An Online Algorithm for Effective Capacity Estimation

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Abstract. Effective Capacity is an important metric to measure the capacity of a wireless channel. However, the estimation algorithm cost a lot of computation time. The current estimation algorithm thus cannot predict the real-time Effective Capacity for online service. An online estimation algorithm is proposed to reduce computation time cost in this paper. A simulation is designed with QoS constraint. The simulation results illustrate that the proposed algorithm save a lot of computation time.

Keywords: Effective capacity · Wireless channel · Quality of service

1 Introduction

In 5G networks, some methods of routing and network measurement [1–3] are proposed. In core network and edge network, a number of traffic characteristic extraction schemes [4–7], scheduling policies are proposed to improve the quality of experience (QoE) [8–11], raise resources utilization [12–15] and energy efficiency [16–18]. To evaluate these new methods, researchers reconstruct traffic in test bed [19–21]. At the edge of 5G network, more antennas are used to improve the quality of signal. With limited channel resource, the spectral efficiency (SE) is critical to support a huge number of end devices [22–25]. To utilize spectral efficiency, the traffic prediction [2, 26, 27] and effectively scheduling resource are premises for QoS guarantee [28–30].

To design a QoS-aware system, it is necessary to model the wireless channel with a QoS constraint. By considering the probability of delay constraint in wireless networks, Wu and Negi proposed a concept of effective capacity (EC) [31]. This concept is the duality of the effective bandwidth. The EC is defined as the maximum constant arrival rate that the system is able to afford meeting a fixed delay constraint. Based on the EC model, we can adjust the scheduling strategy to meet the QoS constraint with perfect knowledge of the instantaneous channel state information (CSI) at the transmitter. Unfortunately, the estimation algorithm cost a lot of computation time. The current estimation algorithm thus cannot predict the real-time Effective Capacity for online service. This high cost prevents the real-time QoS aware scheduling. We proposed an online estimation algorithm to save the computation time. The simulation is carried out for a massive

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MIMO case [32, 33]. Our simulation results demonstrate that the proposed algorithm is able to obtain high prediction precision within less time.

The paper is divided into five sections. In Sect. 2, we introduce the effective capacity model and its off-line estimation algorithm. In the Sect. 3, we give the online estimation algorithm. We give our simulation results in Sect. 4 and conclude in Sect. 5.

2 Effective Capacity Model

For a stable channel, the main issue of QoS guarantee is the relationship between the envelope of source rate and the capacity of the system for stable transmission, namely effective bandwidth. For the bursty data services, we can describe the QoS constraint by a threshold of SINR at each time slot. However, in the emerging 5G services, the mobile station experiences a strong channel state fluctuation. For the transmissions of the new services, such as speech recognition cloud and real-time remote control, we need to consider the time-varying channel because of fast-moving mobile station. The key issue for QoS guarantee is to predict the probability of the varying channel rate meeting the delay constraint with special arrival rate. The EC model is a function of source rate with the probability of delay violation. In many mobile scenarios, this model is more suitable for the delay violation probability analysis in a time-varying channel [34–38].

In the EC model, let $Q(t)$ is the queue length, the queue length constraint can be written as [31].

$$P_r(\max Q(0) > B) \leq \epsilon. \tag{1}$$

According to inequality (1), let B denotes a large buffer, given a queue length violation constraint ϵ and selecting $\theta = -\log(\epsilon)/B$, the QoS guarantee problem can be formulated as an EC problem:

$$\mathrm{r}^{(c)}(\theta) = \frac{1}{\theta} \lim_{n\to\infty} \frac{-1}{n} \ln \mathrm{E}\left(e^{-\theta \sum_{t=1}^{n} r(t)} \right) \tag{2}$$

For a smaller buffer size, the queue length probability can be estimated by

$$\sup_{\mathrm{t}} \Pr\{\mathrm{Q(t)} \geq \mathrm{B}\} \approx \gamma(\mathrm{r}) \times \mathrm{e}^{-\theta(\mathrm{r})\times \mathrm{B}} \tag{3}$$

If we consider the delay violation problem, the approximation can be rewritten as

$$\sup_{\mathrm{t}} \Pr\{\mathrm{D(t)} \geq \mathrm{D_{max}}\} \approx \gamma(\mathrm{r}) \times \mathrm{e}^{-\theta(\mathrm{r})\times \mathrm{r} \times \mathrm{D_{max}}}, \tag{4}$$

where $\gamma(\mathrm{r})$ is the probability of a nonempty queue, $\theta(\mathrm{r})$ is a solution of $\alpha(\theta) = \mathrm{r}$, the $\alpha(\theta)$ is a function of accumulated transmitted bit length $\mathrm{S(t)}$ and θ:

$$\alpha(\theta) = \frac{\lim_{\mathrm{t}\to\infty} \frac{-1}{\mathrm{t}} \ln \mathrm{E}\left(\mathrm{e}^{-\theta \mathrm{S(t)}}\right)}{\theta}, \ \forall\theta \geq 0 \tag{5}$$

If we employ a fluid model, the $\theta(r)$ can be obtained by taking a number of samples [31],

$$\hat{\gamma} = \frac{1}{N}\sum_{n=1}^{N} S_n \quad S_n \in \{0, 1\} \tag{6}$$

$$\hat{q} = \frac{1}{N}\sum_{n=1}^{N} Q_n \tag{7}$$

$$\hat{\theta} = \frac{\hat{\gamma} \cdot r^c}{\hat{q}} \tag{8}$$

where S_n indicates whether a packet is in transmission. And Q_n is the length of queue. The subscript n is sequence number of time slot.

The conventional binary search algorithm estimating effective capacity is illustrated in Fig. 1 [31].

3 Online EC Estimation Algorithm

This algorithm searches the suitable source rate from a wide range. Actually, the time-varying channel state does not changing so fast. Therefore, the effective capacity won't change in a wide range. The initial value of service rate is also usually far deviate from the aim value. By using the previous effective capacity, we can reduce significantly the searching range.

Let the expected service rate is equal to access probability times channel capacity. The proposed algorithm is illustrated in Fig. 2.

The QoS metric estimation algorithm is illustrated in Fig. 3. The empirical value of sample number K is set as 10^5 times the expected transmitted bits in 1 time slot.

In our proposed algorithm, we use previous EC estimation value as initial value to reduce the computation time. Because the channel state fluctuation is limited, we expect that this method is able to reduce the iterations.

algorithm 1

```
Initialize the error estimation parameters. Set lower bound and
upper bound of sustainable service rate;
While error estimation is higher than bias
    If the source rate is lower than that of service rate can support
        If the bias is higher than constraint
            Lower bound = source rate
            Set new service rate=1/2(lower bound + upper bound);
        endif
    else
            upper bound = source rate
            Set new source rate=1/2(lower bound + upper bound);
    endif
    Based on new source rate, estimate QoS metric;
Compute new error estimation;
End while
```

Fig. 1. Off-line effective capacity estimation algorithm

Algorithm 2

```
Initialize the error estimation parameters. Set lower bound and upper bound of sustainable service rate;
If previous EC > 0
    If current expected rate < previous expected rate
        Upper bound = previous_EC;
    else
        lower bound= previous_EC;
    endif
endif
    Source rate= previous_EC * ____________ ;
endif
While error estimation is higher than bias
    If the source rate is lower than that of service rate can support
        If the bias is higher than constraint
            Lower bound = source rate
            Set new service rate=1/2(lower bound + upper bound);
        endif
    else
            upper bound = source rate
            Set new source rate=1/2(lower bound + upper bound);
    endif
    Estimate exponential QoS metric.
    Compute new error estimation.
End while
```

Fig. 2. Online effective capacity estimation algorithm

```
Algorithm 3
Set source rate
Set the access probability of mobile station
Initialize the sample number K;
For i=1 to K
    Set transmit rate according to access probability;
    update queue length at current time slot;
endfor
Return Nonempty rate of the queue and QoS metric
```

Fig. 3. QoS metric estimation algorithm

4 Simulation and Results Analysis

In the simulation, we adopt an ON-OFF channel. The channel capacity is fixed at the beginning of each time slot. The user randomly accesses to the channel according to the access probability. The channel capacity is time-varying, the variance range is limited. We execute 20 comparisons.

4.1 Simulation Parameters

We list simulation parameters in Table 1.

Table 1. Effective capacity estimation simulation parameters

Simulation parameter	Value
Delay constraint	100 ms
QoS violation constraint	0.001
Transmission rate changing range	−10%–10%
Access probability of ON-OFF channel	0.8
Initial rate for each comparison	100K–2M bps
Transmission rate increment for each comparison	100 Kbps

In our simulation, the transmission rate changes by 10% for each iteration. The initial rate rises by 100 Kbps for each comparison.

4.2 Simulation Results

Our simulation results are showed in Fig. 4. The traditional algorithm and our proposed online algorithm can both obtain exact EC value. Moreover, the online algorithm uses much less iterations than that of traditional algorithm.

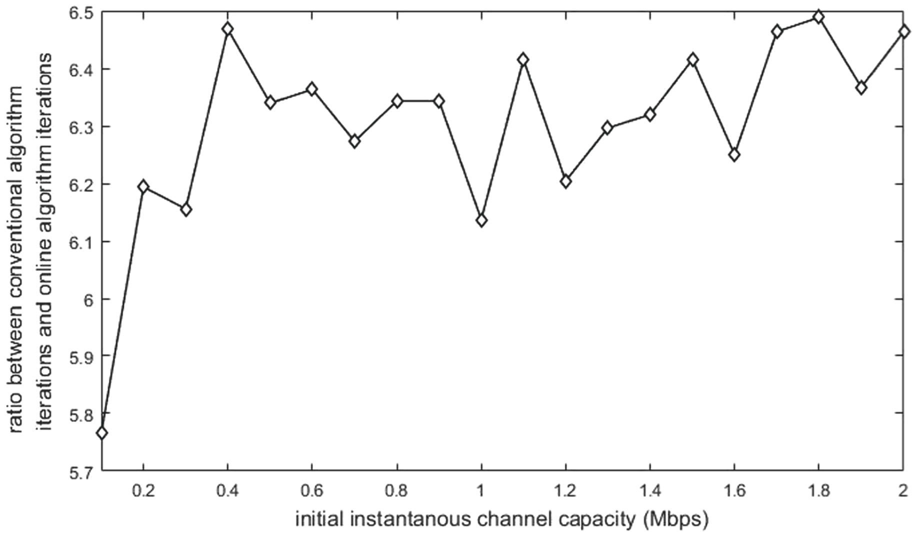

Fig. 4. Ratio between iterations between conventional algorithm and online algorithm

5 Conclusion

In this paper, we discuss the lower cost online effective capacity algorithm for QoS prediction of online services. By using iterative strategy, the proposed estimation algorithm can make an accurate prediction of the effective capacity of wireless channel. This algorithm can monitor the QoS and scheduling communication resource.

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