

A Markov-Based Packet Dropout Model for UAV Wireless Communications

Yifeng Zhou, Jun Li, Louise Lamont, Camille-Alain Rabbath

Abstract—In this paper, we study the problem of modeling packet dropout for unmanned aerial vehicle (UAV) wireless communications. A Markov model is proposed, which incorporates the effects of Ricean fading. Unlike the classic Markov channel models, the proposed model is a two-state hidden Markov model with each state being associated with a time-varying packet error rate. The model is able to capture the non-stationary packet dropout characteristics of wireless channels. Intuitively, we use the time-varying packet error rate associated with the channels to describe the non-stationary nature of the packet dropouts, and the two-state Markov model to capture the correlation of the packet dropouts. A closed-form solution is provided for estimating the model parameters from network packet traces. Computer simulations and analysis are carried out to demonstrate the performance and effectiveness of the proposed model.

Index Terms—*ad hoc* networking, wireless networks, channel modeling, UAV, Ricean fading, Markov chain, non-stationary statistics

I. INTRODUCTION

Channel modeling has been widely used in the areas of wireless communication to study the behavior of wireless transmissions. Channel models can be used for simulation and analysis of communication and networking systems. Network simulators rely on mathematical channel models to produce data traffics that are representative of the statistical behaviors of real data traffics. Accurate channel models are essential to the understanding of network behavior and to the design of communication protocols. For example, the performance of an automatic repeat-request (ARQ) protocol is shown to depend on statistical behaviors of packet loss over a link [1]. Many network applications such as streaming audio and video also benefit from a better understanding of the underlying network behavior. In UAV applications, channel modeling has more recently attracted lots of interest from researchers and engineers in the area of networked control systems (NCS) owing to the rapid development of wireless communication technologies [2]. An NCS is a feedback control system that consists of spatially distributed components, and the control loops are closed over a wireless communication network. NCS has become increasingly popular in many applications such as traffic control, mobile robotics and collaborative networked

UAV operations *etc* [3]. Classical control theory has been focusing on the study of interconnected dynamical systems under ideal channel assumptions, *i.e.*, systems are synchronized in time, data between sensors, actuators and controllers are exchanged without loss and time delays, and data is sampled uniformly with ignorable jitters. These assumptions, however, are not valid for NCS with wireless links due to the use of shared wireless links with limited bandwidth and imperfect channel conditions. Wireless links are known to be prone to errors and failures. Packet dropouts occur due to a number of factors that may include occasional hardware failures, degradation in link quality, and channel congestion *etc*. Although many network protocols have re-transmission mechanisms embedded, for real-time feedback control data, it may be advantageous to discard the failed packets on their first transmission because re-transmitted packets may have too large latency to be useful [4]. Re-transmission may also delay the transmission of new packets. In a typical NCS, due to limited computing power of the communication modules, error correction techniques are not common on the lower network levels. One of the challenges for NCS applications is the stability analysis of the control systems and how the overall control system's performance degrade in the presence of packet dropouts. All these require accurate modeling of the wireless links and detailed understanding of their error behavior.

In this paper, we focus on wireless channel modeling for packet dropouts for UAV applications. In general, there are two types of approaches for modeling packet dropouts for wireless applications. The first approach is to derive a channel model by computing the signal-to-noise (SNR) ratio based on the channel conditions [6] [5]. In theory, this type of models is optimum since they allow for accurate reproduction (depending on the chosen model complexity) of radio propagation between a transmitter and a receiver. However, they are computationally complex for network simulations, since they would involve the simulations of modulation, transmission, reception and demodulation of huge amounts of packets with each containing thousands of bits. Furthermore, the performance of these models depends on the accuracy of the propagation and receiver models assumed. The second approach is to construct channel models from simulated or collected network traffic traces [7] [8] [5] [9] [10] [12]. The resulting mathematical models are able to provide a simple but approximate solution. In this approach, certain models are selected, which contains a set of unknown parameters. The model parameters are then estimated

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using simulated or collected network traffic data. This approach requires that appropriate models be selected and representative network traffic data be available. The Bernoulli model (independent channel model) and the Gilbert-Elliott model are the two most popular models for wireless channels [7] [8]. The Gilbert-Elliott model is able to more accurately represent wireless channels with burst errors. These models, however, are based on the assumption that the error statistics are stationary over time, and are not suitable for UAV applications. UAVs typically have good line-of-sight (LOS) conditions between them, and there usually exists a dominant direct path between two UAVs. In addition, wireless links between UAVs experience time-varying effects due to the highly dynamic movements. In other words, the error statistics of the wireless channels exhibit non-stationarity. In [10], Konrad *et al.* studied the time-varying effects of wireless channels, and demonstrated that time-varying effects result in wireless traces with non-stationary behavior over small window sizes. They presented a Markov-based Trace Analysis (MTA) algorithm that extracts stationary components. The stationary components are each modeled independently using a two-state Markov model. A more recent result is the model proposed by Kung *et al.*, where the authors used a finite-state model to predict the performance of the Transmission Control Protocol (TCP) over a varying wireless channel between a UAV and ground nodes [11]. By capturing packet run-length and gap-length statistics at various locations on the flight path, a location-dependent model was proposed to predict TCP throughput over a varying wireless channel. The model was trained by using packet traces from flight tests in the field and validated by comparing TCP throughput distributions for model-generated traces against those for actual traces randomly sampled from field data. Both approaches are able to show improved performance in generating artificial traces that closely match collected traces' statistics. However, since these approaches are *ad hoc* and the resulting models are application specific, they have limited applications.

In this paper, we propose a novel channel model that is capable of handling the non-stationary packet dropout characteristics for UAV applications. A two-state Markov model is proposed, which incorporates the effects of Ricean fading. Unlike the classic Markov channel models, a time-varying packet error rate is associated with each channel state. The model is able to capture the non-stationary packet dropout characteristics of the channels. Intuitively, we use the time-varying packet error rate associated with the channels to describe the non-stationary nature of the packet dropouts, and the two-state Markov model to capture the correlation of the packet dropouts. A closed-form solution is provided for estimating the model parameters from packet traces. The new model has the advantages of flexibility and simplicity, and is suitable for modeling UAV wireless channels. The rest of paper is organized as follows. In Section II, some commonly used channel models for wireless channels are

discussed, which include the Bernoulli model and the Markov chain governed models. Section III is devoted to the development of the new Markov model for packet dropout for UAV applications. A closed-form solution is provided for estimating the model parameters from a trace of packets. Finally, in Section IV, computer simulations and analysis are carried out to demonstrate the performance and effectiveness the proposed model.

II. PACKET DROPOUT MODELS

In this section, we discuss some of the common channel models for wireless communications including the Bernoulli model and the Markov governed models. Note that traditional channel models have been mostly developed at the bit or symbol level. Bit level channel models are computationally complex for network simulation purposes because modulation/demodulation and detection need to be performed for each bit transmitted. For a network of multiple nodes, the run-time of networking simulations would increase by orders of magnitude. Thus, from the point of view of computational complexity, it is desirable to develop channel models at the packet level for network simulations. Packet level channel models have the advantage of computational efficiency since simulation of networking protocols only requires a few simulation events for each packet instead of each bit. In addition, since most networking protocols are implemented at the packet level, there is considerable interest in studying the error statistics at the packet level. However, development of accurate channel models at the packet level is difficult since packet errors or dropouts depend not only on channel conditions but also on source characteristics and packet length distribution. For that reason, channel models constructed at the packet level are usually considered an approximate solution.

A. Bernoulli Model

The Bernoulli model is based on the use of the Bernoulli process in probability and statistics. A Bernoulli process is a sequence of independent identically distributed (*i.i.d.*) trials, where each trial has a probability of failure, p , and a corresponding probability of success, $(1 - p)$ [13]. The Bernoulli model has the advantage of simplicity and is mathematically tractable for analysis. However, the Bernoulli model is a memoryless model and is not capable of characterizing the correlation among packet dropouts.

B. Markov Models

In practice, packet dropouts are correlated or occur in bursts. When a packet dropout occurs, it is likely that the next packet is a dropout. Packet dropouts are caused mainly by receiver faults and channel conditions such as degraded link quality and channel congestions. Since channel conditions typically change at a slow pace when compared to packet transmission rate, packet dropouts are likely to occur in bursts. Markov models for burst

errors have been widely used in the past for modeling and simulation of communication systems. One popular model is the Gilbert-Elliot (G-E) model [7] [8]. The G-E model uses a two-state discrete Markov process. The two states are referred to as the good and the bad state, respectively. Each state corresponds to a specific channel condition, and is assigned an independent error probability that represents the channel quality. The Markov process is characterized by transition probabilities, p_{gg} , p_{gb} , p_{bb} and p_{bg} , which denote the one-step transition probabilities of staying in the good state, from the good to the bad state, staying in the bad state, and from the bad to the good state, respectively. In addition,

$$p_{gg} = 1 - p_{gb}, \quad p_{bb} = 1 - p_{bg}. \quad (1)$$

The parameters p_{gb} and p_{bg} are also referred to as the failure and the recovery rate, respectively. In general, a large p_{bg} and a small p_{gb} means that the state of the Markov process is more likely to stay in the good state. The independent error probabilities associated with the good and the bad state are denoted by p_g and p_b , respectively. The error probabilities identify the quality of their associated channels or states. They are determined by frequency, waveforms, fading and environmental conditions. This class of Markov models is also referred to as a Hidden Markov Model (HMM) [14] since the channel state is hidden and only observable through the status of the packets. For a time-homogeneous Markov process, there exist stationary distributions that describe the probabilities of the process staying in each state when $t \rightarrow \infty$ (or the process is in the steady state). The stationary distributions for the good and the bad state are given by [13]

$$\pi_g = \frac{p_{bg}}{p_{gb} + p_{bg}} \quad \text{and} \quad \pi_b = \frac{p_{gb}}{p_{gb} + p_{bg}}, \quad (2)$$

respectively. The mean error rate, which has been traditionally used in the area of networking, is related to the limiting probabilities by

$$p_e = \pi_g p_g + \pi_b p_b. \quad (3)$$

The correlation or burst status of packets are characterized by the transition probabilities of the Markov process. Consider the state sojourn time for the two-state Markov process. The sojourn time of a state is defined as the time duration that the process remains in the state. The sojourn time of a state can be shown to be geometrically distributed [13], and the mean sojourn time of the good and the bad state is given by

$$T_g = \frac{1}{1 - p_{gg}} \quad \text{and} \quad T_b = \frac{1}{1 - p_{bb}}, \quad (4)$$

respectively. It should be noted that the Bernoulli model is a special case of the G-E model, where the transition

probability matrix has identical rows, and the error probabilities are $p_g = 0$ and $p_b = 1$.

The Markov model contains unknown parameter, *e.g.*, the transition probabilities and the error probabilities associated with each state. In the construction of a channel model, one of the major tasks is to determine the model parameters from observed error traces so that the resulting channel model can represent the underlying channel characteristics accurately. Gilbert [7] considered the special case of an error-free good state with $p_g = 0$. In his method, the model parameters are estimated using three measurements of a binary error process. This method is effective for long traces of traffic and may fail to provide meaningful results for short traces [15]. Yajnik [16] considered a simplified Gilbert method, where $p_g = 0$ and $p_b = 1$, and estimated the transition probabilities using a maximum likelihood estimator. In [9] [17], a more intuitive way was used for estimating the model parameters by assuming error free state, and measuring the average error rate and error length of an error process. In [18], improved results were obtained by treating the G-E model as an HMM and applying the Baum-Welch algorithm [14]. The Baum-Welch algorithm consists of a recursive procedures for computing the maximum likelihood state sequence corresponding to a given observation sequence (the error process) [18] [19] [14]. A shortcoming of the Baum-Welch algorithm is that the algorithm is computationally intensive. In [19], a faster procedure was proposed for estimating the parameters of Markov models for burst errors from a given observation sequence. The method is based on the decomposition of an arbitrary transition matrix into a unique block diagonal transition matrix.

The G-E model contains two states and may not be suitable when the channel quality varies dramatically. The use of a finite state Markov model [5] is seen to be a natural extension. In [20] [21], experiments were shown, which support the use of the finite state model for wireless links. In [5], by partitioning the range of the received SNR into a finite number of intervals, a finite state Markov model was constructed for the case of BPSK signals over Rayleigh fading channels. The model parameters are then obtained based the physical channel properties and error statistics. In general, the problem of determining the parameters of a finite state Markov model can be considered the one of estimating the parameters of an HMM. The Baum-Welch algorithm and techniques that are based on gradient-search principles [22] can be applied. Computationally efficient algorithms are available when certain HMM model structures are assumed. The Fritchman model, for example, assumes that a channel can be in one bad state and more than one good states.

III. MODELING PACKET DROPOUT FOR UAV APPLICATIONS

In this section, we propose a Markov model for packet dropout for UAV applications. The model combines a

two-state Markov model and the effects of the Ricean fading, which is typically observed in multiple UAV scenarios.

A. Wireless Channel and Ricean Fading

Wireless channels in UAV applications have two unique characteristics. First, the error statistics of the wireless channels are non-stationary. As discussed before, traditional channel models all assume that the packet error statistics are constant over time. For UAVs, the error statistics (*e.g.*, error rate) varies as the distance between a pair of UAVs changes. Secondly, UAVs have relatively good LOS conditions between them, and there is typically a direct path between a pair of UAVs and scattering is considered less significant. The existence of a direct path means that the received power caused by the direct path will be dominant, and the received signal power depends on the relative locations of the transmitting and receiving UAVs. Multipath effects may exist when UAVs fly in low altitudes, and signals may arrive at the receiver from different paths due to reflection from ground and other UAVs. There are various models for multipath effects in radio propagation in the literature including Rayleigh fading, Ricean fading and Nakagami model [23]. In general, Rayleigh fading is suitable for modeling channels when there is no dominant LOS propagation between a transmitter and a receiver while Ricean fading is applicable to scenario where there is a strong LOS path. For UAV applications, Ricean fading is seen to be an appropriate model for describing the wireless channels.

In Ricean fading, the amplitude of the received signal is characterized by a Rice distribution with parameters [24]

$$\nu^2 = \frac{\mathcal{K}}{1 + \mathcal{K}} \quad \text{and} \quad \sigma^2 = \frac{\Omega}{2(1 + \mathcal{K})}, \quad (5)$$

where \mathcal{K} is the ratio of the received signal power in the direct path to that from the scattered paths, and Ω denotes the mean of the total received signal power. When $\mathcal{K} = 0$, the Ricean fading model turns into the Rayleigh fading model, and $\mathcal{K} = \infty$ means that the does not have fading at all. For a Ricean fading channel, the Rice distribution for the received amplitude can be written as

$$f_R(r) = \frac{r}{\sigma^2} \exp \left\{ -\frac{r^2 + \nu^2}{2\sigma^2} \right\} I_0 \left(\frac{r\nu}{\sigma^2} \right), \quad (6)$$

where I_0 denotes the 0th order modified Bessel function of the first kind. From the propagation theory of electromagnetic waves, it is known that the power of electromagnetic waves attenuates as they propagate. In free space, the power of propagated electromagnetic signal decays proportional to d^2 , where d denotes the distance between transmitter and receiver. In real world, RF signal propagation varies depending on the environment and is affected by many factors such as multipath and shadowing [23]. Shadowing refers to the power attenuation of signal

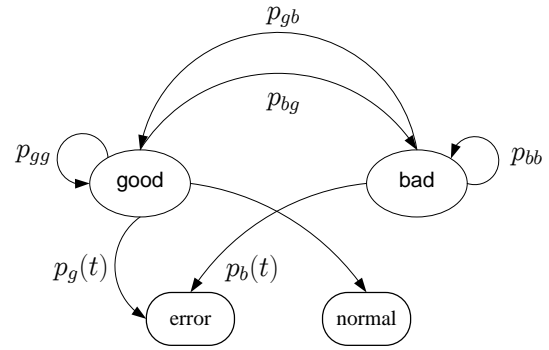


Figure 1. State transition diagram of the proposed two-state Markov process.

due to obstructions between the transmitter and receiver. Signals must pass through or diffract around the objects to arrive at the receiver. The mean received signal power in the direct path is determined by the distance between transmitter and receiver and can be computed as [23]

$$P(d) = P_0 \left(\frac{d}{d_0} \right)^{-\alpha}, \quad (7)$$

where α is the path-loss exponent used to represent the non-ideal environment, d_0 is a reference distance from the transmitter and P_0 is the received power level at the reference distance d_0 . The path-loss exponent α is typically between 2 and 4, and $\alpha = 2$ represents the ideal free space model [23]. In UAV applications, since UAVs typically have good LOS conditions between them, the free space model, $\alpha = 2$, is considered a reasonable propagation model and can be used to compute the received signal power in the direct path.

B. Markov Based Channel Model

The proposed Markov model consists of two states: a good and a bad state. When the channel is in the bad state, the probability of packet drops, or the error rate associated with the bad state, is 1. When the channel is the good state, however, the associated error rate is determined by the Rice distribution assuming that the channels are Ricean fading. Figure 1 is the block diagram of the two-state Markov model.

The two-state Markov is similar to the classic model except that in the proposed model, the associated error rates are time-varying. Intuitively, the time-varying error rates are used to describe the time-varying nature of packet dropout due to the relative movements of the UAVs while the Markov model captures the correlation of the packet dropouts. By doing so, the Markov process is able to provide improved accuracy of modeling the channel states.

Given the distance between a pair of UAVs, d , the mean received signal power via the direct path can be computed by (7). If the channel is assumed to be Ricean fading, the PDF of the amplitude of the received signal at the receiver is given by (6). Since the Ricean distribution depends on the received signal power in the direct path and the

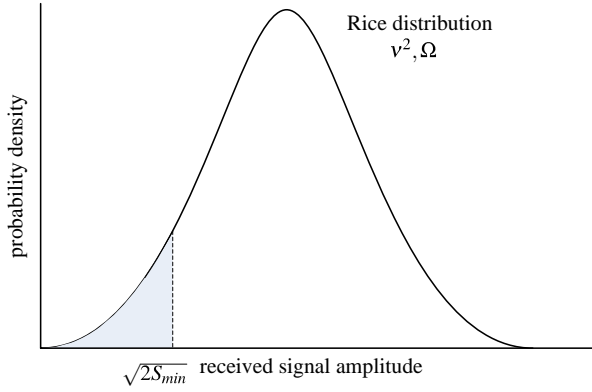


Figure 2. Rice distribution and the error probability associated with the good state.

ratio \mathcal{K} , we use $f_R(r | P(d), \mathcal{K})$ to denote the Ricean distribution function. Denote the receiver sensitivity by S_{min} . The sensitivity of a receiver is normally taken as the minimum input signal required to successfully produce a desired output signal. The error probability is computed as the following cumulative distribution function (CDF)

$$p_g(t) = \int_{-\infty}^{\sqrt{2S_{min}}} f_R(r | P(d), \mathcal{K}) dr. \quad (8)$$

The error probability $p_g(t)$ can be written as [25]

$$p_g(t) = 1 - Q_1\left(\frac{\nu}{\sigma}, \frac{\sqrt{2S_{min}}}{\sigma}\right), \quad (9)$$

where Q_1 is the Marcum Q -function. In Figure 2, the error probability $p_g(t)$ is the shaded area between $(-\infty, a]$ under the PDF curve. Assuming that the Markov process in Figure 1 is time-homogeneous, then, limit distributions exist for the good and the bad state, which are given

$$\pi_g = \frac{p_{bg}}{p_{gb} + p_{bg}} \text{ and } \pi_b = \frac{p_{gb}}{p_{gb} + p_{bg}}, \quad (10)$$

respectively. The average error rate can be computed as

$$p_e = \frac{1}{N} \sum_t [\pi_g p_g(t) + \pi_b] = \varphi_0 \pi_g + \pi_b, \quad (11)$$

where N is total number of observations and

$$\varphi_0 = \frac{1}{N} \sum_t p_g(t) \quad (12)$$

is the averaged $p_g(t)$ over time. Denote the observation sequence as

$$\{x(t); t = 1, 2, \dots, N\},$$

where $x(t) = 1$ indicates that the corresponding packet is successfully transmitted at time instance t , and $x(t) = 0$ means that the packet is a dropout. Let $s(t)$ denote the Markov state corresponding to $x(t)$, where $s(t)$ takes the value of 1 or 0, indicating that the corresponding state is in the good and the bad state, respectively. In the following, we show that, given a sequence of trace

observation, the parameters of the Markov model can be estimated based on two statistical parameter estimates: average packet dropout rate and the correlation coefficient of packet dropout. The average packet dropout rate can be approximated by

$$\hat{\epsilon} = 1 - \frac{1}{N} \sum_{t=1}^N x(t) = \varphi_0 \pi_g + \pi_b. \quad (13)$$

where $\hat{\epsilon}$ is the averaged packet error rate from the packet trace. Equation (13) can be re-written in terms of p_{gg} and p_{bb} as

$$a_0 p_{gg} + (a_0 - 1) p_{bb} = 2a_0 - 1, \quad (14)$$

where $a_0 = (1 - \hat{\epsilon}) / (1 - \varphi_0)$. In order to solve for the model parameters p_{gg} and p_{bb} , a second relation is required. Consider the following expectation

$$\begin{aligned} \mathbb{E}\{x(t)x(t+M)\} &= \mathbb{E}\{\mathbb{E}\{x(t)x(t+M) | x(t)\}\} \\ &= \mathbb{E}\{x(t)\mathbb{E}\{x(t+M) | x(t)\}\} \\ &= \pi_g [1 - p_g(t)][1 - p_g(t+M)] p_{gg}. \end{aligned} \quad (15)$$

where $x(t)$ and $x(t+M)$ correspond to two adjacent state of the Markov process (M packets are assumed between two adjacent states). From the packet trace, we can estimate the correlation as

$$\hat{r} = \frac{1}{N-M} \sum_{t=1}^{N-M} x(t)x(t+M) = \pi_g p_{gg} \varphi_1, \quad (16)$$

where

$$\varphi_1 = \sum_{t=1}^{N-1} [1 - p_g(t)][1 - p_g(t+1)]. \quad (17)$$

From (13) and (16), we can obtain the following quadratic equation in p_{gg}

$$-\frac{a_0 \varphi_1}{a_0 - 1} \cdot p_{gg}^2 + \frac{a_0 \varphi_1 + \hat{r}}{a_0 - 1} \cdot p_{gg} - \frac{\hat{r}}{a_0 - 1} = 0. \quad (18)$$

It can be verified that quadratic equation (18) has two roots with one being identically equal to 1. Since p_{gg} is a probability, it is positive and less than one. It follows that the estimate of p_{gg} is given by

$$\hat{p}_{gg} = \frac{\hat{r}}{a_0 \varphi_1},$$

and p_{bb} can be obtained from the linear relationship (14)

$$\hat{p}_{bb} = -\frac{a_0}{a_0 - 1} \cdot \hat{p}_{gg} + \frac{2a_0 - 1}{a_0 - 1}. \quad (19)$$

IV. COMPUTER SIMULATION STUDY

In this section, we use computer simulations to demonstrate the effectiveness and performance of the proposed Markov models for simulating packet dropout for UAV applications. Two UAVs are simulated with their initial positions at the origin of the coordinate system and (4000, 0) m, respectively. Both UAVs are assumed to move at a speed of 80 km/h or 22.22 m/s. Their heading directions are simulated to be $\pi/2$ and $3\pi/4$, respectively, with reference to the x axis.

The transmission rate is assumed to be 2Mbps, and the packet size is 512 bytes. A slot is defined, which consists of a number of packets. The Markov model changes its state only at slot boundaries. The distance between the two UAVs is sampled in a time interval of Δ . In the simulation, Δ is assumed to be equal to the length of 5 slots. The transmission power of the communication module on each UAV is assumed to be 2 watts, which is measured at one meter from the transmitter. The ideal free space model is used for signal propagation. The Ricean factor \mathcal{K} is selected to be 10, which is also 10 in dB. The transition probabilities of the Markov model are given by $p_{gg} = 0.995$ and $p_{bb} = 0.96$. The initial state is selected to be in the good state.

Figure 3 shows how error statistics of packet dropout change with the distance between two UAVs. In the simulation, Δ is about 0.4 seconds, and the total number of Δ is 2500. The duration of the packet trace is 976.56 seconds. Figure 3(a) shows the variation of distance between the two UAVs as they move along. Figure 3(b) plots the variation of the received power level in dBm versus time. The red line in the figure indicates the receiver sensitivity, which is -50 dBm in this case. Due to the effects of Ricean fading, the received signal power perturbs around its mean values. In general, the received signal power decreases as the distance between the UAVs increases. Figure 3(c) shows the error probability associated with the good state versus time. The error probability increases as the distance between the UAVs increases. When the received signal power is close to and below the receiver sensitivity, the error probability is seen to approach 1. This shows that the packet trace simulated for UAVs has non-constant error statistics over time. The non-constant phenomenon can be further observed from the averaged packet dropout rate versus time in Figure 3(d), where the averaged packet dropout rate is computed by sliding a window consisting of 3125 packets. The packet dropout rate varies over time as the distance between UAVs changes. Again, when the UAVs are far away, the packet dropout rate approaches 1.

Figures 4 and 5 show the sample means and root mean squared errors (RMSE) of the estimated transition probabilities, P_{gg} and P_{bb} , versus the receiver sensitivity. The popular Gilbert method is used for the purpose of comparison. The Gilbert method assumes that one state of the Markov model is error free and the other state has a constant but unknown error rate. The receiver sensitivity varies from -40 to -50 dBm with a step size of -1

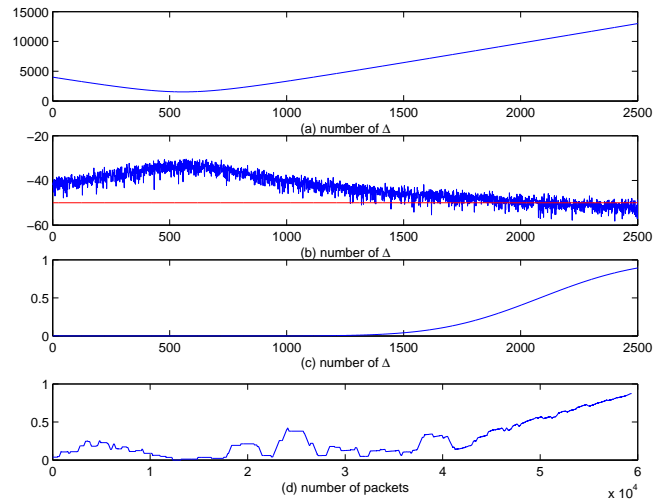


Figure 3. Variation of error statistics of packet dropout versus distance between two UAVs.

dBm. The duration of the packet trace is 1000Δ , which is about 390.63 seconds. The packet trace consists of 25000 packets. The link speed is assumed to be 256 kbps. Figures 4(a) and (b) plot the means of the estimated p_{gg} and p_{bb} by the proposed approach and the Gilbert method. The probability estimates by proposed approach are seen to be unbiased while the estimates by the Gilbert method are biased when the receiver sensitivity is low. At high receiver sensitivity levels, both methods are able to produce unbiased estimates. Intuitively, when the receiver sensitivity is high, the error probability associated with the good state tends to be small and the all states have near-constant error probability. The Gilbert method still works since all the assumptions are not completely invalid. However, when the receiver sensitivity is low, the Gilbert method tends to produce biased estimates due to the fact that the error probability associated with the good state varies over time. The estimates are usually underestimated due to its inability of isolating the error statistics of the trace from the Markov process. Figure 5(a) and (b) plot the RMSEs of the estimated p_{gg} and p_{bb} by the proposed approach and the Gilbert method. It shows that the proposed approach outperforms the Gilbert method with lower RMSEs at low receiver sensitivities.

Figures 6 and 7 show the sample means and RMSEs of the estimated transition probabilities, respectively, versus the number of packets. The number of Δ is fixed to 200, and the time duration of the packet trace is 312.5 seconds. The variation of the number of packets is achieved by varying the number of packets in each slot from 1 to 20. Since the total time of the packet trace is fixed, the variation of the packets in a slot means changes of link speed. The link speed varies from 12.8 kbps to 256 kbps. The receiver sensitivity is assumed to be -40 dBm. In Figures 6(a) and (b), the proposed solution is able to produce unbiased estimates for p_{gg} and p_{bb} for all numbers of packets (except for P_{gg} when the number of packet is 100). The Gilbert method, on the

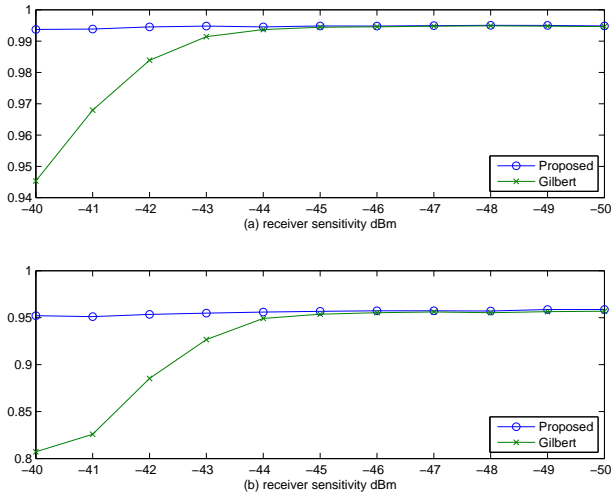


Figure 4. Sample means of the estimate transition probabilities.

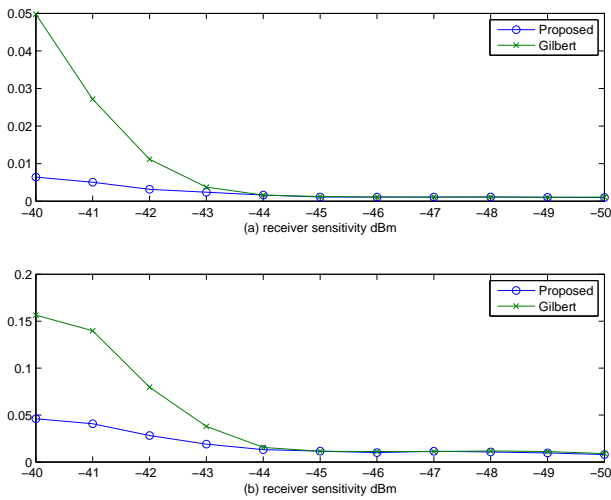


Figure 5. RMSE of the estimated transition probabilities.

other hand, produces biased estimates for all numbers of packets. The biased estimates by the Gilbert method may be partially due to the low receiver sensitivity, which results in time-varying error probabilities associated with the good state. The proposed approach outperforms the Gilbert method with smaller RMSEs for p_{gg} , as shown in Figures 7(a). The two methods both perform well for p_{bb} as the number of packet increases. However, the proposed solution outperforms the Gilbert method for low numbers of packets, indicating that the proposed solution is more robust.

V. CONCLUSIONS

In this paper, the problem of packet dropout modeling for UAV communications was discussed. A novel model was proposed, which is able to capture the non-stationary characteristics of wireless channels between UAVs. A closed-form solution is provided for estimating the model parameters. The proposed model has the advantages of flexibility and simplicity, and is suitable for modeling

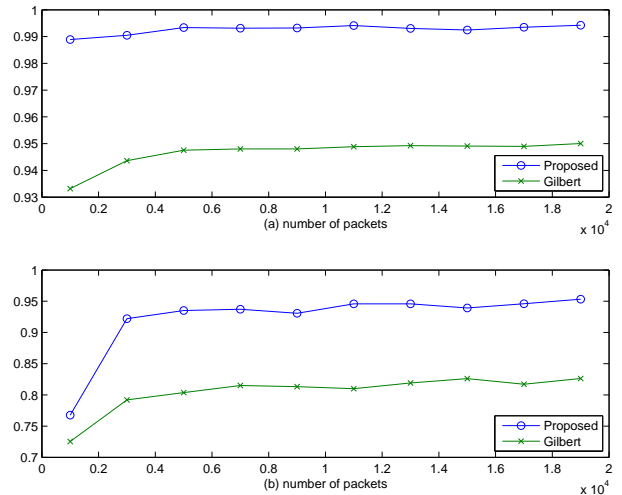


Figure 6. Sample means of the estimated transition probabilities versus number of packets.

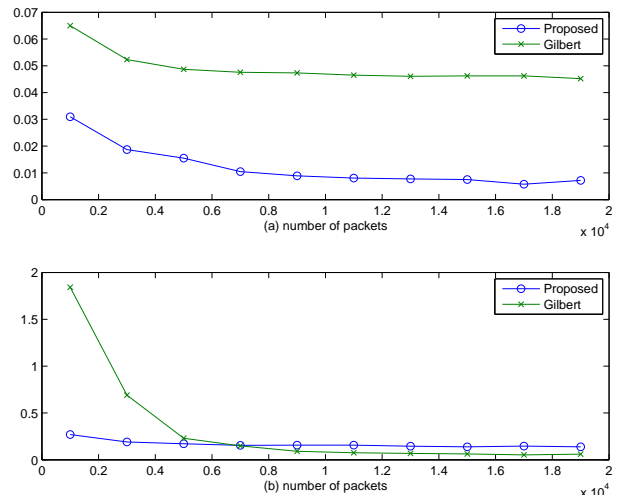


Figure 7. RMSE of the estimated transition probabilities versus number of packets.

wireless channels in UAV applications. Computer simulations were carried out and compared to the popular Gilbert method. The simulation results showed that the proposed solution outperformed the Gilbert method in the estimation of model parameters. From the simulation viewpoint, the proposed model is able to simulate packet dropouts with non-stationary error statistics.

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