Analysis on Relationship Between Fractional Calculus Fluid Model and Effective Capacity of Bursty Data Service in Multi-hop Wireless Networks

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Abstract. A fractional calculus fluid model can be used to better explain the traffic of bursty data service. It is long-range dependence and has a fractal-like feature of network data flow. This paper builds a fluid model to describe the traffic of multi-hop wireless networks with QoS constraint. We use effective capacity model to depict the performance of bursty data service in wireless networks with QoS constraint. Finally, experiment results show that the heavy-tailed delay distributions, the hyperbolically decay of the packet delay auto-covariance function and fractional differential equations are formally related. Our method is effective and feasible.

Keywords: Fluid model · QoS · Effective capacity · Multi-hop wireless networks

1 Introduction

Because user behavior become more and more complicated and many kinds of traffic flow exist in the network, researchers proposed much more routing approaches and measurement methods for new network architecture [1–3]. Many researches concentrate on how to measure the traffic, build the traffic model and improve the scheduling by using the traffic model [4–7]. For guaranteeing the QoS of emerging services, new scheduling strategies are proposed [8–11]. Due to the situation of the crowed mobile communication, resources utilization [12–15], spectral efficiency [16–19] and energy-efficiency [20–22] become hotspots. A large number of researches also focus on flow level of traffic reconstruction [23–25]. New scheduling schemes, which based on the traffic characters, effectively improve the experience of users [26–29].

Researchers have explored the relationship between the number of scheduled user and the QoS requirement by the effective capacity model of wireless communication theory [12]. To some extent, the QoS is influenced by the traffic flow. Unlike the other services, the bursty data service has more sophisticated flow which is very difficult

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to predict [30–32]. The measurements of network traffic of bursty data service have shown that traffic characteristics include features which are more efficiently described in terms of fractal rather than conventional stochastic processes [33]. We found fractal dimension and long-range dependence in statistical moments that exist in corporate, local, and wide-area networks.

The rest of this paper is organized as follows. In the second section, we introduce the system model. In the third section, we present the traffic model under QoS constraint for multi-hop wireless networks. Simulation parameters and results are described in the fourth section. Finally, the conclusions are presented in the fifth section.

2 System Model

In a communication system with stable links, the switching and routing devices usually employ a large buffer to prevent the loss of packets when the arriving rate from the service source is higher than transmission rate over a short time. The key problem of QoS guarantee thus lies in analyzing the arriving queue. However, during the transmissions of these emerging bursty data services, such as speech cloud and remote control based on real-time video, we must consider the low reliability, time-varying channel and moving users of wireless environment. The effective capacity concept is a function of the probability of nonempty buffer and the QoS exponent of connection. In many researches, effective capacity is more suitable to measure the transmission capacity of time-varying channels [34–38]. Effective capacity model is shown in Fig. 1.

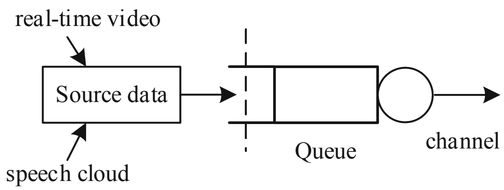

Fig. 1. Effective capacity model

The QoS requirement can be formulated as

$$P_r\left(\max_{1\le i\le N} Q_i(0) > B\right) \le \in \cdot \tag{1}$$

With a large buffer size B, given a QoS constraint $\in$ and by choosing $\theta = -\log(\in)/B$, the QoS requirement can be expressed as an effective capacity problem:

$$\lambda \le \min_{1\le j\le N} C_k(\theta) \tag{2}$$

where

$$C_k(\theta) = \frac{1}{\theta}\lim_{n\to\infty}\frac{-1}{n}\ln \mathrm{E}\left(e^{-\theta\sum_{t=1}^{n} r_k(t)}\right) \tag{3}$$

and $r_k(t)$ is the rate allocated to user k in cell j at time t. We assume that the scheduling scheme at the base station picks the K users out of a set of N active users for stochastic transmission with the same probability. Thus, the r_k can be written as

$$\mathrm{r}_k(t) = \begin{cases} \frac{N_f}{K}\left(1-\frac{B}{S}\right)\log_2\left(1+\frac{1}{I_j^{scheme}}\right), w.p.\frac{K}{N}, \\ 0, w.p.1-\frac{K}{N}. \end{cases} \tag{4}$$

In a multi-hop wireless networks, the average packet latency at a site meets the condition [33]:

$$< t >= \int_0^{\infty} \mathrm{t} \cdot \mathrm{f(t)dt} = \infty \tag{5}$$

where, $\mathrm{f(t)} > 0$; $\int\limits_0^{\infty} \mathrm{f(t)dt} = 1$. The corresponding expression for f(t) is a PDF:

$$\mathrm{f(t)} = \frac{\gamma}{(1+\mathrm{t})^{\gamma+1}}, 0 < \gamma < 1 \tag{6}$$

This probability density function characterizes the long-range statistical dependence in bursty data service traffic model. A CDF function can be introduced as $\mathrm{F}(\tau)$ [33]:

$$\mathrm{F}(\tau) = 1 - \int\limits_0^{\tau} \mathrm{f(t)dt} = \frac{1}{(1+\tau)^{\gamma}} \tag{7}$$

where τ is the time a packet stays at an intermediate site x of the virtual connection. We suppose that the site is a connection device with an infinite buffer, the most probable number of packets in site x at the moment t can be denoted as:

$$\mathrm{n(x;t)} = \int\limits_0^{\mathrm{t}} \mathrm{n(x-1;t-\tau)f(\tau)d\tau} + \mathrm{n_0(x)F(t)} \tag{8}$$

where $n_0(x)$ is the initial number of packets in the buffer of site x before the packet's arrival from site *x-1*. In this notation, the equation of packet migration can be presented as

$$\Gamma(1-\gamma)\mathrm{D_t^{\gamma}[n(x;t)]} = -\frac{\partial \mathrm{n(x;t)}}{\partial \mathrm{x}} + \frac{\mathrm{n_0(x)}}{\mathrm{t}^{\gamma}} \tag{9}$$

Where the left part of Eq. (9) is the fractional derivative of function n(x; t) with an exponent parameter γ, and

$$\mathrm{D_t^{\gamma}[n(x;t)]} = \frac{1}{\Gamma(1-\gamma)} \int\limits_0^{\mathrm{t}} \frac{\mathrm{n(x;t)}}{(\mathrm{t}-\tau)^{\gamma}} \mathrm{d}\tau \cdot \tag{10}$$

Taking into account the discrete character of change of the variable x, [33] solves Eq. (17) subject to the following initial conditions: $\mathrm{n_0(0)} = \mathrm{n_0}$ and $\mathrm{n_0(k)} = 0$, $\mathrm{k} = 1, 2, \ldots$ In [33], the Eq. (8) can be rewritten as:

$$\mathrm{n(k;t)} = \mathrm{n_0}\left\{\frac{1}{\mathrm{t}^{\gamma}} - \mathrm{k}\frac{\Gamma^2(1-\gamma)}{\Gamma(1-2\gamma)t^{2\gamma}} - \mathrm{k}\Gamma(1-\gamma) \cdot \frac{1}{\Gamma(-\gamma)\mathrm{t}^{\gamma+1}}\right\} \tag{11}$$

$$n(k;t) = n_0 \left\{ \frac{1}{t^{\gamma}} - k \left[\frac{\Gamma^2(1-\gamma)}{\Gamma(1-2\gamma)} \cdot \frac{1}{t^{2\gamma}} + \frac{\Gamma(1-\gamma)}{\Gamma(-\gamma)} \cdot \frac{1}{t^{\gamma+1}} \right] \right\} \tag{12}$$

Taking into account the asymptotic property of the obtained solution, we can get

$$n(0;t) = n_0 \left\{ \frac{1}{t^{\gamma}} \right\} \tag{13}$$

For $k = 1$, the following expression is obtained:

$$n(1;t) = n_0 \left\{ \frac{1}{t^{\gamma}} - \left[\frac{\Gamma^2(1-\gamma)}{\Gamma(1-2\gamma)} \cdot \frac{1}{t^{2\gamma}} + \frac{\Gamma(1-\gamma)}{\Gamma(-\gamma)} \cdot \frac{1}{t^{\gamma+1}} \right] \right\} \tag{14}$$

Finally in [33], with the initial conditions $n(0;t) = n_0 \cdot \delta(t)$, the cumulative number of blogged packets is presented as:

$$\begin{aligned} c(m;t) &= n_0^2 \Gamma(1-\gamma) \left[\frac{1}{\Gamma(1-2\gamma+1)} \cdot \frac{1}{t^{2\gamma-1}} - m \frac{\Gamma(1-\gamma)}{\Gamma(1-3\gamma+1)} \cdot \frac{1}{t^{3\gamma-1}} \right] \\ &= n_0^2 \Gamma(1-\gamma) t^{1-2\gamma} \left[\frac{1}{\Gamma(2-2\gamma)} - m \frac{\Gamma(1-\gamma)}{\Gamma(2-3\gamma)} \cdot \frac{1}{t^{\gamma}} \right] \end{aligned} \tag{15}$$

This correlation function decays hyperbolically with increasing t. Therefore for $\gamma < 1$, such random processes have a fractal-like scaling behavior. Set $m = 0$, we get:

$$D(t) = c(0;t) = \frac{n_0 \Gamma(1-\gamma)}{\Gamma(2-2\gamma)} t^{1-2\gamma} \tag{16}$$

3 Traffic Model Under QoS Constraint

Effective capacity theory provides a powerful framework to describe the relationship between transmission rate fluctuations and QoS constraints. The proposed model adopts only one QoS exponent parameter that represents two parameters, namely a delay constraint and buffer size. When the QoS exponent θ is equal to 0, rate fluctuations do not affect the effective capacity, which is equal to the average transmission rate. As the QoS requirement becomes stricter, the transmission rate fluctuations lead to a decline in effective capacity, which corresponds to the probability of delay violation. More specifically, higher fluctuation levels lead to lower effective capacity, which means higher probability of delay violation. The transmission rate fluctuations and QoS constraints is shown in Fig. 2.

With a fixed buffer size B and QoS constraint:

$$\theta = \frac{-\ln(\in)}{B} \tag{17}$$

The $\in$ represents the violation probability:

$$\Pr\left(t > \frac{B}{C(\theta)} \right) < \in \tag{18}$$

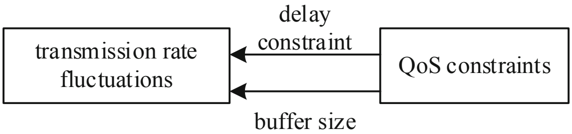

Fig. 2. The transmission rate fluctuations and QoS constraints

Combining the Eq. (7), we obtain:

$$\in = \mathrm{F}(\tau) = \frac{1}{(1+\tau)^{\gamma}} \tag{19}$$

Finally, we get a rough relationship between QoS parameter and the fluid model parameter γ:

$$\gamma = \log_{\left(1+\frac{\mathrm{B}}{\mathrm{C}(\theta)}\right)}\left(\frac{1}{\in}\right) \tag{20}$$

4 Simulation and Results

We make simulation with fixed buffer size and QoS constraint to investigate the relationship between the QoS requirement and traffic model. Considering 10 intermediate sites, the violation probability is set as 0.001. The buffer size and bandwidth are set as 10Mbits and 10 MHz, respectively.

The simulation results are shown in Fig. 3. It shows the relationship between latency constraint and the distribution character of the fluid model. The expected blogged packet in one site is presented in Fig. 4. It based on the dynamic channel state that can achieve a certain QoS.

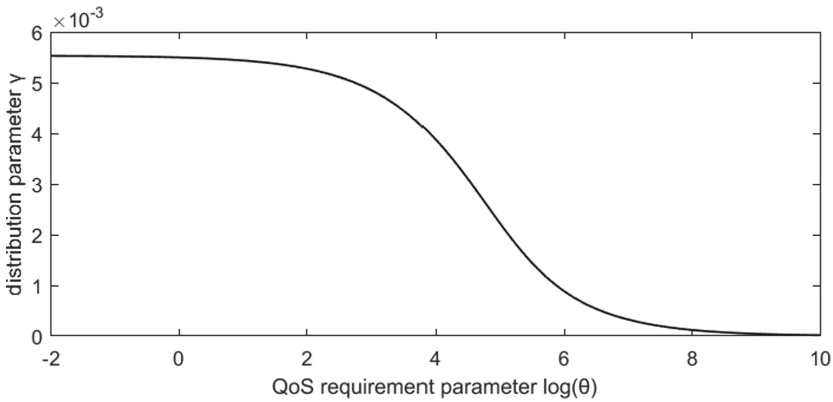

Fig. 3. QoS requirement and distribution of fluid model.

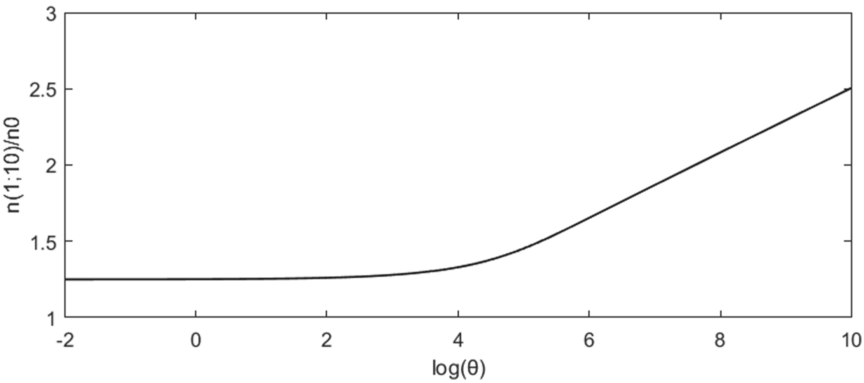

Fig. 4. QoS requirement and blogged length.

As shown in Fig. 3, When the latency constraint is between [−2, 2], the allowable arrival rate remains constant; when the latency constraint is between [2, 8], the allowable arrival rate gradually decreases; when the latency constraint is between [8, 10], the allowable arrival rate almost approaches 0. As shown in Fig. 4, When the latency constraint is between [−2, 4], the expected blogged packet number remains constant, When the latency constraint is between [4, 10], the expected blogged packet number gradually increase.

As shown in Fig. 5, in the scope of our simulation, we can find that the probability of data loss increases gradually with the decrease of buffer capacity. So in order to reduce packet loss, we should increase the buffer size as much as possible.

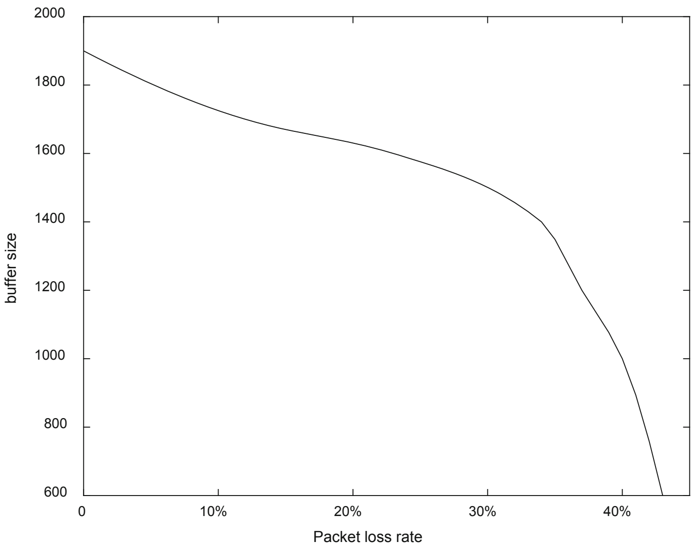

Fig. 5. Packet loss rate and buffer size

5 Conclusion

We explore the possibility of an indefinitely long packet delay at an intermediate node in Multi-hop wireless networks with QoS constraint. The QoS constraint is described as effective capacity, which is related to violation probability. To describe the traffic model of busrty data service, we adopt fractional calculus fluid model. The simulation results show that the effective capacity affects the traffic model. As the latency constraint increases, the allowable arrival rate remains constant. It will gradually decreases after specific number of the latency constraint. On the other hand, the packet loss rate increases as the buffer gets smaller, so we should try to maximize the buffer size.

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