Analysis of Queuing Behaviors with Self-similar Traffic in Wireless Channels

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***Abstract*—Many measurement studies showed that network traffic usually exhibits self-similar nature, meanwhile, wireless fading channels lead to the time-variant service rates of network nodes. Compared with classical queuing systems with Markov sources or constant service rates, the queuing system with self-similar input in a wireless fading channel is more complicated, and it is very difficult to obtain closed-form formulae for the queuing performances. In this paper, we study queuing behaviors with self-similar traffic input in wireless channels by establishing a queuing system model, and present a convenient and efficient algorithm to estimate the queue length distributions. Simulation results validate the accuracy of the proposed estimation algorithm. Finally, we analyze effective service rates of wireless channels based on the estimation algorithm, and draw some meaningful conclusions.**

***Index Terms*—self-similar traffic, wireless channel, queuing system, queue length distribution, estimation algorithm, effective service rate**

I. Introduction

With rapid development of wireless technology, demand for wireless data services is continuously increasing. How to provide quality of service (QoS) guarantees plays an important role in the design of wireless networks. Since queuing behavior is closely related to the QoS guarantees, it has attracted much attention as a research topic [1-7].

Since the characteristic of self-similarity of network traffic was found by Leland et al. in 1993 [8], a large number of study results indicate that network traffic in a variety of modern communication networks exhibits self-similar nature [9], such as in computer networks [10], in Ad hoc networks [11] and in wireless LANs [12]. As self-similar traffic exhibits scale-invariant burstiness, the analytical models developed under short-range-dependent traffic are no longer valid in the presence of self-similar traffic, for example, classical Markov-based queuing analysis is not suitable any more [13].

There have been many studies on queuing performance with self-similar traffic. Norros proposed the Fractional Brownian Motion (FBM) model to characterize self-similar traffic [14], and obtained the queue length distribution. The formulae of average queue length, queue length variance, average delay and jitter were derived in [3]. In [1], the loss probability with self-similar traffic in a finite partitioned buffer was analyzed. All the literatures above are based on the assumption that the service rates of the queuing systems are constant. However, in wireless environments, wireless features such as fading and Doppler spread lead to the variable channel capacity, that is to say, the service rate of the queue is a variable. Although [4] considered the variable service rate, which was characterized by a FBM process, the practical features and parameters of wireless channels were still not discussed.

In [6], [7], [15] and [16], the authors studied the queuing performances in practical fading channels based on the theories of effective bandwidth and effective capacity, but all of them didn't investigate the queuing behavior with self-similar traffic. Ref. [6] assumed that the source rate is constant, and [7] adopted an ON-OFF Markov source, which was also used in [15] and [16] with a first-order autoregressive (AR) source.

In this paper, we consider a wireless network model as shown in Fig. 1. The confluent traffic flow at node A exhibits self-similarity, and is forwarded to node B over a wireless channel. Our interest is focused on the queuing behavior of node A. We establish a queuing system model, based on which further analysis of queuing performances with self-similar traffic input in wireless channels is conducted, and then a convenient and efficient algorithm is proposed to estimate the queue length distributions. By taking samples of the queue, our estimation algorithm works well with no need for the source and the channel parameters. Then, we analyze effective service rates of different wireless channels based on the proposed estimation algorithm.

The rest of this paper is organized as follows: The queuing system model is introduced in section II. In section III, we study the queuing behaviors based on the model and present an estimation algorithm for the queue length distributions. Section IV validates the accuracy of the proposed estimation algorithm by simulation. We analyze effective service rates of wireless channels in section V. Finally, section VI concludes the paper and points out future research directions.

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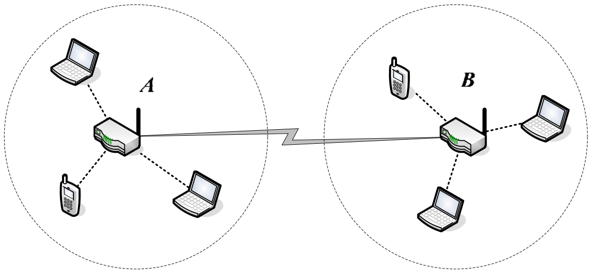


Figure 1. Wireless network model

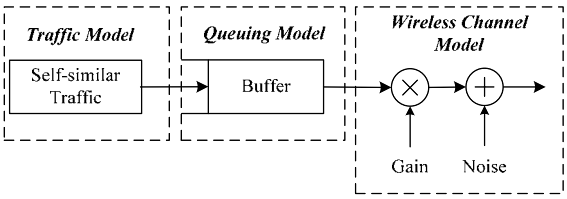


Figure 2. Queuing system model

II. QUEUING SYSTEM MODEL

To investigate the queuing behavior of node A in Fig. 1, we establish a queuing system model including three sub-modules: the traffic model, the queuing model and the wireless channel model, as shown in Fig. 2. We will specify these three sub-modules respectively.

A. Self-similar Traffic Model

Many analytical models have been developed to characterize self-similar traffic flows. Among these models, FBM model is identified as an efficient way [1], [3], [4], [14], and hence adopted in this paper. A FBM traffic flow [14] can be expressed as:

$$A(t) = mt + \sqrt{am} Z_H(t), \quad t > 0, \tag{1}$$

where $A(t)$ denotes the amount of traffic arriving in time interval $[0,t]$, m is the mean traffic arrive rate, and a is the variance coefficient of $A(t)$. In this expression, $a = \sigma^2 / m$, where σ^2 is the variance of traffic in a time unit. $Z_H(t)$ is a standard FBM process with: (i) $Z_H(0) = 0$, (ii) $\mathrm{Var}(Z_H(t)) = t^{2H}$, and (iii) $\mathrm{Cov}(Z_H(t), Z_H(s)) = (|t|^{2H} + |s|^{2H} - |t-s|^{2H})/2$, where $H \in [0.5,1)$ is the Hurst parameter. The closer H is to one, the greater the degree of self-similarity is.

B. Wireless Channel Model

In order to analyze queuing behaviors with self-similar traffic in wireless channels, we adopt three fading channel models, which are two-state Markov channel model, Rayleigh fading channel model and Rician fading channel model, respectively. We will describe them as below:

1) Two-state Markov channel model

In wireless environments, wireless features such as fading and Doppler spread lead to the variable channel capacity. And the wireless channel can be modeled as a two-state Markov chain for simplicity, as shown in Fig. 3.

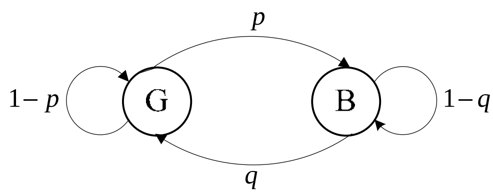


Figure 3. Two-state Markov channel model

The channel capacity in state G (good) is lager than that in state B (bad). p is the transition probability from G to B and q is the transition probability from B to G.

In this paper, we assume that the channel capacity is equal to a fixed value C_G with channel state G, and is C_B with state B ($C_G > C_B$). The channel state changes at each sample interval.

2) Rayleigh fading channel model

Rayleigh fading model is a commonly used channel model to describe the fading feature of wireless channels. The instantaneous capacity of the Rayleigh fading channel at the *n*th sample interval can be expressed as:

$$C_n = B_c \log_2\left(1 + |h_n|^2 \times \overline{\gamma}\right), \tag{2}$$

where B_c is the channel bandwidth, h_n is the channel gain and $|h_n|$ is a Rayleigh random variable. Average signal-to-noise ratio (SNR) $\overline{\gamma} = S/(N_0 B_c)$, S and N_0 are the average transmit power and the power spectral density of the noise, respectively. It is well known that the envelope of the sum of two quadrature Gaussian noise signals obeys a Rayleigh distribution, so that h_n can be generated by a first-order AR model [6]:

$$h_n = \kappa h_{n-1} + v_n, \tag{3}$$

where the noise v_n is zero-mean complex Gaussian with variance of $1-\kappa^2$ per dimension, and is statistically independent of v_{n-1}. The coefficient κ can be determined by

$$\kappa = 0.5^{T_S/T_C}, \tag{4}$$

where T_S is the sampling interval, T_c is the coherence time, and can be computed by

$$T_c \approx \frac{9}{16\pi f_m}, \tag{5}$$

where f_m is the maximum Doppler shift.

3) Rician fading channel model

When there is a dominant stationary signal component present, the small-scale fading envelope distribution is Rician. The instantaneous capacity of the Rician fading channel at the *n*th sample interval can still be expressed as (2), but $|h_n|$ is a Rician random variable here. $|h_n|$ can be generated as follows [17]:

$$|h_n| = \sqrt{\frac{(x_i + \sqrt{2K})^2 + y_i^2}{2(K+1)}} . \quad (6)$$

Here x_i and y_i are samples of zero-mean stationary Gaussian random processes each with unit variance. The parameter K is the Rician factor, which is defined as the ratio between the deterministic signal power A^2 and the variance of the multipath $2\sigma_m^2$. It is given by $K = A^2/2\sigma_m^2$.

C. Queuing Model

We consider a single-input single-output (SISO) queuing model as shown in Fig. 2, and assume that the buffer size is infinite and the transmitter has prefect knowledge of the channel gain h_n at each sample interval. Therefore, rate-adaptive transmissions and strong channel coding can be used to achieve error-free transmission. Thus, the service rate of the queue is equal to the instantaneous channel capacity C_n.

For simplicity, we adopt a fluid model [3], [4], [6], where the size of a packet is assumed to be infinitesimal. Let R_n and Q_n denote the amount of traffic arrives and the queue length at the *n*th sample interval, respectively. The units of R_n and Q_n are bits in this paper. Thus, we have:

$$Q_{n+1} = (Q_n + R_n - C_n T_s)^+ , \quad (7)$$

where $(x)^+ = \max(0, x)$.

III. QUEUE LENGTH DISTRIBUTION AND ESTIMATION ALGORITHM

The arrival and service processes of the queue presented in section II are both complicated, therefore, it is difficult to obtain closed-form formulae to describe the queuing behaviors such as the queue length distribution. In this section, based on background knowledge and simulation results, a convenient and efficient algorithm is proposed to estimate the queue length distribution.

A. Background Knowledge

Some conclusions of queue length distributions in relatively simple scenarios are presented as follows:

Conclusion I: If the input of a infinite buffer is a FBM process, and the service rate is constant, the queue length approximately follows a Weibull distribution [14], which is given by

$$P(Q > B) \approx \exp\left(-\alpha B^{\varepsilon}\right), \quad (8)$$

where $$\varepsilon = 2 - 2H ,$$

$$\alpha = \frac{(C-m)^{2H}}{2H^{2H}(1-H)^{2-2H}\sigma^2} ,$$

B is the queue length, and C is the constant service rate.

Conclusion II: If the arrival and service processes of a infinite buffer are Markov processes, the queue length approximately follows an exponential distribution [6], [18], which is given by

$$P(Q > B) \approx \gamma \exp\left(-\theta B\right), \quad (9)$$

where $\gamma = P(Q > 0)$ is the probability that the buffer is nonempty, θ is a certain positive constant called the QoS exponent. γ and θ are difficult to be calculated if the arrival and service processes are complicated, but can be estimated instead [6], [19]. Take N samples of the queue, let S_n denote whether a packet is in service ($S_n \in \{0,1\}$), Q_n denotes the number of bits in the queue, then the estimated values of γ and θ can be computed as

$$\hat{\gamma} = \frac{1}{N}\sum_{n=1}^{N} S_n , \quad (10)$$

$$\hat{\theta} = \frac{\hat{\gamma}}{\hat{q}} , \quad (11)$$

where $\hat{q} = \frac{1}{N}\sum_{n=1}^{N} Q_n$.

B. Queuing Behavior with Self-similar Input in Rayleigh Fading Channel

In order to investigate the queuing behaviors with self-similar traffic input in wireless channels, we first simulate the system depicted in Fig. 2 to obtain some preliminary results.

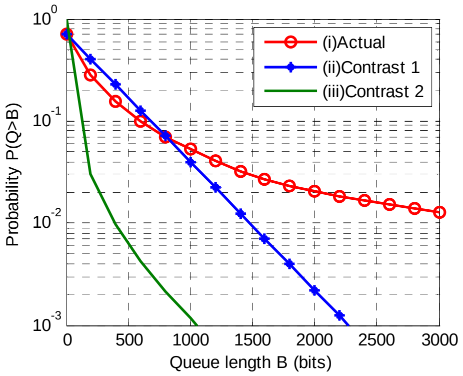
1) We adopt the fast Fourier transform (FFT) method [20] to generate two independent traffic flows, which can be characterized by FBM models. The parameters are set to be $m_1 = m_2 = 50$, $\sigma_1^2 = \sigma_2^2 = 100$, $H_1 = 0.80$, and $H_2 = 0.85$.

2) We adopt Rayleigh fading channel as our channel model here. The parameters of the Rayleigh fading channel are set as follows: channel bandwidth $B_c = 10kHz$, average SNR $\overline{\gamma} = 10dB$, maximum Doppler shift $f_m = 30Hz$ and sampling interval $T_S = 2ms$.

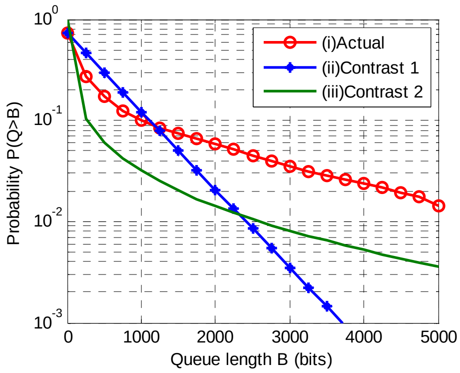
By simulations, the curve of actual queue length distribution and two contrast curves are shown in Fig. 4(a) and (b) with $H = 0.80$ and 0.85, respectively. The two contrast curves are defined as bellow:

Contrast curve 1: Simulation curves by substituting (10) (11) into (9), which approximately follow an exponential distribution;

Contrast curve 2: Simulation curves by using the mean of the channel capacity $\overline{C} = \frac{1}{N}\sum_{n=1}^{N} C_n$ to replace C in (8), and the curves approximately follow a Weibull distribution.



(a) $H = 0.80$



(b) $H = 0.85$

Figure 4. Queue length distribution with self-similar input in Rayleigh fading channel

It can be observed in Fig. 4 that as B increases, the actual probability $P(Q > B)$ decreases much more slowly than curve (ii), which decreases exponentially with B. The results show that in Rayleigh fading channel, the queue length distribution with self-similar traffic is different from that with Markov traffic. Comparing curve (i) with curve (iii), it can also be observed that the actual probability is larger than that with a constant service rate, but at the same time, curve (i) and (iii) exhibit a similar shape, especially when H is larger.

Moreover, we can ***draw the following conclusions*** from Fig. 4(a) and (b):

In the same fading channel, if the input self-similar traffic flows have the same mean and variance, then

1) the larger the Hurst value is, the more slowly the probability $P(Q > B)$ decreases with B;

2) the larger the Hurst value is, the more significantly it impacts the queue length distribution, and the less significantly the channel condition does.

C. Estimation Algorithm for the Queue Length Distribution

We have observed by simulation that curve (i) and curve (iii) exhibit a similar shape in Fig. 4, so that we use a Weibull distribution to approximate the queue length distribution with self-similar traffic input in Rayleigh fading channel as bellow:

$$P(Q > B) \approx \exp\left(-\eta B^{\varphi}\right). \tag{12}$$

Due to the complexity of the arrival and service processes of the queue, we adopt an estimation algorithm to calculate η and φ in (12) approximately. Considering that φ is related with the Hurst parameter of the traffic flow, we set $\varphi = 2 - 2H$ according to (8). if H is unknown, it can be estimated by the periodogram-based method [8]. Thus, we have:

$$\hat{\varphi} = 2 - 2\hat{H}, \tag{13}$$

where $\hat{H}$ is the estimated value of H. Take N samples of the queue, let Q_n denote the queue length at the nth sample interval, and then the average queue length can be estimated by:

$$\hat{q} = \frac{1}{N}\sum_{n=1}^{N} Q_n. \tag{14}$$

From (12), the theoretic mean value of the queue length can be expressed as:

$$\bar{Q} = \Gamma\left(\frac{1}{\varphi} + 1\right)\eta^{-\frac{1}{\varphi}}, \tag{15}$$

where $\Gamma(\cdot)$ is the Gamma function. Substituting $\hat{\varphi}$ and $\hat{q}$ into (15), we obtain the estimated value of η as:

$$\hat{\eta} = \hat{q}^{2\hat{H}-2}\left[\Gamma\left(\frac{3-2\hat{H}}{2-2\hat{H}}\right)\right]^{2-2\hat{H}}. \tag{16}$$

Finally, we can estimate the queue length distribution by substituting $\hat{\varphi}$ and $\hat{\eta}$ into (12), as follows:

$$\hat{P}(Q > B) \approx \exp\left(-\hat{\eta} B^{\hat{\varphi}}\right). \tag{17}$$

Our estimation algorithm for the queue length distribution is summarized below:

Step 1: Take N samples of the queue, meanwhile, record the amount of traffic arrives and the queue length at each sample interval;

Step 2: Estimate the Hurst parameter of the input traffic flow by the periodogram-based method, and calculate $\hat{q}$ by (14);

Step 3: Calculate $\hat{\varphi}$ and $\hat{\eta}$ by (13) and (16), respectively;

Step 4: Estimate the queue length distribution by (17).

It is worth noticing that our estimation algorithm works by taking samples of the queue only, and needn't to know the source and the channel parameters, which are difficult to get in actual environments. Although the algorithm is obtained from Rayleigh fading channel, we show that it can estimate queue length distributions in other wireless channels in the following section.

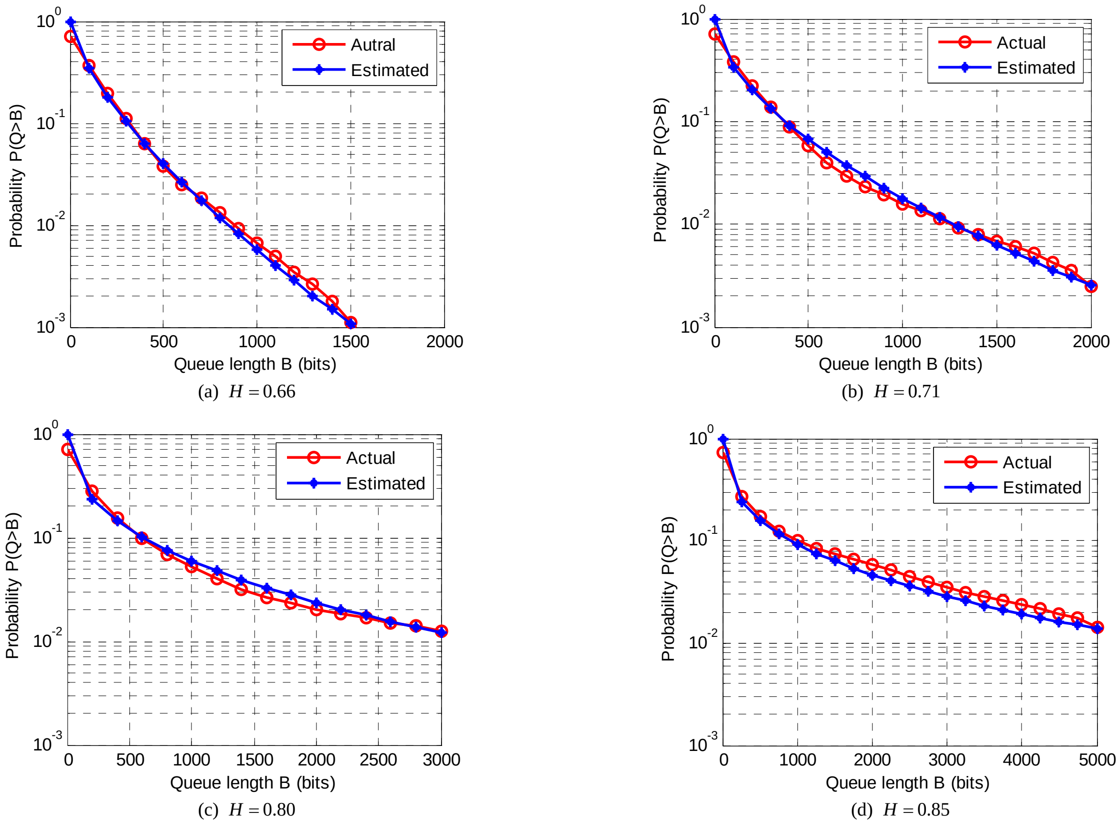


Figure 5. Estimation of the queue length distributions with different traffic flows in Rayleigh fading channel

IV. Simulation Results

We simulate the queuing system depicted in Fig. 2, and validate the accuracy of the proposed estimation algorithm via comparing the actual queue length distributions with the estimated results. We first estimate the queue length distributions with different self-similar traffic flows in Rayleigh fading channel, and then show that our estimation algorithm also works well in two-state Markov channel and Rician fading channel.

A. Performance of the Estimation Algorithm in Rayleigh Fading Channel

In this simulation, we still adopt the FFT method to generate four independent flows, and set $m = 50$ and $\sigma^2 = 100$ for all of them, but $H = 0.66$, 0.71, 0.80, 0.85, respectively.

The parameters of Rayleigh fading channel are chosen as presented in section III-B: channel bandwidth $B_c = 10kHz$, average SNR $\bar{\gamma} = 10dB$, maximum Doppler shift $f_m = 30Hz$ and sampling interval $T_S = 2ms$. The number of samples is $N = 1.3\times 10^5$. Actual and estimated results are shown in Fig. 5, where the horizontal axis represents the queue length and the vertical axis denotes the corresponding probability.

From Fig. 5, we can see that for the traffic flows with different Hurst values, the estimated results all match the corresponding actual results closely. That is to say, for a queuing system with self-similar traffic in Rayleigh fading channel, the proposed estimation algorithm can predict the queue length distributions accurately.

B. Performance of the Estimation Algorithm in Two-state Markov Channel

We aim at investigating the accuracy of the proposed estimation algorithm in a two-state Markov channel. As described in section II-B, we set the channel capacity $C_G = 40kbps$ and $C_B = 15kbps$, the state transition probability $p = 0.5$, $q = 0.5$, and sampling interval $T_S = 2ms$. The parameters of traffic flows are the same as the ones in section IV-A. The queue length distributions with different self-similar flows are shown in Fig. 6.

We note that the estimated results still match the corresponding actual ones. Thus, our estimation algorithm is efficient in a two-state Markov channel with different self-similar flows.

C. Performance of the Estimation Algorithm in Rician Fading Channel

This scenario is intended to examine the accuracy of the developed estimation algorithm in Rician fading channel. The parameters of the simulation are: Rician factor $K = 3dB$, channel bandwidth $B_c = 10kHz$, average SNR $\bar{\gamma} = 9dB$, sampling interval $T_S = 2ms$. We still use the traffic flows generated in section IV-A. The results are shown in Fig. 7. It shows that the proposed estimation algorithm also hold for Rician fading channel.

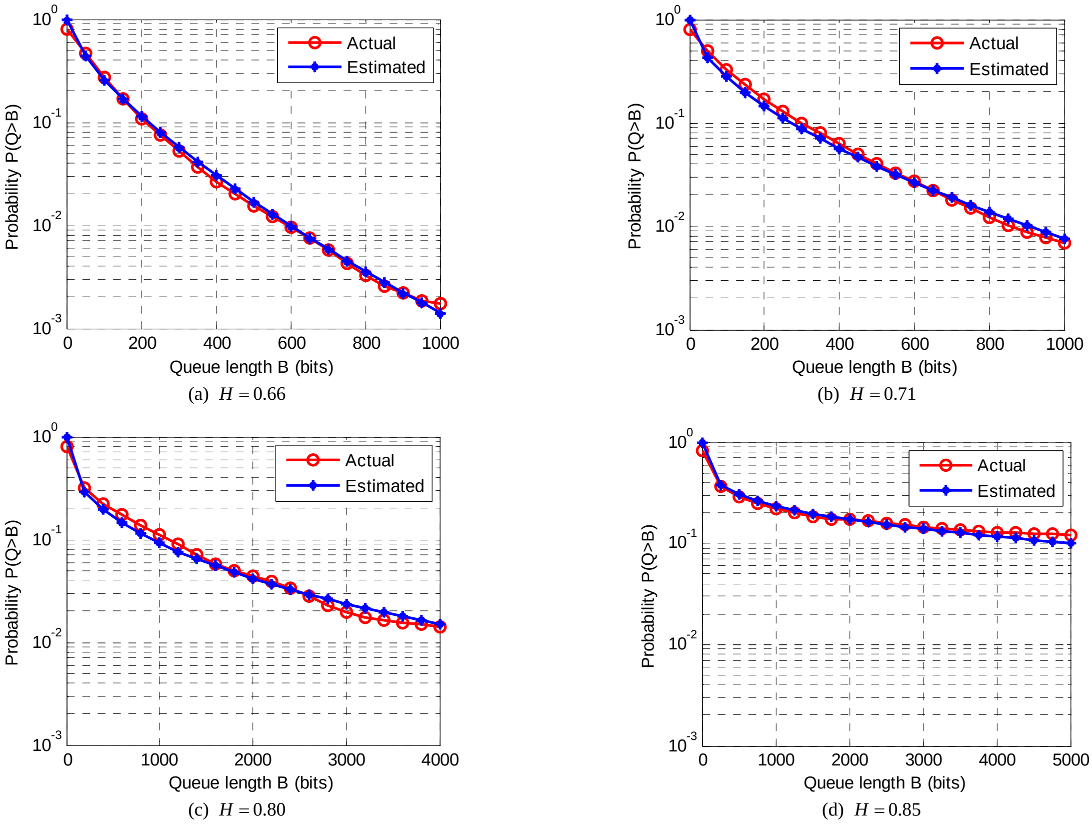


Figure 6. Estimation of the queue length distributions with different traffic flows in a two-state Markov channel

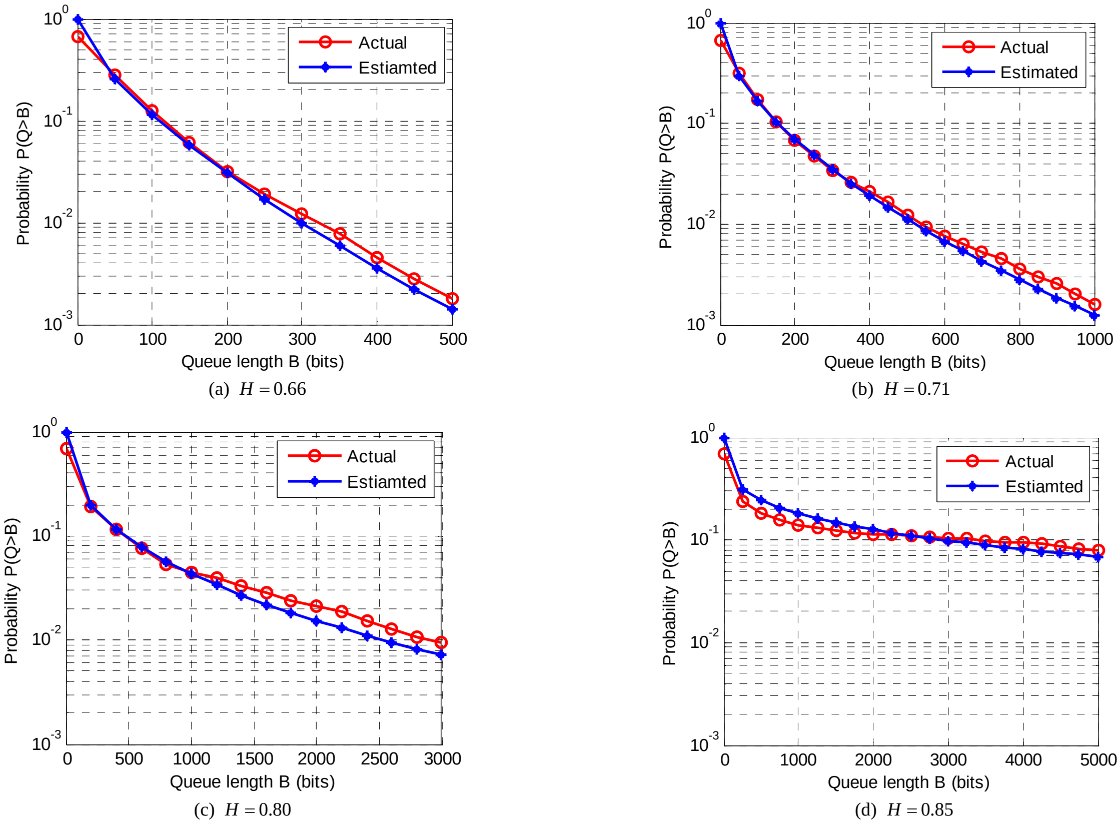


Figure 7. Estimation of the queue length distributions with different traffic flows in Rician fading channel

In summary, the results in Fig. 5-7 have shown that queue lengths with self-similar traffic input in different wireless channels (two-state Markov channel, Rayleigh and Rician fading channels) follow Weibull distributions approximately, and our proposed algorithm can estimate the queue length distributions accurately. In the following section, we make further analysis of the queuing behaviors based on the estimation algorithm.

V. Effective Service Rates of Wireless Channels

From Fig. 4, we can see that the actual probability is larger than the probability by using the mean of the channel capacity $\bar{C} = \frac{1}{N}\sum_{n=1}^{N} C_n$ to replace C in (8). It means that the utilization ratio of a stable channel (channel capacity is constant) is larger than that of a wireless fading channel. So it is meaningful to investigate the effective service rates of wireless channels.

From (12) to (17), we know that queue length distributions with self-similar traffic in wireless channels depend on two parameters: φ and η. φ is only related with the self-similar traffic, while η is related with the traffic and the channel condition. For the same traffic input, different channel conditions are reflected by different values of η. According to (8) and (12), we define:

$$\eta = \frac{(C_{eff} - m)^{2H}}{2H^{2H}(1-H)^{2-2H}\sigma^2}, \qquad (18)$$

where C_{eff} is called *effective service rate*, and defined as follows.

Effective service rate: With the same self-similar traffic input, if the queue length distribution in a wireless fading channel is the same as that in a constant-rate channel, the service rate of the constant-rate channel is C_{eff}.

C_{eff} reflects the effective service rate of a wireless fading channel with a certain traffic flow. By solving (18), we have:

$$C_{eff} = [2H^{2H}(1-H)^{2-2H}\sigma^2\eta]^{\frac{1}{2H}} + m. \qquad (19)$$

Based on the simulation results in section IV, C_{eff} can be calculated as shown in Table I-III.

Considering that the input traffic flows have the same mean and variance, but different Hurst values, we can draw a conclusion that in a certain wireless channel (Rayleigh fading channel, two-state Markov channel, or Rician fading channel), C_{eff} increases with H. That is to say, in the same wireless channel, the greater the degree of traffic self-similarity is, the closer the effective service rate C_{eff} is to the average channel capacity $\bar{C}$. The conclusion is consistent with that drawn from Fig 4. in section III-B, that is, the larger the Hurst value is, the more significantly it impacts the queue length distribution, and the less significantly the channel condition does.

TABLE I.
C_{eff} IN RAYLEIGH FADING CHANNEL

$\bar{C}$ (bit/ms)	58.303			
H	0.66	0.71	0.80	0.85
C_{eff} (bit/ms)	51.991	52.950	54.794	56.941
$C_{eff}/\bar{C}$	0.8917	0.9082	0.9398	0.9766

TABLE II.
C_{eff} IN TWO-STATE MARKOV CHANNEL

$\bar{C}$ (bit/ms)	55.065			
H	0.66	0.71	0.80	0.85
C_{eff} (bit/ms)	52.387	53.224	54.319	54.817
$C_{eff}/\bar{C}$	0.9514	0.9666	0.9865	0.9955

TABLE III.
C_{eff} IN RICIAN FADING CHANNEL

$\bar{C}$ (bit/ms)	56.467			
H	0.66	0.71	0.80	0.85
C_{eff} (bit/ms)	53.434	54.207	55.139	56.105
$C_{eff}/\bar{C}$	0.9463	0.9600	0.9765	0.9936

VI. Conclusions

Considering the self-similarity of traffic and the fading characteristic of channels in wireless networks, this paper have studied the queuing system with self-similar traffic and variable service rate in wireless channels. A convenient and efficient algorithm has been proposed to estimate the queue length distributions for this queuing system. By taking samples of the queue, our estimation algorithm works well with no need for the source and the channel parameters. Simulation results have shown that the proposed estimation algorithm can predict queue length distributions accurately in different wireless channels (two-state Markov channel, Rayleigh fading channel and Rician fading channel). We have further analyzed effective service rates of wireless channels based on our estimation algorithm, and have demonstrated that in a certain wireless channel, if the input traffic flows have the same mean and variance, the effective service rate increases with the value of the Hurst parameter.

In the future, we plan to use our estimation algorithm in resource management, meanwhile, analyze the delay and packet loss characteristics with self-similar traffic input in wireless channels.

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