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ERROR MODELING SCHEMES FOR FADING CHANNELS IN WIRELESS COMMUNICATIONS: A SURVEY

HAOWEI BAI, HONEYWELL AEROSPACE
MOHAMMED ATIQUZZAMAN, UNIVERSITY OF OKLAHOMA

ABSTRACT

Network system designers need to understand the error performance of wireless mobile channels in order to improve the quality of communications by deploying better modulation and coding schemes, and better network architectures. It is also desirable to have an accurate and thoroughly reproducible error model, which would allow network designers to evaluate a protocol or algorithm and its variations in a controlled and repeatable way. However, the physical properties of radio propagation, and the diversities of error environments in a wireless medium, lead to complexity in modeling the error performance of wireless channels. This article surveys the error modeling methods of fading channels in wireless communications, and provides a novel user-requirement (researchers and designers) based approach to classify the existing wireless error models.

Modeling the error performance of wireless channels is usually a complex task, because the performance of wireless channels inherently depends on radio propagating modes, such as, line of sight (LOS) radiation, reflections from a smooth surface, diffractions around a corner, and scattering caused by an object with dimensions on the order of the wavelength. The radio link is highly variable over short distances due to the statistical distribution of path loss (PL) and the physical properties of propagation environments, thereby making it difficult to generalize the results of error performance analysis.

Schemes to improve the reliability of wireless channels range from innovative transport-layer protocols to robust physical-layer schemes, including better modulation and coding. The development and selection of the schemes are based on the understanding of the statistical nature of errors. Therefore, a good understanding of the nature of errors in wireless channels is critical in having a reliable wireless communication for upper-layer applications. Some of the main causes of bit errors, and consequently packet losses, in the widely deployed CDMA wireless channel are described below.

- Attenuation: This is due to a decrease in the intensity of electromagnetic energy at the receiver (e.g., due to long distance), which leads to low signal-to-noise ratio (SNR).
- Intersymbol interference (ISI): This is caused by delay spread (the arrival of a transmitted symbol is delayed), resulting in partial cancellation of the current symbol.
- Doppler shift: This is due to the relative velocities of the transmitter and the receiver. Doppler shift causes frequency shifts in the arriving signal, thereby complicating the successful reception of the signal.
- Multipath fading: This is caused by multipath propagation of radio frequency (RF) signals between a transmitter and a receiver. Multipath propagation can lead to fluctuations in the amplitude, phase, and angle of the signal received at a receiver. We will describe multipath fading in more detail later.

It is challenging for wireless network protocol developers to consider the large number of factors that affect the error performance of wireless channels. Typically, if a wireless channel's propagation characteristics are not specified, one usually assumes that the signal attenuation versus distance behaves as if the propagation takes place over ideal free space [1]. The free space model treats the region between the transmitter and the receiver as free of all objects that might absorb or reflect radio frequency energy. It also assumes that the atmosphere is perfectly uniform and nonabsorbing. However, in practice, the free space model is not accurate enough to describe the performance of a real wireless mobile channel.

Three main physical phenomenon affect radio propagation in a real-world scenario: reflection, diffraction, and scattering. When electromagnetic radiation reflects off objects or diffracts around objects, it can travel from the transmitter to the receiver over multiple paths, giving rise to multipath propagation [2]. This can result in fluctuations in the received signal's amplitude, phase, and angle of arrival, giving rise to multipath fading. System modeling and design, which mitigate the effects of fading, are usually challenging [1]. Therefore, error models of fading channels in wireless mobile communications are very helpful in designing and evaluating the performance of wireless networks and communication systems.

The error performance of wireless channels is usually modeled by capturing the statistical nature of the interaction among reflected radio waves. The statistical calculations for Bit Error Rate (BER), which is generally used to characterize channel errors at the physical layer, is a well known practice. From the perspective of higher layers, network protocol developers and algorithm designers are interested in block errors (packet errors), since most of the higher-layer applications (running on top of link layers) exchange blocks of data between peers. For example, bit errors in a link-layer packet may result in the loss of the entire packet; a single packet loss within a message may lead to the loss of the entire message. Therefore, it is desirable to have accurate packet-level error models for wireless channels, which can be used by network protocol developers and network system engineers to simulate and analyze the end-to-end performance at the packet level. It has been observed empirically [3] that errors in wireless fading channels can be approximated by a two-state Markov process. In other words, a well designed channel may enter a state where bursty errors occur for a small time interval.

Analytical models which can be used for the statistical calculation of BER at the physical layer, and error approximation at higher layers, are described in this survey. In addition to analytical models, it is highly desirable to model wireless networks in a thoroughly repeatable fashion. This is especially important for people who must experiment with realistic channel parameters. However, the results from analytical models are either inaccurate due to errors in the approximation and simplification of environmental characteristics, or unlikely to be reproduced due to complex and inefficient algorithms. This gives rise to *empirical distribution-based models*.

In this article, our *objective* is to survey the existing error modeling methods for fading channels in wireless communication systems, and classify them according to their modeling approach, viz., analytical and empirical. In contrast to traditional classification methods, our approach is based on differing requirements of wireless communication (and network) researchers and designers. The goal of this article is to help researchers who need to analyze characteristics of wireless error channels, and network protocol designers who need to synthesize wireless error channels for their simulations and evaluations, find appropriate error models for wireless fading channels.

We must emphasize that it is not the aim of this article to present various wireless channel propagation models, but to describe some existing efforts on error (specifically, BER at the physical layer, and packet loss rate at upper layers) modeling methods for wireless fading channels. The propagation models for wireless communication channels are used to predict the path propagation loss (e.g., the Lee model [4]). Design engineers use an accurate estimation of path loss to help select the locations of base stations, and determine a proper frequency plan. The field signal strength (or signal power) can be derived from the estimation result of path loss. However, the system error performance (typically measured by SNR) not only depends on the desired signal power, but also depends on the noise power. It is the objective of this article to present existing error modeling methods where both parameters are considered. Readers who are interested in wireless channel propagation models are encouraged to read the article by Neskovic, *et al.* [5], which presents a good overview of popular prediction models based on two main categories, outdoor (macrocell and microcell) and indoor propagation models, and describes some useful algorithms to improve their accuracy.

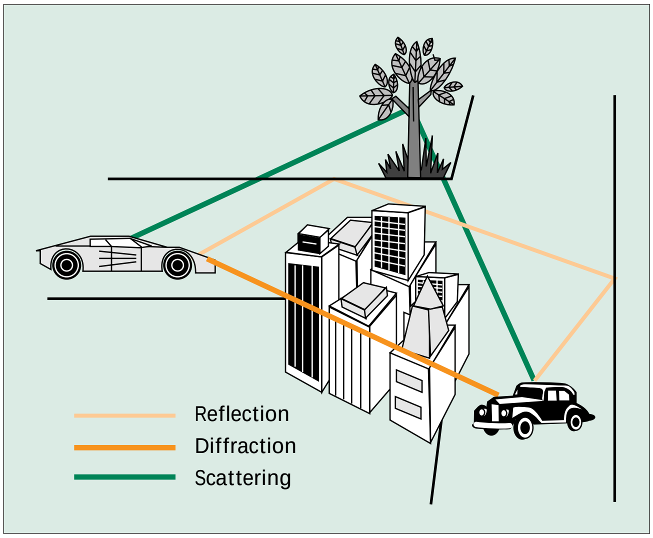


FIGURE 1. *Three radio propagation mechanisms.*

The rest of this article is organized as follows. The nature of radio propagation, and characteristics and models of fading channels, are described. Several fading-channel error modeling schemes are classified and introduced. Finally, concluding remarks are presented.

MULTIPATH FADING

Electromagnetic waves reflecting off objects or diffracting around objects can result in the signal travelling over multiple paths from the transmitter to the receiver. This phenemonon, called multipath propagation, can cause fluctuations in the received signal's amplitude, phase, and angle of arrival, giving rise to *multipath fading*. In this section, we briefly describe the various types and models of fading channels.

There are three main mechanisms that impact radio propagation in wireless channels [6], as illustrated in Fig. 1.

Reflection, which may interfere constructively or destructively at the receiver, occurs when an electromagnetic wave impinges on a smooth surface with very large dimensions when compared to the wavelength of the radio wave.

Diffraction occurs when the path of the electromagnetic wave is obstructed by an impenetrable body of large dimensions as compared to the RF signal wavelength. This causes secondary waves to be formed behind the obstructing body, without any LOS path between the secondary waves. Diffraction, which is also called shadowing because the diffracted field can reach the receiver even when shadowed by an impenetrable obstruction, explains how RF energy can travel in urban and rural environments without a LOS path.

Scattering occurs when the radio channel contains objects of dimensions that are on the order (or less) of the electromagnetic wavelength, causing energy from a transmitter to be radiated in many different directions. In urban environments, typical objects that cause scattering are lamp posts, street signs and foliage.

Environment	Channel type
Mobile systems with no LOS path between transmitter and receiver antenna, propagation of reflected and refracted paths through troposphere and ionosphere, ship-to-ship radio links [11].	Rayleigh [10].
Satellite links subject to strong ionospheric scintillation [12].	Nakagami-q (Hoyt) (spans range from one-sided Gaussian ($q = 0$) to Rayleigh ($q = 1$)) [13].
Propagation paths consisting of one *strong direct LOS* component and many random weaker components — microcellular urban and suburban land mobile, picocellular indoor and factory environments [15].	Nakagami-n (Rice) (spans range from Rayleigh ($n = 0$) to no fading ($n = \bullet$)) [14].
Land mobile [16], *indoor mobile* multipath propagation as well as ionospheric radio links.	Nakagami-m (spans range from one-sided Gaussian $m = 1/2$), Rayleigh ($m = 1$) to no fading ($m = \bullet$)) [17].
Terrain, buildings, trees — urban land mobile systems, land mobile satellite systems [19].	Log-normal shadowing [18].
Nakagami-m multipath fading superimposed on log-normal shadowing. *Congested downtown areas with slow-moving pedestrians and vehicles.* Also in land mobile systems subject to vegetative and/or urban shadowing [20].	Composite gamma/log-normal [18].
Convex combination of *unshadowed multipath* and a *composite multipath/ shadowed* fading. Land mobile satellite systems [21].	Combined (time-shared) shadowed/unshadowed [21].

Table 1. *Models that can be used to characterize various wireless environments.*

The above three radio propagation mechanisms impact the strength of the received signal in different ways. If there is a strong LOS between the transmitter and the receiver, diffraction and scattering are not the dominant factors in the propagation of the radio waves. However, in the absence of a LOS between the transmitter and the receiver, diffraction and scattering become the dominant factors in the propagation. Typically, the received signal is a sum of the components arising from the above three phenomena. The strength of the received signal fluctuates rapidly with respect to time and the displacement of the transmitter and the receiver.

LARGE-SCALE FADING AND SMALL-SCALE-FADING

Based on the distance over which a mobile moves, there are two different types of fading effects: large-scale fading and small-scale fading [1]. If the mobile moves away from the transmitter over a large distance, the received signal will experience large-scale signal variation. Large-scale fading represents the average signal power attenuation due to motion over large areas. The receiver is often represented as being shadowed by prominent terrains, such as hills, forests, billboards, clumps of buildings, etc. Small-scale fading refers to the dramatic changes in signal amplitude and phase that can be experienced as a result of small changes (as small as a half-wavelength) in the distance between the transmitter and the receiver. When there are a large number of reflective paths with no LOS signal components, the envelope of the received signal can be statistically described by the Rayleigh distribution [7, 8]. If dominant non-fading components exist, such as a LOS propagation path, the small-scale fading envelope is Rice distributed [7, 8]. A mobile radio propagating over a large area will experience both types of fading, i.e., small-scale fading superimposed on large-scale fading.

DIFFERENT TYPES OF FADING-CHANNEL MODELS

In this section, we present the different types of fading channels that are typical in communication environments, and the mathematical models that can be used to describe the channels. Table 1 [9] shows various fading-channel models, classified by the environments to which they apply.

Multipath fading arises from the constructive and destructive combination of randomly delayed reflected, scattered, diffracted signal components. Based on the nature of the radio propagation environment, different mathematical models exist to describe the statistical behavior of the multipath fading envelope.

- The Rayleigh distribution [10] is used to model the propagation environment where the mobile antenna receives a large number of reflected and scattered waves. Because of wave cancellation effects, the instantaneous received power seen by a moving antenna becomes a random variable, dependent on the location of the antenna.
- The Nakagami-q distribution [13] is typically observed on satellite links subjected to strong ionospheric scintillation.
- The Nakagami-n distribution, known as the Rice distribution [14], is often used to model similar environments to Rayleigh fading channels, except that the set of reflected and scattered waves are dominated by one strong component.
- The Nakagami-m distribution [17] can be used to model fading-channel conditions that are more severe than the Rayleigh distribution. It often gives the best fit to land-mobile, indoor-mobile multipath propagation, as well as scintillating ionospheric radio links.

In terrestrial and satellite land-mobile systems, the link quality is also affected by slow variation of the mean signal level, resulting from the effects of shadowing from terrain, buildings, and trees. The shadowing can generally be modeled by a log-normal distribution for various outdoor and indoor environments [22]. If the receiver is able to average out the fast multipath fading, the performance of mobile systems depends only on shadowing. However, in an environment consisting of multipath fading superimposed on shadowing, the receiver does not average out the fading envelope. This scenario, called composite multipath/shadowing, is typically observed in congested downtown areas with slow moving pedestrians and vehicles [20]. A detailed discussion of this topic, and the corresponding probability density functions of fading amplitude and SNR, can be found in [23].

ERROR MODELS OF FADING CHANNELS

With the proliferation of wireless networks, much research has focussed on improving the quality of fading channels. This has led to a growing interest in characterizing the packet loss behavior of fading channels. A number of error models have been proposed in the literature to characterize the loss behavior of fading channels. The error models can be classified into two groups: analytical models and empirical distribution-based models.

ANALYTICAL MODELS

Errors occurring in wireless channels are due to the diversity of wireless connections and the complicated physical impairments. As a result, it is difficult to generalize the mathematical results from one specific domain to another. Therefore, analytical models are highly dependent on the characterization of error environments, such as fading channels. The traditional metric used for characterizing channel errors at the physical layer is the average BER. This gives rise to the first type of analytical modeling methods, called *physical-layer oriented* modeling, which deals with bit errors.

It is expected that future wireless communications will include image, video, and data applications. Accordingly, higher-layer encoding algorithms for multimedia transmissions will have to be carefully designed to overcome the impact of errors on wireless channels. Higher-layer applications, running on top of a link layer, usually manage data transfer in blocks of multiple bits or symbols, and employ various block error detection and retransmission mechanisms. In this case, it is important to examine the effects of multipath fading-channel dynamics on block data throughput, delay, and queuing performance. This gives rise to the second type of analytical modeling methods, called *higher-layer oriented* modeling, which is based on block errors. In the following subsections, we describe physical-layer oriented modeling and higher-layer oriented modeling.

Physical-Layer Oriented Modeling — This method aims at determining the BER performance of a wireless communication system over fading channels. Based on the specific channel model and modulation/detection combination, the average BER is obtained through statistical calculations. One of the approaches is to approximate the probability density function (PDF) of SNR at the receiver, and then average the BER over that PDF. Much work on this modeling approach has been reported in the literature.

In many applications, it is difficult to track the phase of the received signal. It is therefore impossible to perform coherent detection, which requires reference in phase with the received carrier signal. In such cases, the design of a communication receiver must depend on either noncoherent detection, where no attempt is made to determine the phase of the incoming signal, or differentially coherent detection, where the carrier phase of the previous signaling interval can be used as a phase reference. In a randomly fading channel, it may be difficult to establish and maintain a coherent reference. Therefore, a noncoherent system or a differentially coherent system is more desirable. Readers are encouraged to read [24] for more details. In the rest of this section, we briefly describe some reported BER calculations for noncoherent and differentially coherent detections.

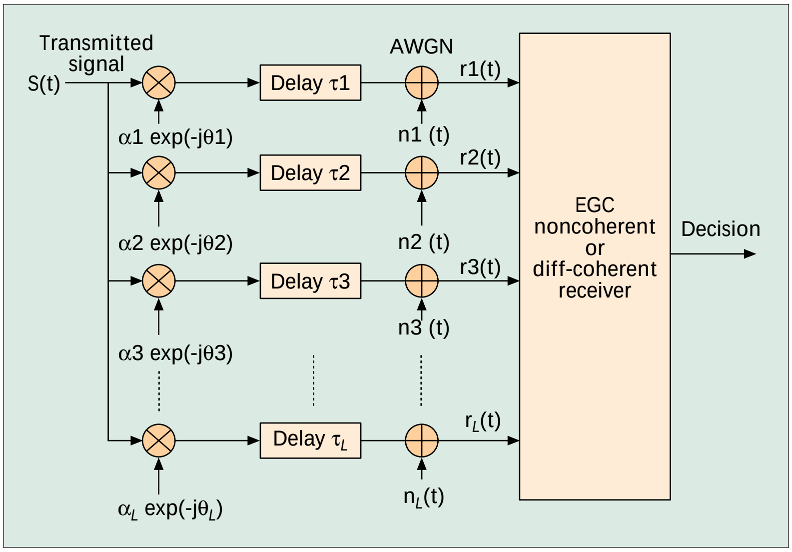


FIGURE 2. *Generalized fading channel.*

Proakis [25] derived a generic equation for evaluating the BER of multichannel noncoherent and differentially coherent reception of binary signals over multiple independent additive white Gaussian noise (AWGN) channels. Lindsey [26] developed a generic expression for the average BER of binary correlated FSK for multichannel reception over multiple independent Rician fading channels, where the strength of the scattered component is assumed to be constant for all the channels. Charash [27] performed the average BER performance analysis for binary orthogonal FSK with multichannel reception over multiple independent and identically distributed (i.i.d.) Nakagami-*m* fading channels. Weng *et al*. in [28] derived a closed form average BER expression for binary DPSK with multichannel reception over multiple Nakagami-*m* fading channels. In [29] Patenaude *et al*. extended the results of [27] and [28]. They derived a closed form expression for the average BER of binary orthogonal square-law detected FSK and binary DPSK with multichannel reception over multiple independent, but not necessarily i.i.d., Nakagami-*m* fading channels. Tjhung *et al*. [30] and Tanda [31] analyzed the average BER for Differential Quadrature PSK (DQPSK) over Rician and Nakagami-*m* fading channels, respectively. Tellambura *et al*. [32] presented an alternate unified BER analysis of DQPSK over Rician and Nakagami-*m* fading channels.

In contrast to the above approaches, Simon and Alouini [9] deploy an alternate form of the Marcum *Q*-function and the resulting alternate integral representation of the conditional BER, as well as some well known Laplace transforms, to independently average over the PDF of each fading channel. This results in a useful generalized expression for the average BER performance of noncoherent and differentially coherent communication systems over AWGN and fading channels, thus unifying all the results mentioned above.

Figure 2 [9] shows a multilink channel model, which is used to develop the generalized model for the determination of the BER performance. This model is general enough to include the cases where different independent channels are not necessarily identically distributed, nor even distributed according to the same family of distributions, and systems that employ postdetection equal gain combining [18] (EGC). The transmitted signal is received over L independent channels, each of them being a fading channel. $\{r_l(t)\}_{l=1}^{L}$ is a set of L received replicas of the signal, where l is the index of the channel, and , , and are the random fading-channel

Detection type	Modulation (signal set)	Parameters of Marcum Q-Function
Noncoherent	Equal energy, equiprobable correlated binary signals (= complex correlation coefficient)	$\eta=1,\ a=\sqrt{\frac{1-\sqrt{1-\lvert\lambda\rvert^2}}{2}},\ b=\sqrt{\frac{1+\sqrt{1-\lvert\lambda\rvert^2}}{2}}$
	Equal energy, equiprobable uncorrelated binary signals, e.g., BFSK	= 1, a = 0, b = 1
Differentially coherent	Binary phase-shift-keying (DPSK)	= 1, a = 0, b = ÷2
	Quadrature phase-shift-keying (DQPSK) with Gray coding	$\eta=1,\ a=\sqrt{2-\sqrt{2}},\ b=\sqrt{2+\sqrt{2}}$

Table 2. *Special cases of generalized equation for specific modulation/detection schemes.*

amplitudes, phase, and delays, respectively. The first channel (with index of 1) is assumed to be the reference channel whose delay is 0. The fading amplitude, $_l$, of the lth channel is a random variable with a mean squared value of $\overline{}^2_l$ which is denoted by $_l$. The probability distribution of the random variable $_l$ is any of the family of distributions presented in Table 1. Based on this channel model, the authors in [9] use alternate representations of Gaussian and Marcum Q-functions that are characteristic of error-probability expressions for differentially coherent and noncoherent forms of detection to obtain the generalized BER expression as follows:

$$\begin{aligned} P_b(E;\gamma) &= Q_1\left(a\sqrt{\gamma},b\sqrt{\gamma}\right)-\left[1-\frac{\sum_{l=0}^{L_r-1}\binom{2L_r-1}{l}\eta^l}{(1+\eta)^{2L_r-1}}\right] \\ &\times\exp\left[-\frac{(a^2+b^2)\gamma}{2}\right]I_0(ab\gamma)+\frac{1}{(1+\eta)^{2L_r-1}} \qquad (1) \\ &\times\left[\sum_{l=2}^{L_r}\binom{2L_r-1}{L_r-1}\eta^{L_r-1}\times\left[Q_l\left(a\sqrt{\gamma},b\sqrt{\gamma}\right)-Q_1\left(a\sqrt{\gamma},b\sqrt{\gamma}\right)\right]\right. \\ &\left.-\sum_{l=2}^{L_r}\binom{2L_r-1}{L_r-l}\eta^{L_r-1+l}\times\left[Q_l\left(b\sqrt{\gamma},a\sqrt{\gamma}\right)-Q_1\left(b\sqrt{\gamma},a\sqrt{\gamma}\right)\right]\right], \end{aligned}$$

where the function $Q(\cdot)$ is the generalized Marcum Q-function obtained by the authors in [9] and is given by

$$Q_l(\alpha,\beta)=\frac{1}{\alpha^{l-1}}\int_\beta^\infty x^l\exp\left[-\left(\frac{x^2+\alpha^2}{2}\right)\right]I_{l-1}(\alpha x)dx. \qquad (2)$$

The $I(\cdot)$ function in Eq. 2 is the modified Bessel function of the first kind and order (l – 1). The parameter l in Eq. 1 is the channel index, and $= {}_{l=1}^{L_r}\ l$ is the total instantaneous SNR per bit.

Typical values of , a, and b, corresponding to specific modulation/detection schemes, are shown in Table 2 [9]. Note that in all possible cases, a and b are independent of the fading-channel model. For the case of single-channel reception, the value of L_r in Eq. 1 is equal to one. Otherwise, $L_r \geq 1$, which corresponds to the case of multichannel detection. Details on the derivation of this generalized expression can be found in [9].

The effectiveness of the generalized BER equation (as given by Eq. 1) is shown by an example below. The well-known conditional BER expression for orthogonal DPSK with single-channel reception is obtained by plugging in appropriate parameters summarized in Table 2.

For L_r = 1 (i.e., single-channel reception), the latter two summations in Eq. 1 do not contribute. One can immediately obtain

$$\begin{aligned} P_b(E;\gamma) &= Q_1\left(a\sqrt{\gamma},b\sqrt{\gamma}\right) \\ &-\left(\frac{\eta}{1+\eta}\right)\exp\left[-\frac{(a^2+b^2)\gamma}{2}\right]I_0(ab\gamma). \end{aligned} \qquad (3)$$

For = 1, a = 0, and b = ÷2 (Table 2), Eq. 3 can be reduced to the well known expressions for DPSK as reported by a number of authors:

$$P_b(E;\gamma)\Big|DPSK=\frac{1}{2}\exp(-\gamma). \qquad (4)$$

Contributions made by hundreds of authors dealing with BER probability performance over generalized AWGN and fading channels, using alternate representations of Marcum Q-functions, are now unified in a common framework [9]. The coverage of this framework is broad enough to represent and describe almost all combinations of modulation/detection types and fading-channel types.

Most wireless communication system designers make use of commercially available tools. To determine the parameters for a specific design module, they carry out many on-site measurements. However, this does not mean that the analytical error models we presented here are not useful. The merger of networking technology and wireless communications requires a modern wireless network to be more mobile, capable of higher data rates, easy to configure and use, and more affordable. Apparently, achieving such a near-optimal set of requirements requires careful balancing of trades. Simulation assessment of performance is the currently widely used method to achieve this goal. Results presented in this article (e.g., BER expression of orthogonal DPSK over Nakagami-*m* fading channel) could be easily plugged into the receiver's BER calculation procedure of commercially available network simulation tools (e.g., OPNET) to facilitate the physical-layer performance analysis.

Although simulation plays an essential role in comparing competing design alternatives, simulation of wireless network systems, especially wireless links, is sometimes unreliable, which may lead to incorrect design choices. This is due to errors in the modeling, including unwanted approximations and simplifications. Generally, higher accuracy in modeling requires more complexity of computation. In this case, it is desirable to have models with low computation complexity, while maintaining the desired accuracy. The unified expression of BER performance for noncoherent and differentially coherent modulations over generalized fading channels, which is presented above, is a good example of such models. The expression of average BER only involves a single finite-range integral whose integrand contains only elementary functions. It can, therefore, be easily computed numerically. Such contributions are very useful and helpful to refining the existing simulation models and tools, resulting in more accurate and fair design choices.

Higher-Layer Oriented Modeling — As mentioned earlier, modeling of fading errors at higher layers aims at calculating the average block error rate (packet error rate). In the literature, most of the models are based on the assumption that data packet transmissions are i.i.d. In addition, many coding schemes and protocols were initially designed for i.i.d. channels. One may consider an apparent alternative solution to this problem: the study of channels with memory by deploying some prediction techniques. Unfortunately, little work is available on such models.

It has been shown that the special structure of Markov approximation makes it naturally useful and tractable for this purpose [33]. The Markov chain assumes that an adequate description of a system is given by a finite number of states. Each state is assigned a probability of the system being in that state. For example, the typical movement of the stock market could be considered as a simple two-sate model in terms of *up* and *down* movement of the index. The study of Markov approximation for fading channels dates back to the early work of Gilbert [34] and Elliott [35]. They built a two-state Markov channel known as the Gilbert-Elliott channel. In a simplified Gilbert model [36], the error probabilities in bad and good states are 1 and 0, respectively. Assuming 1 and 0 denote successful and erroneous transmission in a given slot, the state transition diagram is shown in Fig. 3. Accordingly,

$$\mathbf{P} = \begin{pmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{pmatrix} \tag{5}$$

is the transition matrix for the packet error process. Therefore, the probability of having packet errors is given by [33]

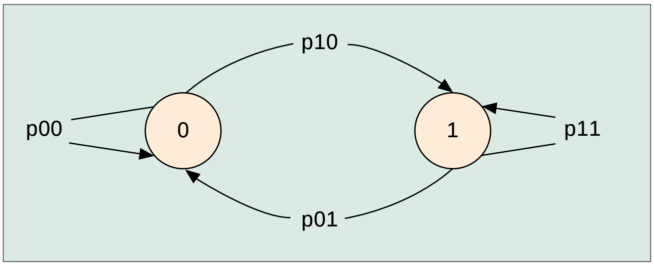
$$\varepsilon = \frac{p_{01}}{p_{10} + p_{01}} \tag{6}$$

This Markovian model for average packet error probability can be easily extended for diversity. The performance can be improved by using two (or more) suitably spaced antennas over fading channels [33]. For example, if a diversity of order two (i.e., two antennas) is employed, and the signals received at the two antennas fade independently, the channel can be modeled by three states: both channels are good (state 0), two channels have different states (state 1), and both channels are bad (state 2). If the transition matrix of each channel has the same form as Eq. 5, the transition matrix of this three-state Markov chain can be written as [33]

$$\mathbf{P} = \begin{pmatrix} p_{00}^2 & 2\,p_{01}\,p_{00} & p_{01}^2 \\ p_{10}\,p_{00} & p_{11}\,p_{00} + p_{10}\,p_{01} & p_{01}\,p_{11} \\ p_{10}^2 & 2\,p_{10}\,p_{11} & p_{11}^2 \end{pmatrix}. \tag{7}$$

In this three-state Markov model, states 0 and 1 correspond to successful transmission, while state 2 corresponds to a transmission failure.

A binary symmetric channel (BSC) with a given crossover probability can be associated with each state so that the channel quality for each state can be identified. The Gilbert-Elliott channel is a special case of this type of channel, where the crossover probabilities of the BSC are 0 and 0.5, respectively [37]. Each state represents a specific channel quality that is either totally noisy or noiseless. When the channel quality varies dramatically, a two-state Gilbert-Elliott model is not adequate. As a solution, a finite-state Markov channel (FSMC) model is proposed in [37] as an extension of the two-state Markov model. By partitioning the range of the received SNR into a finite number of intervals, the FSMC model is constructed for Rayleigh fading channels [37].



■ **FIGURE 3.** *State transition diagram for an example simplified Gilbert model.*

As wireless network technology evolves, the design of communication networks becomes more complicated because most of the existing network protocols were designed for wireline networks. Analyzing and evaluating the performance of existing protocols in wireless environments provides many insights and possible solutions on how to adapt existing network protocols to wireless environments. Therefore, accurate models of network dynamics such as packet error probabilities is very essential to wireless network protocol design and development. The higher-layer oriented modeling methods directly provide packet error probabilities without the need to understand the complex physical-layer schemes and long conditional probability calculations. One may easily put such a higher-layer oriented model to a prevalent network simulation tool (e.g., OPNET, or NS), and evaluate (and furthermore, improve) the existing higher-layer network protocols. For example, by simulating link-layer error control protocols, such as automatic repeat request (ARQ), one may be able to tune the existing parameters of the protocol and even find performance improvement schemes. By simulating TCP over wireless links with random link errors generated by such a higher-layer error model, many TCP improvement algorithms have been proposed during the past several years. These algorithms provide different ways for TCP to react differently in front of congestion errors and link corruption errors.

EMPIRICAL DISTRIBUTION-BASED MODELS

A large number of measurements have been conducted by telecommunication companies, research laboratories, and universities in order to determine reasonable fading-channel parameters (such as error rates) for wireless communication systems. These measurements show that environmental factors, such as terrain, construction materials, speed of pedestrians and vehicles, etc., have a direct impact on radio propagation characteristics. Therefore, although analytical modeling methods as described here are sound in theory, in practice it is hard to determine the values of the parameters in these models, especially when we want to build a specific model under a special environment. This gives rise to *empirical distribution-based* modeling methods.

The development of empirical distribution-based models consists of three phases: data collection, statistical analysis and model construction, and model validation.

- In the data collection phase, a large number of statistical data are collected and recorded by network tracing or measurements for many different scenarios.
- Those statistical data are extracted in terms of interests, such as packet errors, and are modeled in the statistical analysis and model construction phase. The model is built by fitting known probability distributions to data.

- In the model validation phase, the models are simulated or analyzed, and validated. The models are refined to make them consistent with the collected data and traces.

An impressive example is presented in [3], where the loss behavior of the AT&T WaveLAN, an in-building wireless interface, is characterized and modeled using empirical distribution-based modeling methods. Though IEEE 802.11b has been prevalent among wireless LAN technologies, we still choose this example to show the usefulness and effectiveness of empirical distribution-based models, because as a result of conducting network tracing, the traditional method of evaluating wireless network protocols with a uniform error model has been shown to be inaccurate by [3]. Furthermore, the authors in [3] also reveal that the wireless error behavior of WaveLAN cannot be accurately modeled by a simple two-state Markov chain using analytical modeling methods. Instead, another improved two-state Markov model, based on the distribution of the error length (defined to be the number of packets that are lost consecutively) and error-free length (defined to be the number of packets that are successfully received between two adjacent bursts of errors [3]) of the packet stream, has been shown to be more accurate. The key difference between the two lies in the probability distribution of the error and error-free length. The simple two-state Markov model assumes that the error length and error-free length are *geometrical* distributed. However, results of the empirical distribution-based modeling shows that the error length is better described by a combination of two *exponential* distributed segments, and the error-free length is better described by a combination of three segments, two *Pareto* distributions and one *exponential* distribution.

In addition to validating and refining the existing models, the empirical modeling method can also be used to find inappropriate hypotheses that have been used in analytical modeling in the past. This indicates limitations of some widely used analytical models. The authors in [38] point out that the tracing data on wireless links is non-stationary in nature by performing error traces on a GSM network platform. (The authors define a trace to be *stationary* when the error statistics remain relatively constant over time.) They arrived at the above conclusion by applying the Run Test [39] (a method used to test stationarity) to the tracing data. Many users have used the assumption of stationarity of Markov chains to model errors in wireless channels, including the Gilbert model introduced earlier. The authors show the inaccuracy of the Gilbert model as a result of inappropriate stationarity assumptions. Furthermore, they propose a new method, called Markov-based trace analysis (MTA), which results in a more accurate error burst distribution model for wireless networks. MTA takes advantage of a Markov process by decomposing a non-stationary trace into a set of piece-wise stationary traces consisting of *lossy* and *error-free* states. The error-free trace is a deterministic process, whereas the lossy trace is a stationary random process that is modeled by a Markov process.

Many advantages and uses of empirical distribution-based models have been discussed above. However, in order to build an empirical model, many resources are required. These include real communication networks, measurement equipment, data tracing and recording tools (hardware and software), and data processing algorithms, which definitely lead to high costs. The authors applying the MTA method in [38] required access to a GSM network platform. A study of wireless communication for aircraft systems, performed by Aerospace Vehicle Systems Institute (AVSI), even required a Boeing-777 airplane as part of their testbed. Their purpose of tracing was to build a model.

SUMMARY

Wireless error modeling methods have been surveyed and classified in this article. The models that have been developed to approximate the loss behavior of transmission channels have been classified into two groups: *analytical models* and *empirical distribution-based models*. Since errors in wireless channels are due to the diversity of wireless connections and the complicated error environment, analytical modeling methods are highly dependent on the characterization of error environments, such as fading channels. Although physical-layer oriented modeling methods and higher-layer oriented modeling methods can be used to evaluate the BER performance and packet error performance, respectively, it is highly desirable that wireless errors be modeled in a thoroughly reproducible way. This is especially important for developers of network protocol and mobility algorithms who must experiment with realistic channel parameters. The empirical distribution-based modeling approach, which alleviates the above problem, has been described in this article.

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REFERENCES

[1] B. Sklar, "Rayleigh Fading Channels in Mobile Digital Communication Systems, Part I: Characterization," *IEEE Commun. Mag.*, vol. 35, no. 9, Sept. 1997, pp. 136–46.
[2] D. Eckhardt and P. Steenkiste, "Measurement and Analysis of the Error Characteristics of an In-Building Wireless Network," *Proc. ACM SIGCOMM '96*, Stanford, CA, Aug. 1996, pp. 243–54.
[3] G. T. Nguyen *et al.*, "A Trace-Based Approach for Modeling Wireless Channel Behavior," *Proc. Winter Simulation Conf.*, Coronado, CA, Dec. 1996, pp. 597–604.
[4] W. C. Y. Lee, *Mobile Communications Design Fundamentals*, New York: John Wiley, 1993.
[5] A. Neskovic, N. Neskovic, and G. Paunovic, "Modern Approaches in Modeling of Mobile Radio Systems Propagation Environment," *IEEE Commun. Surveys*, vol. 3rd Quarter, Sept. 2000, pp. 2–12.
[6] T. S. Rappaport, *Wireless Communications*, Upper Saddle River, NJ: Prentice Hall, 1996.
[7] F. Babich and G. Lombardi, "Statistical Analysis and Characterization of the Indoor Propagation Channel," *IEEE Trans. Commun.*, vol. 48, no. 3, Mar. 2000, pp. 455–64.
[8] W. C. Jakes, *Microwave Mobile Communications*, New York: John Wiley, 1974.
[9] M. K. Simon and M. S. Alouini, "A Unified Approach to the Performance Analysis of Digital Communication over Generalized Fading Channels," *Proc. IEEE*, vol. 86, no. 9, Sept. 1998, pp. 1860–77.
[10] L. Rayleigh, "On the Resultant of a Large Number of Vibrations of the Same Pitch and of Arbitrary Phase," *Philosophical Mag.*, vol. 27, no. 6, June 1889, pp. 460–69.
[11] H. B. James and P. I. Wells, "Some Tropospheric Scatter Propagation Measurements Near the Radio-Horizon," *Proc. IRE*, vol. 43, Oct. 1955, pp. 1336–40.
[12] B. Chytil, "The Distribution of Amplitude Scintillation and the Conversion of Scintillation Indices," *J. Atmospheric and Terrestrial Physics*, vol. 29, no. 9, Sept. 1967, pp. 1175–77.
[13] R. S. Hoyt, "Probability Functions for the Modulus and Angle of the Normal Complex Variate," *Bell System Tech. J.*, vol. 26, no. 4, Apr. 1967, pp. 318–59.
[14] S. O. Rice, "Statistical Properties of a Sine Wave Plus Random Noise," *Bell System Tech. J.*, vol. 27, no. 1, Jan. 1948, pp. 109–57.

[15] R. J. C. Bultitude, S. A. Mahmoud, and W. A. Sullivan, "A Comparison of Indoor Radio Propagation Characteristics at 910 MHz and 1.75 GHz," *IEEE JSAC*, vol. 7, no. 1, Jan. 1989, pp. 20–30.

[16] T. Aulin, "Characteristics of a Digital Mobile Radio Channel," *IEEE Trans. Vehic. Tech.*, vol. VT-30, no. 5, May 1981, pp. 45–53.

[17] M. Nakagami, *Statistical Methods in Radio Wave Propagation*, Oxford, England: Pergamon, 1960, pp. 3–36.

[18] G. L. Stuber, Principles of Mobile Communications, ch. sec. 2.4, Norwell, MA: Kluwer, 1996.

[19] T. S. Rappaport, S. Y. Seidel, and K. Takamizawa, "Statistical Channel Impulse Response Models for Factory and Open Plan Building Radio Communication System Design," *IEEE Trans. Commun.*, vol. 39, no. 5, May 1991, pp. 794–807.

[20] M. J. Ho and G. L. Stuber, "Co-Channel Interference of Microcellular Systems on Shadowed Nakagami Fading Channels," *Proc. IEEE Vehic. Tech. Conf.*, Secaucus, NJ, May 1993, pp. 568–71.

[21] E. Lutz *et al.*, "The Land Mobile Satellite Communication Channel–Recording, Statistics, and Channel Model," *IEEE Trans. Vehic. Tech.*, vol. VT-40, no. 5, May 1992, pp. 375–86.

[22] H. Suzuki, "A Statistical Model for Urban Multipath Propagation," *IEEE Trans. Commun.*, vol. COM-25, no. 7, July 1977, pp. 673–80.

[23] M. K. Simon and M. S. Alouini, "A Unified Approach to the Probability of Error for Noncoherent and Differentially Coherent Modulations over Generalized Fading Channels," *IEEE Trans. Commun.*, vol. 46, no. 12, Dec. 1998, pp. 1625–38.

[24] B. Sklar, *Digital Communications Fundamentals and Applications*, Upper Saddle River, NJ: Prentice Hall, 1988.

[25] J. G. Proakis, "On the Probability of Error for Multichannel Reception of Binary Signals," *IEEE Trans. Commun. Tech.*, vol. COM-16, no. 2, Feb. 1968, pp. 68–71.

[26] W. C. Lindsey, "Error Probability for Ricean Fading Multichannel Reception of Binary and *n*-ary signals," *IEEE Trans. Info. Theory*, vol. IT-10, no. 10, Oct. 1964, pp. 339–50.

[27] U. Charash, "Reception through Nakagami Fading Multipath Channels with Random Delay," *IEEE Trans. Commun.*, vol. COM-27, no. 4, Apr. 1979, pp. 657–70.

[28] J. F. Weng and S. H. Leung, "Analysis of DPSK with Equal Gain Combining in Nakagami Fading Channels," *IEEE Electronics Letters*, vol. 33, no. 4, Apr. 1997, pp. 654–56.

[29] F. Patenaude, J. H. Lodge, and J. Y. Chouinard, "Error Probability Expressions for Noncoherent Diversity in Nakagami Fading Channels," *Proc. IEEE Vehic. Tech. Conf.*, Phoenix, AZ, May 1997, pp. 1484–87.

[30] T. T. Tjhung, C. Loo, and N. P. Secord, "BER Performance of DQPSK in Slow Rician Fading," *IEEE Electronics Letters*, vol. 28, no. 8, Aug. 1992, pp. 1763–65.

[31] M. Tanda, "Bit Error Rate of DQPSK Signals in Slow Nakagami Fading," *IEEE Electronics Letters*, vol. 29, no. 3, Mar. 1993, pp. 431–32.

[32] C. Tellambura and V. K. Bhargava, "Unified Error Analysis of DQPSK in Fading Channels," *IEEE Electronics Letters*, vol. 30, no. 12, Dec. 1994, pp. 2110–11.

[33] M. Zorzi and R. R. Rao, "Lateness of Probability of a Retransmission Scheme for Error Control on a Two-State Markov Channel," *IEEE Trans. Commun.*, vol. 47, no. 10, Oct. 1999, pp. 1537–1548.

[34] E. N. Gillbert, "Capacity of a Bursty-Noise Channel," *Bell System Tech. J.*, vol. 39, no. 9, Sept. 1960, pp. 1253–65.

[35] E. O. Elliott, "Estimates of Error Rates for Codes on Bursty-noise Channels," *Bell System Tech. J.*, vol. 42, no. 9, Sept. 1963, pp. 1977–97.

[36] J. R. Yee and E. J. Weldon, "Evaluation of the Performance of Error Correcting Codes on a Gilbert Channel," *IEEE Trans. Commun.*, vol. 43, no. 8, Aug. 1995, pp. 2316–23.

[37] H. S. Wang and N. Moayeri, "Finite-State Markov Channel: A Useful Model for Radio Communication Channels," *IEEE Trans. Vehic. Tech.*, vol. 44, no. 1, Feb. 1995, pp. 163–71.

[38] A. Konrad *et al.*, "A Markov-Based Channel Model Algorithm for Wireless Networks," *Proc. 4th ACM Int'l. Wksp. Modeling, Analysis and Simulation of Wireless and Mobile System*, Rome, Italy, July 2001, pp. 28–36.

[39] J. Bendat and A. Piersol, *Random Data: Analysis and Measurement Procedures*, New York: John Wiley, 1986.

BIOGRAPHIES

HAOWEI BAI (haowei.bai@honeywell.com) received his M.Sc. degree in electrical and computer engineering from the University of Dayton, Dayton, Ohio, and his B.E. degree from the Department of Information and Communication Engineering, Xi'an Jiaotong University, P.R. China. He is currently a research scientist at AES Technology Centers of Excellence, Honeywell Aerospace. He has previously been a research scientist at the Communication and Systems Architecture Lab of Honeywell Laboratories. Much of his current research has focused on communication network architectures and protocols, high-speed avionic data buses, broadband wireless communication systems, QoS of next-generation Internet, TCP over wireless links, and SCTP over satellite links. He has several publications on these areas. He is a member of IEEE and SAE. He serves as a committee member on SAE AS-1A Avionic Networks Subcommittee, and referees for various technical journals and IEEE conferences.

MOHAMMED ATIQUZZAMAN (atiq@ou.edu) received the M.Sc. and Ph.D. degrees in electrical engineering from the University of Manchester, England. Currently he is faculty member in the School of Computer Science at the University of Oklahoma. He has previously held faculty positions at the University of Dayton, Dayton, Ohio, and Monash University, Australia. He is the co-editor-in-chief of the journal *Computer Communications*, and serves on the editorial board of *IEEE Communications Magazine*, as well as the journals *Telecommunications Systems*, *Wireless and Optical Networks*, and *Real Time Imaging*. He has guest-edited many special issues in various journals, including feature topics on switching and traffic management for multimedia in *IEEE Communications Magazine*; architecture, protocol and quality of service in the *European Transactions on Telecommunications*; ATM switching and ATM networks in the *International Journal of Computer Systems Science & Engineering*; and parallel computing on clusters of workstations in *Parallel Computing*. He was the conference chair of the 2003 Workshop on High Performance Switching and Routing, and the SPIE Quality of Service over Next-Generation Data Networks conference. He has also served on the technical program committee of many national and international conferences, including IEEE INFOCOM, IEEE GLOBECOM, and the IEEE Annual Conference on Local Computer Networks. He is a senior member of the IEEE. His current research interests are in quality of service for next-generation Internet, broadband networks, multimedia over high-speed networks, wireless and satellite networks, TCP/IP over ATM, multiprocessor systems, and image processing. He is the co-author of the book *TCP/IP over ATM Networks* (Artech House). He has taught many short courses to industry in the area of computer and telecommunication networking. His research has been supported by state and federal agencies including NASA (USA), the Ohio Board of Regents (USA), and DITARD (Australia). He has more than 100 refereed publications in the above areas, most of which can be accessed at http://www.cs.ou.edu/~atiq