Modeling of Packet Dropout for UAV Wireless Communications

Yifeng Zhou Jun Li Louise Lamont
Communications Research Centre
3701 Carling Ave. Ottawa, Ontario, K2H 8S2 Canada
{yifeng.zhou,jun.li,louise.lamont}@crc.gc.ca

Camille-Alain Rabbath
Defence Research and Development Canada Valcartier
2459 Boul. Pie XI North, Quebec, QC, G3J 1X5 Canada
camille-alain.rabbath@drdc-rddc.gc.ca

***Abstract*—In this paper, we investigate the problem of channel modeling of packet dropout for unmanned aerial vehicle (UAV) communications. A two-state Markov model is proposed, which incorporates the effects of Ricean fading. The proposed model is able to capture the non-stationary packet dropout characteristics of the channels. A closed-form solution is provided for estimating the model parameters from packet traces. Computer simulations and analysis are carried out to demonstrate the performance and effectiveness of the proposed model.**

I. Introduction

Channel modeling has been widely used in wireless communication areas to study the behavior of wireless transmissions. Channel models are usually constructed based on simulated or collected network traffic traces. They can be used for further analysis and simulation of communication systems. In this paper, we focus on the problem of channel modeling, in particular modeling of packet dropout, for UAVs connected with wireless links. While UAV applications such as streaming audio and video can benefit from a better understanding of the underlying network behavior, channel modeling has 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 [1].

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* [2]. 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 [3]. 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.

There are in general two types of approaches for modeling packet dropouts. The first approach is to derive a channel model by computing the signal-to-noise (SNR) ratio based on the channel conditions [5]. The second approach is to construct channel models from simulated or collected network traffic traces [6][7][4][8][9][11]. The Bernoulli model (independent channel model) and the Gilbert-Elliot model are the two most popular models for wireless channels [6][7]. The G-E 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 particular, 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 [9], 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 an algorithm that extracts stationary components, which are each modeled independently using a two-state Markov model. A more recent result is the model proposed 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 [10]. 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 it by comparing TCP throughput distributions for model-generated traces against

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those for actual traces randomly sampled from field data. In this paper, we propose a new model for packet dropouts, which combines a two-state Markov model and the effects of Ricean fading. The proposed model is able to capture the non-stationary characteristics of a wireless channel. A closed-form solution is provided for estimating the model parameters. 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, which include the Bernoulli model and the Markov governed models. Traditional channel models have been mostly developed at the bit or symbol level. The development of channel models at packet level or block level are difficult because the models would depend not only on channel conditions but also on source characteristics and packet length distribution. Modeling at the bit level, however, involves heavy computational burden, making it less tractable to networking simulations.

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, $(1-p)$ [12]. 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 [6][7]. 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,

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

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) [13] 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 $t \to \infty$ (or the process is in the steady state). The stationary distributions for the good and the bad state are given by [12]

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

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

$$p_e = \pi_g p_g + \pi_b p_b. \tag{3}$$

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 [12], and the mean sojourn time of the good and the bad state is given by

$$T_g = \frac{1}{1 - p_{gg}} \text{ and } T_b = \frac{1}{1 - p_{bb}} \tag{4}$$

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 channel modeling and simulation, one of the major tasks is to determine the model parameters accurately from observed error trace, and use these model for further analysis and simulation. Gilbert [6] 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 [14]. Yajnik [15] considered a simplified Gilbert method, where $p_g = 0$ and $p_b = 1$, and estimated the transition probabilities using a maximum likelihood estimator. An intuitive way for estimating the Markov model parameters is by assuming error free state and determining the state transition parameters by measuring the average error rate and error length of an error process [8][16]. Improved results can be obtained by treating the G-E model as an HMM and applying the popular Baum-Welch algorithm [17][13]. The Baum-Welch algorithm is computationally intensive. In [18], Sivaprakasam proposed a fast procedure 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 [4] is seen to be a natural extension. In [19][20], experiments were shown, which support the use of the finite state model for wireless links. In [4], 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 [21] 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. A Packet Dropout Model 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, the traditional channel models all assume that the 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 [22]. In general, Rayleigh fading is suitable for modeling channels when there is no dominant LOS propagation between the transmitter and 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.

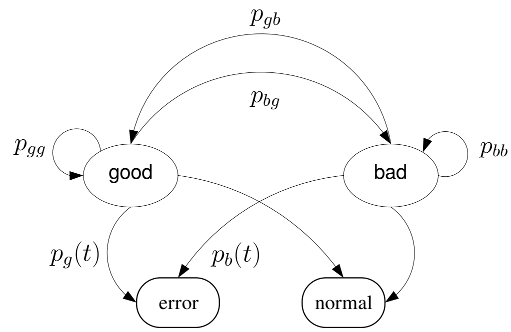

Fig. 1. State transition diagram of the proposed two-state Markov process.

In Ricean fading, the amplitude of the received signal is characterized by a Rice distribution with parameters [23]

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

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.

The power of electromagnetic waves is known to attenuates as they propagate. In real world, the propagation of electromagnetic waves varies depending on the environment and is affected by many factors. Multipath signals and shadowing are considered two major environment-dependent sources that affect the received signal power [22]. In the presence of shadowing and multipath, the ensemble mean received power decays proportional to $d^{-\alpha}$, where d is the distance between the transmitter and the receiver and α is the path-loss exponent that represents the non-ideal environment [22]. 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 a 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. Fig. 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. 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. For Ricean fading channels, the error probability can be computed by

$$p_g(t) = 1 - Q_1(\frac{\nu}{\sigma}, \frac{\sqrt{2S_{min}}}{\sigma}), \tag{6}$$

where Q_1 is the Marcum Q-function [24]. The average error rate can be computed as

$$p_e = \frac{1}{N}\sum_t [\pi_g p_g(t) + \pi_b] = \varphi_0 \pi_g + \pi_b \tag{7}$$

where N is total number of observations and φ_0 is the averaged $p_g(t)$ over time. Denote $\{x(t);\ t = 1, 2, \ldots, N\}$ as the observation sequence, 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

$$\hat{\epsilon} = 1 - \frac{1}{N}\sum_{t=1}^{N} x(t) = \varphi_0 \pi_g + \pi_b. \tag{8}$$

where $\hat{\epsilon}$ is the averaged packet error rate from the packet trace. Equation (8) can be re-written in terms of p_{gg} and p_{bb} as

$$a_0 p_{gg} + (a_0 - 1)p_{bb} = 2a_0 - 1, \tag{9}$$

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

$$\mathbb{E}\{x(t)x(t+M)\} = \pi_g[1 - p_g(t)][1 - p_g(t+1)]p_{gg}. \tag{10}$$

where $x(t)$ and $x(t+M)$ are from two adjacent state (each state is assumed contain M packets). From the pack trace, we can estimate the correlation as

$$\hat{r} = \frac{1}{N-M}\sum_{t=1}^{N-M} x(t)x(t+M) = \pi_g p_{gg} \varphi_1 \tag{11}$$

where

$$\varphi_1 = \sum_{t=1}^{N-1} [1 - p_g(t)][1 - p_g(t+1)]. \tag{12}$$

From (8) and (11), we can obtain the following quadratic equation in p_{gg}

$$-\frac{a_0\varphi_1}{a_0 - 1} \cdot p_{gg}^2 + \frac{a_0\varphi_1 + \hat{r}}{a_0 - 1} \cdot p_{gg} - \frac{\hat{r}}{a_0 - 1} = 0. \tag{13}$$

It can be verified that quadratic equation (13) has two roots with one being identically equal to 1 independent of the packet trace. 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 (9).

IV. Computer Simulation Study

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 packet size is 512 bytes. Each slot is assumed to consist of a number of packets, and the Markov model changes its state only at slot boundaries. The distance between the two UAVs is sampled in each time interval of Δ. Δ is assumed to be equal to the length of 5 slots. The transmission power of the communication module on a 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.

Fig. 2 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. Fig. 2(a) shows the variation of distance between the two UAVs as they move along. Fig. 2(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. Fig. 2(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 Fig. 2(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.

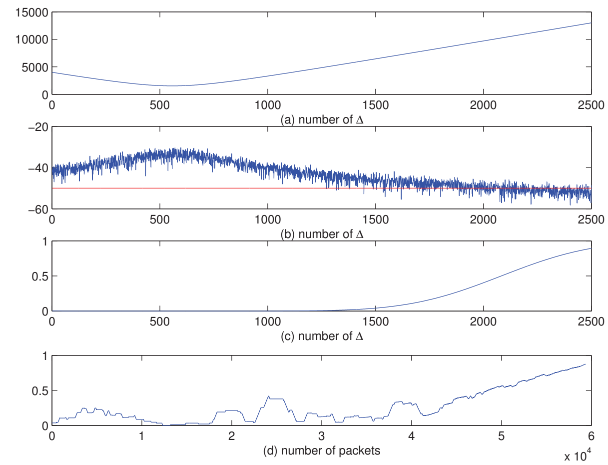

Fig. 2. Variation of error statistics of packet dropout versus distance between two UAVs.

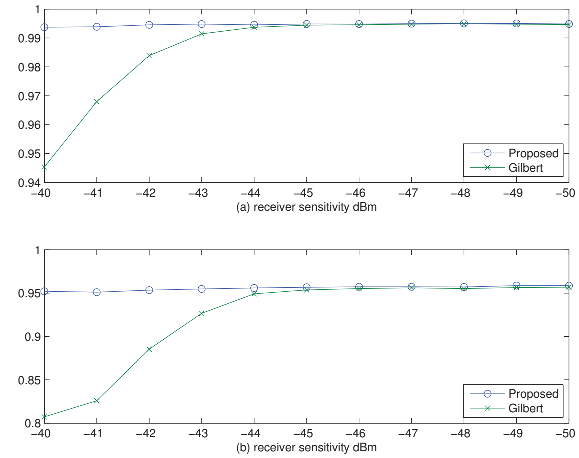

Fig. 3. Sample means of the estimate transition probabilities.

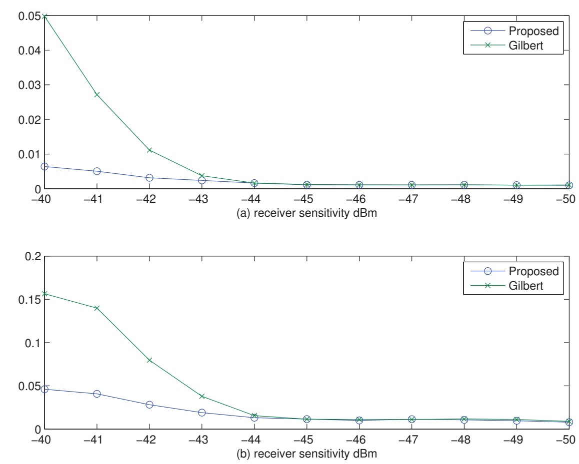

Fig. 4. RMSE of the estimated transition probabilities.

Figs. 3 and 4 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 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. Figs. 3(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 produced 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 under-estimated due to its inability of isolating the error statistics of the trace from the Markov process. Fig. 4(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.

Figs. 5 and 6 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 Figs. 5(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 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 Figs. 6(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

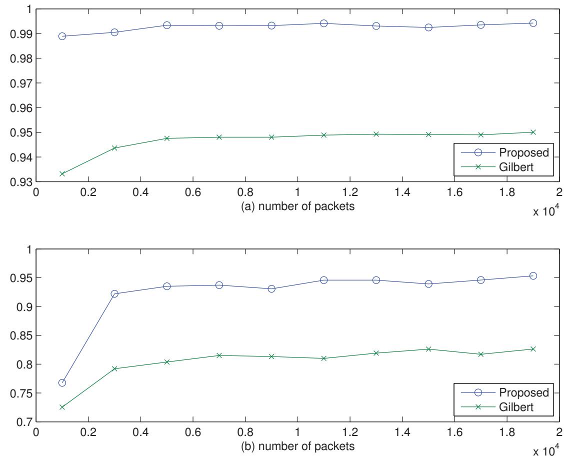

Fig. 5. Sample means of the estimated transition probabilities versus number of packets.

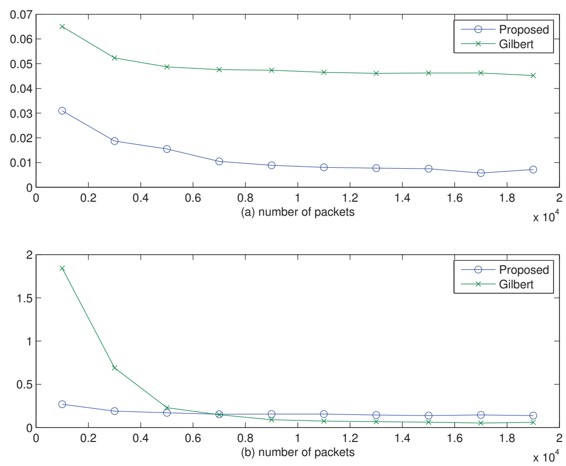

Fig. 6. RMSE of the estimated transition probabilities versus number of packets.

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 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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