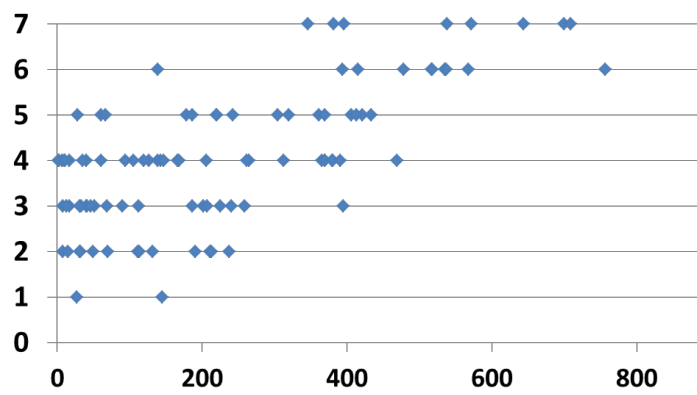
Regarding the horizontal distribution of delay for a given distance, the results based on the geometric shadowing model have the widest range. The reason is that the geometric model captures spatial diversity in the most detail, e.g., consistently distinguishing between node pairs on the same road segment, near an intersection, or on parallel road. The diverse for a distance indicates the spatial variation of link property (at the same distance). Since both the empty world and stochastically uncorrelated models are spatially independent (or homogeneous in all directions) by nature, the horizontal diverse range is minimum compared to other models. The stochastically correlated model falls in between.

Hop Counts

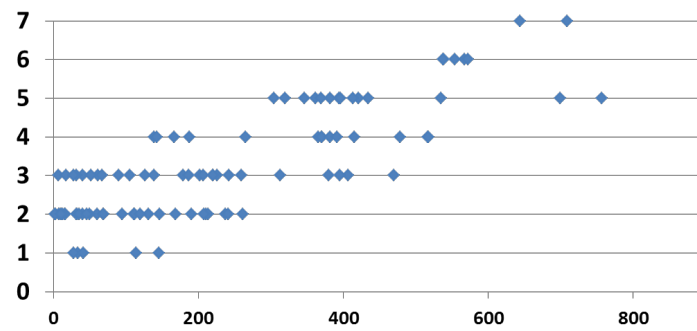
To examine the actual delivery time over the space, we calculate how many hops are required for new messages to be delivered to each vehicle. The results are visualized in Figure 5.10 and Figure 5.9. Naturally, hop count increases steadily in all directions, as distance increases from the center of the area. However, when using the Geometric Model, the rate at which hop count increases depends on the direction across directions. Packets travel faster in the horizontal and vertical directions, following roads, but they take longer to reach corners. Such effect is also observed in correlated-stochastic models, but not in the bottom two models (Stochastic and Empty world). The reason that adding correlation in the stochastic model helps to preserve local consistency across links, which helps to reflect dependency among adjacent links, but this effect is missing from the Stochastic and Empty world models.



(a) No Obstructions



(b) Geometric



(c) Correlated Stochastic

Figure 5.9: Hop Counts v.s. Distance

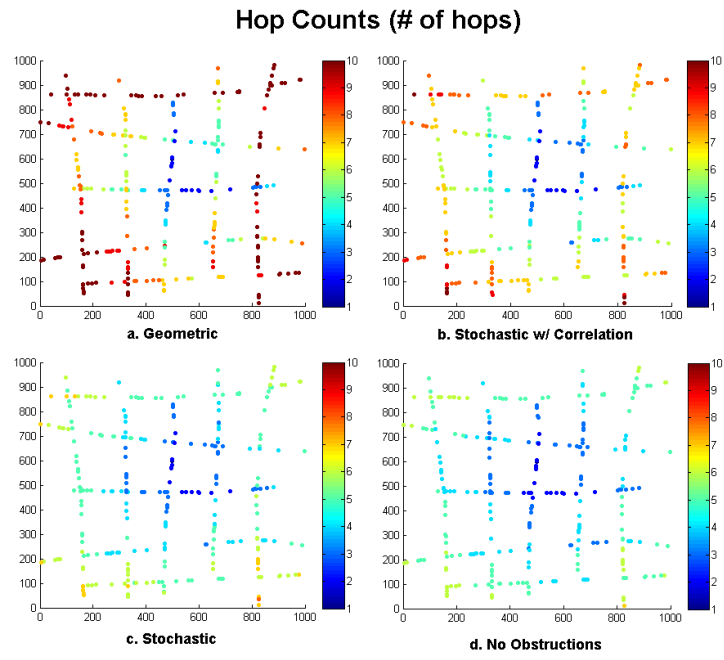


Figure 5.10: Hop Counts

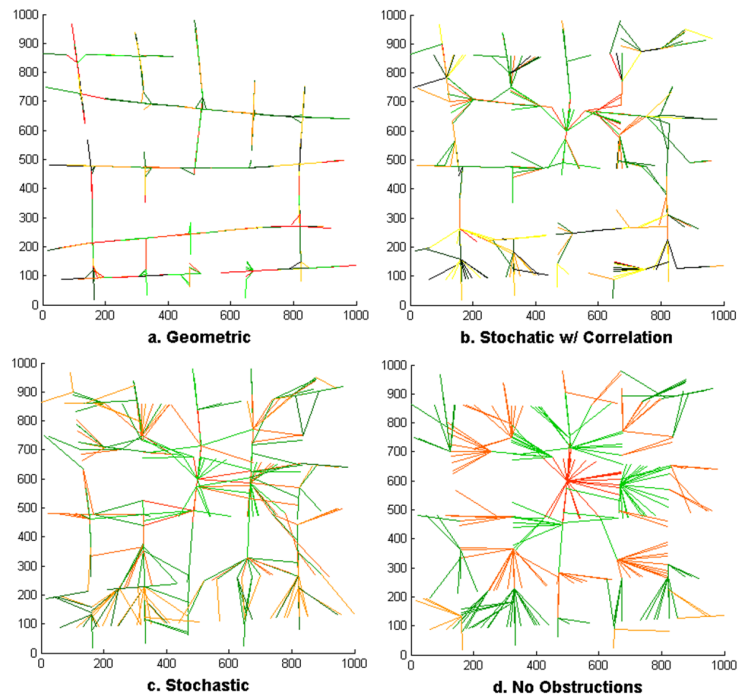


Figure 5.11: Actual Packet Routes

Actual Packet Routes

The local consistency preserved by the correlated-stochastic model is more evident when we examine the actual route taken by each packet (message) in Figure 5.11. The geometric model constraints packet routes to be on road segments and around intersections, while the correlated-stochastic model enforces correlation between nearby links, which results in a similar outcome.

5.7 Discussion on Complexity

In this section, we analyze the modeling complexity of a network-wide simulation of network of correlated wireless channels. We compare the complexity of the geometric and stochastic strategies discussed earlier in § 5.4 and § 5.5.

5.7.1 Simulation Model

We assume a simulation of a network of N nodes that move around in a physical environment, results in N^2 potential links. Simulators often only model links for which the end-points have a realistic chance of being within communication range. Let us assume that on average n ($0 \leq n \leq N$) nodes are within range of a node, then the number of links to simulate drops to order nN links. n depends on both the node density as well as the communication range. We also need to determine, for each node, what nodes are within range which requires order $N \log N$ time, e.g., by organizing objects in a tree based on their geographic location in the environment, which is a common practice in spatial database systems [35].

Movement in the simulated network requires that the simulator will have to regularly update both the channel state and internal data structures regularly. We can distinguish between three different update frequencies corresponding to different types of data. First, the simulator will have to make frequent updates of the channel state, which can then be used to calculate packet level errors and link state. We will denote the update frequency of the channels as f_c and the interval between updates as t_c , i.e., $f_c = 1/t_c$. The minimum frequency $f_{c,min}$ at which channels must be updated depends on the speed of both the wireless devices and other objects in the environment. For example for small-scale fading, movement of objects by a significant fraction of

a wavelength of the wireless signals affects the way multi-path signals combine, e.g., constructively or destructively. Other channel properties, such as path loss, LOS, and Doppler shift, will typically change more slowly. The update frequency f_c can usually be determined based on the maximum speed of objects in the environment.

For both geometric and stochastic channel models, the channel state needs to be recomputed every t_c seconds to properly reflect the instantaneous channel state. Geometric channel models directly model the physical environment, so the impact of wireless device and object mobility is automatically taken into account. Stochastic models also account for movement in model parameters. e.g., the fading model may take input parameters representing the speed of the wireless radios and objects. In both cases, the update frequency f_c can be determined based on the maximum speed of objects in the environment.

Next there are a number of channel parameters that need to be updated at a frequency that is directly related to the speed at which physical devices move. We will represent this frequency as f_p and the period as t_p . f_p is typically much lower than f_c . Finally, as we describe later, we need to update the correlation matrix of each link with a frequency f_{corr} . Generally, $f_{corr} \leq f_p$ because link topology (updated at f_{corr}) changes less frequently than channel parameters (updated at f_p). Given this notation, the partial simulation cost so far is

$$f_c C_c N n + f_p C_n N \log(N) \quad (5.6)$$

where C_c is the cost of updating the channel state of a link and C_n is the per unit cost of determining n .

Next, we consider the complexity of simulating a single link and the correlation between links for the cases when geometric and stochastic channel models are used.

5.7.2 Geometric Models

Geometric channel models explicitly model objects in the environment that may have an impact on signal propagation. The impact may include reflections that contributes to multi-path effects, blocking direct LOS that causes additional attenuation, and scattering that contributes to fast-fading.

We denote by M the total number of objects modeled in the simulated environment. The model for the channel between a transmitter and a receiver must incorporate the impact of the objects in the area surrounding the link. The average number of objects to be considered when modeling a link is denoted as m . m represents the density of objects in the surrounding area and it depends strongly on both the type of environment (e.g., a desert versus a suburban area), and the level of granularity at which the environment is modeled (e.g., the size of the smallest object that is represented). The geographic range within which objects must be considered is also environment dependent. It will be much larger in a rural area than in an urban area, where buildings along the road block the LOS to objects behind them. In addition, the range also depends on both the channel model and the channel property being considered. The area could for example be represented as a Fresnel zone of the link of a certain order.

The per link cost associated with a geometric channel model includes two components. A first cost consists of identifying the m objects that may impact the link, i.e., that are within a certain range. A brute solution has cost M , but this can be reduced to $\log(M)$, similar to what we did to compute n , which is incurred with a frequency f_p .

The second cost is the per-link simulation complexity, which increases roughly proportionally with m . For example, m objects may have to be considered as potential reflectors that can add a path to the channel, or as an object that can block LOS and add to the path loss. Finally, m may be different for, e.g., LOS blocking and properties such as interference.

The cost to update the channel state for a link can be approximated as $C_{g0} + mC_{g1}$, where C_{g0} is the constant cost of modeling a link, and C_{g1} is the extra cost for considering one more object in the geometric model. It is incurred with a frequency f_c . With geometric models, there is no extra cost for modeling spatial correlation across channels, it is already reflected in the overhead associated with modeling the objects.

5.7.3 Stochastic Models

Stochastic channel models simulate the variation in link properties using parameterized stochastic process, where the parameter values are selected to match statistical properties of the variations in the signal propagation properties measured in the real world. Input parameters can

capture properties of the mobile wireless devices (e.g., speed, distance) and physical environment (e.g., density and mobility of objects).

The per-link cost for a stochastic channel model includes three components. The first is that of updating the channel state of each link, C_{stoch} , which is incurred with a frequency f_c . The second is determining proper parameter values in the channel model, denoted C_i , per link. This occurs with a frequency f_p . When modeling correlation among multiple links, a third cost is required to calculate desired correlation properties. For example, the correlated simulation model described in § 5.4 considers the first-order spatial correlation, where all links in the vicinity of a given link are modeled collectively. In this case, there are three major steps: (a) calculate correlation coefficients in a correlation matrix, (b) spectral decomposition of the correlation matrix, and (c) calculate correlated random input, which corresponds to the cost C_{stoch} . The first two steps occur with a frequency of f_{corr} , while the last step occurs with a frequency f_c .

The complexity of each of the above step is determined by the size of the correlation matrix. Assuming nN links, the size of the correlation matrix is nN by nN . Therefore, the overall cost for all links combined can be determined as follows. n^2N^2 correlation coefficients for step (a). For step (b), a reasonable cost for eigenvector decomposition in Equation 5.3 is $O(n^3N^3)$ [64]. For step (c), the complexity is nN for each link in Equation 5.4, thus $O(n^2N^2)$ for all links.

In reality, only links in a certain range are correlated since the degree of correlation will be higher for nearby links, and will become negligible for links that are far away. Moreover, the correlation range also depends on the type of channel properties modeled in the stochastic model. For example, when considering multi-path models, 2-Ray ground reflection model [71] considers transmitting, receiving antennas and ground to be the only objects in the range; while vehicle-to-vehicle small-scale fading model [22] considers any objects along the road to be in range.

Similar to what we did for determining the number of objects that might impact a link for the geometric link, We can assume that on average n_{corr} be the average number of nodes in the correlated vicinity of a given link, i.e., near the endpoints or in the area of between them. The range of the area to consider will depends on the property being modeled, similar to what we discussed for m .

Therefore, the cost for step(a), (b), (c) for each subset of n_{corr}^2 links are $O(n_{corr}^4)$, $O(n_{corr}^6)$ and $O(n_{corr}^4)$ respectively.

Notice that calculating correlation using a subset of the network reduce the matrix dimension dramatically, but the same correlation is calculated multiple times for a pair of links. Therefore, it is practical to use this process in simulation large-scale sparse networks, where for any given link the correlation with most of the links can be ignored (smaller n_{corr}). For small-scale networks with condense links (larger n_{corr}), the complexity of calculating correlation increases dramatically, thus an overall correlation matrix is more desired.

5.7.4 Overall Complexity Discussion

The complexity of modeling a specific environment is different for geometric models and stochastic models. To simulate a desired environment, geometric models require not only modeling objects individually but also accurate input of both dimension and mobility of these objects. [90] One the other hand, stochastic models requires statistical properties of each link to configure the models, and link dynamics are approximated using random input seed. In addition, while correlation among links are present by nature in geometric models, the correlated link properties need to be addressed explicitly in stochastic models. The modeling complexity for correlated links in stochastic models depends mainly on the density of links in the network (the ratio between n_{corr} and N). For link-dense network, the cost increases dramatically for stochastic correlate models, and geometric models become more attractive. On the other hand, geometric models complexity also depends on the density of affecting objects (value m) in range, and the accuracy is limited by input parameter accuracy.

5.8 Summary

Representing spatial correlation across multiple channels in simulation depends strongly on how properties of individual links are modeled: geometric models with extreme details automatically capture spatial correlation while a separate spatial correlation model is often required for link properties stochastically modeled.

In this chapter, we first discuss correlation among channel dynamics, especially in vehicular networks, in §5.2 which motivates the need for modeling channel cross-correlation. In §5.3 we provide background on the different types of models for properties of individual links.

The design space for modeling spatial correlation and a novel correlated stochastic model are presented in §5.4. As an example of the proposed solution, we implemented a new simulation component in ns-3 which handles correlated channel shadowing properties which is presented in §5.5. Both channel shadowing properties and actual link connectivity properties are compared using a basic message distribution (gossiping) protocol. Simulation results in § 5.6 show that correlated channel models help to preserve local consistency among adjacent links, thus providing the most comparable results approaching reality.

Finally, we analyze the complexity of different approaches (statistical vs. geometrical) in §5.7 to provide a guidance for model selection for large-scale simulations.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Wireless simulation and emulation platforms support controlled experiments to efficiently prototype and evaluate wireless designs. To simulate channel properties and dynamics in physical environments, various channel models have been developed to represent the impact of different physical world effects. In Chapter 1, we discussed that different physical world effects have different impact on wireless channel properties. The impact can be modeled using different channel models, in particular at different time scales, using either a geometric model or a stochastic model. The realism of simulated wireless environment is determined by the exact channel models along with parameterization methods used in these simulation platforms.

As discussed in Chapter 4, geometric models are powerful in representing accurate dynamics and spatial correlation by modeling each object explicitly. For large factors, such as large-scale path loss based on distance and large reflectors, it is practical to use a geometric model when the exact dimension, location of such objects can be obtained. On the other hand, information of small factors, such as scatterers, is often impractical to obtain.

In Chapter 4, we proposed a novel stationary scatterer estimation approach to obtain accurate input on scatterer density, and showed significant improvement on dynamic realism compared to the common practice of using area averaged parameter values. In addition, when the more accurate models input for geometric models are not available, stochastic models are more practical

and sufficient to reflect the impact of a large number of small factors.

This thesis proposed an environment model that achieves high simulation realism using both geometric and stochastic models, with special focus on vehicular networks with high dynamics. The proposed model includes the design and implementation of a variety of environment models that enhance the realism in simulation. These models capture realistic signal propagation properties across multiple connections, and over time: first, the impact of realistic physical world features, such as channel dynamics and cross link correlation are characterized at different time scales; then, both geometrical and statistical simulation models are developed to recreate desired channel dynamics among wireless network links efficiently. A flexible channel simulation model is also presented to support fast generation of channel updates from complicated channel models.

In this chapter, we first summarize the contributions of this thesis work. Then we discuss possible future work based on the results of this thesis.

6.1.1 Contribution

System Design for Realistic Simulations

To motivate the challenges of simulating complicate wireless environments with high dynamics, we discussed the control mechanisms that are used in wireless protocol designs to handle channel dynamics. Next, we reviewed features of the physical world that impact wireless communication, followed by discussion on the level of accuracy and realism available on current wireless simulation and emulation platforms.

We presented a system design of a wireless simulation platform that provides flexible configuration of realistic wireless environment, and is capable of represent related physical world impact through experiment configurations. The proposed system includes four major components: a *World Model* module that represents objects and events, a *Wireless Feature Analysis* module that performs spatial and temporal analysis to select channel models, a *Channel Model Control* for channel configuration and a *Flexible Channel Control* module that generates channel updates at real-time. Provided with information obtained from the *World Model* module, the *Wireless Feature Analysis* module supports both temporal and spatial correlation analysis for a

large-scale wireless network, which is a unique feature of this system design.

Flexible Channel Simulation Model

Achieving a high degree of realism in channel models in high speed environments requires frequent channel updates in wireless simulation and emulation. Channel updates in complex channel models are resource consuming, which limits the number of channels, and essentially the size of a simulated network, in real-time emulation. We implemented a general channel model that can support a wide variety of wireless technologies and environments and validated it using high dynamic vehicle-to-vehicle channels, which is particularly challenging because of the speed of the wireless devices and objects. The proposed solution utilizes off-line preparation and run-time adaptation to generate channel updates efficiently.

Temporal Correlation with High Realism

The outputs of a model are only as good as its inputs. Complex channel models often require environment-specific configuration to achieve high accuracy and realism for desired scenarios. Accurate parameter values for these scenarios are often hard to obtain but are essential for obtaining realistic temporal correlation of wireless properties.

We presented a land-cover based approach for modeling and reproducing environment-specific channel properties. The proposed modeling approach is systematic and suitable for large-scale real-time simulation and emulation.

Compared to previous solutions where averaged parameter values were used for any given area, our results show that supplying location-specific parameter estimates to an existing channel model **halved** the error level relative to using fixed area-average parameters. This improvement requires only coarse-grained estimates based on readily-available data, not a detailed “ground truth”. 802.11a packet-level experiments performed over emulated channels show that our improved fading realism directly translates into a comparable improvement in packet delivery ratio (PDR) accuracy to the results using average parameter values.

The discussion focuses on fading and line-of-sight effects in V2V channels, and specifically on the effect of improving the estimated density of stationary scatterers along roads. We also

discuss the generalization of our approach to be applied to other environments where geometric properties plays critical roles in simulation realism.

Cross-Link (Spatial) Correlation Models

We addressed challenges in modeling correlated dynamics for wireless channels.

We presented the design space for modeling spatial correlation across wireless channels, both for link properties that are modeled geometrically and stochastically. The focus is on network-level simulation involving many channels. We also showed that such correlation has a significant impact on network- and application-layer performance, at least for some applications.

A novel correlated stochastic model is proposed for simulating shadowing and NLOS effects. We presented a technique for creating such correlation on top of channel models that do not inherently provide it. To validate the design, different spatial correlation channel models were implemented for the line-of-sight link property in ns-3 and used our implementation to quantify the impact of the choice of model on the performance of a gossip protocol. Simulation results shows high approximation of realism compared to other existing stochastic models.

In addition, we analyzed the complexity of the different modeling options and propose guidelines for selecting the best model, considering cost, accuracy requirements, and type of experiment.

6.2 Future Work

6.2.1 General Vehicular Networks Environment

Vehicular networks is a collection of diverse environments due to variation of road topology and roadside constructions. In this thesis, we validate our design on suburban areas where measurement data are available. However, some of the design components may not suit situations in other vehicular networks, such as higher speed in freeway. In addition, the same design concept can be applied to other wireless network environments, such as outdoor environment with mobile objects and indoor environment with diverse channels properties.

6.2.2 Address Temporal Correlation at Different Time Scales

Temporal correlation properties exist at multiple time scales. For example, MIMO models consider channel coherence time at μs ; scatterer distribution estimation considers temporal consistency at a longer-term basis. For other mobile scatterers and obstacles, the temporal correlation of channel properties introduced by such objects would range between these two extremes. It is desired to represent the temporal dependency at desired time scale by either improving parameter accuracy as we did for stationary scatterer, or enforcing the correlation in stochastic models which is not addressed in this thesis. When design correlation models, how sensitive radios are regarding the subtle variation of signals should be considered to avoid over-correction in representing channel properties that are computationally expensive with negligible impact on protocol performance.

6.2.3 Sophisticated Cross-Link Correlation for Different Channel Properties

Cross-Link correlation properties are observed for channel properties at different time scales in different area. In this thesis, the discussion focuses on small-scale fading properties and large-scale shadowing properties in vehicular networks. With regard to correlation models, our discussion focused on distance-based correlation among channel properties. In general wireless networks, the cross-link correlation properties at different time scales should be examined, likely from measurement databases or simulation results using geometric model, to determine different correlation profiles for each scenario. For example, the multipath properties in indoor environments would exhibit similarity among rooms with similarity inside rooms similar layout, rather than distance between rooms.

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