Queue Regret Analysis Under Fixed Arrival Rate and Fixed Service Rates

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Abstract. In wireless communication, transmitter often need choose one channel from several available ones. Since the instantaneous channel rate is time-varying with unknown statistics, the channel selection is based on observation. Evaluating the lost of scheduling based on observation is an important for design scheduling policy. By adopting the concept of queue regret fact, we carry out simulation under different arrival rate and channel service rate. As arrival rate is approaching the service rate of the best channel, the queue regret has a shape increase in our simulation. However, even if the arrival rate is higher than best service rate, the transmitter have still chance to find the best channel, and the queue regret will converge. The relationship between arrival rate, service rate, queue length and queue regret is analyzed in the simulation.

Keywords: Queue regret · Scheduling policy · Wireless communication

1 Introduction

Recently, some new approaches are proposed to improve network routing and measurement [1–3]. Based on effective user behavior and traffic analysis methods [4–7], new scheduling strategies are designed to raise resources utilization [8–11] and energy-efficiency [12–14]. To test these new scheduling strategies, traffic reconstruction is important [15–17]. Because the network traffic changes very fast in mobile communication scenario [18, 19], some intelligent approaches are proposed for traffic reconstruction [3, 20, 21]. The traffic deeply affects the end user's experience [22–25]. Therefore, the resource management must be based on the network traffic model [26–29]. For air interface, a main issue of resource management is channel selection [30–33]. The channel selection approaches are usually based on the channel estimation in short term [34–37]. And most researches only concern about the short term performance index.

The system's regret index is defined to measure the system stability [38]. The regret compares the backlog of real learning controller which select policy based on statistics and the backlog under a controller that knows the best policy. As a stochastic multi-armed bandit problem, the regret bound is drawn in [39]. The practical policies have been studied for a long time to deal these problems [40]. To project a perfect service

H. Song and D. Jiang (Eds.): SIMUtools 2020, LNICST 370, pp. 557–567, 2021.
https://doi.org/10.1007/978-3-030-72795-6_45

rate observation in busy time under fixed arrival rate, the boundary of regret is obtained [41].

In some wireless communication situations, the channel state is stable in short term. Therefore, transmitter could evaluate the candidate channels during idle period. By the channel estimation information, transmitter is able to select optimal channel. The effect of channel estimations is affected by the length of idle period. In this paper, we design a stochastic estimation algorithm to select the optimal channel. In the simulation, the capacity of channel state is treated as service rate. Based on the record of queue length and queue regret, the relationship between arrival rate, service rate, queue length and queue regret is analyzed.

The paper is divided as six sections. In the second section, we give the related work about queue regret problem. The system model is given in the third section. Based on system model an analysis on queue regret facts is presented in the fourth section. The algorithm and simulation results analysis is given in the fifth section. We conclude in the sixth section.

2 Related Work

As a multi-armed bandit problem in which the controller need to allocate limited resource to alternative choices for optimal gain, the stochastic properties of choice must be described [40]. However, the choice's stochastic properties are unknown at the time of allocation. We must make the allocation under observation. The longer observations lead to that we can better understand the choices. In this classic reinforcement learning problem the controller meets a tradeoff dilemma of stochastic scheduling.

During the idle time periods, the offered service is unused, and therefore we can select a candidate service to observe. However, most researches only focus on the relationship between queue regret and the length of passed time [38]. The main issue in these research is that the necessary of take an observation in busy time. Someone argue that observation in busy time would increase the regret if the optimal service has been selected. Others argue that observing only in idle time would lose the chance to obtain a better choice when the busy time is too long.

3 System Model

For our wireless communication scenario, the capacity of N candidate channels is referred to as service rate of N servers in a single queue system. In our model, we assume that a controller schedules the servers over discrete time slots $t = 0, 1, 2\ldots$ Packets arrive to the queue as a Bernoulli process, written as $A(t)$ with rate $\lambda \in (0, 1]$. The service rate is defined as the amount of packets that server $i \in [N]$ can provide follows a Bernoulli process $D^i(t)$ with rate μ_i. The arrival process and server processes are arbitrarily assumed to be independent. If $\mu_i > \lambda$ the system is referred to as stabilizing; otherwise, it is referred to as non-stabilizing.

The controller must select one channel to serve the queue from the N channels (servers) to provide service when the queue is non-empty. We denote the controller's choice at time t as $u(t) \in [N]$ and the service offered to the queue as $D(t)$ which is equal to $\mathrm{D}^{u(t)}(t)$. The queue length $Q(t)$ can be written as [38]:

$$Q(t+1) = (Q(t) - D(t))^{+} + A(t), \text{ for } t = 0, 1, 2, \ldots \tag{1}$$

where $(x)^{+}$ is used to denote the maximum of x and 0. And $Q(0)$ is assumed as 0. We assume that the arrival rate and service rate are stable, however, the controller do not know the values of $D^{i}(t)$ prior to making its decision $u(t)$. To make optimal action, that maximizes expected service, controller should select the best server

$$i^{*} \triangleq \underset{i \in [N]}{\arg\max} \mu_i \tag{2}$$

to provide service. In this work, the controller does not a priori know the values of μ_i and must therefore use observations of $D(t)$ to identify i^{*}. We assume that the controller can observe $D(t)$ at all times t, even when the queue is empty. Define $Q^{*}(t)$ to be the queue length under the controller that always schedules i^{*} and $Q^{\pi}(t)$ the backlog under a policy that must learn the service rates. The performance of policy π is measured by queue length regret [38]:

$$R^{\pi}(T) \triangleq E\left[\sum_{t=0}^{T-1} Q^{\pi}(t) - \sum_{t=0}^{T-1} Q^{*}(t)\right]. \tag{3}$$

The π is scheduling policy, the assumption implies that $R^{\pi}(T)$ is monotonically.

4 Queue Regret Analysis

In the stabilizing scenarios, the controller has enough idle periods to observe the service rate of each channel. Therefore, the queue regret is expected to stop increasing after initial phase. In the non-stabilizing scenarios, the queue length would increase sharply and the queue will keep a backlogged situation for long time.

To investigate the possibility that the controller change a bad decision, we assume that the controller selects a channel with service rate μ_i and another channel have service rate μ_j, $\mu_j > \mu_i$. With a long busy period, the observation value of μ_i will approach the real value. The controller only keep use ith channel while the observation value of μ_j is less than μ_i. This possibility can be written as:

$$\mathrm{P}\{\mathrm{X} \le \mathrm{n} \cdot \mu_i\} = \sum_{\mathrm{k}=0}^{\mathrm{n}\cdot\mu_i} \binom{\mathrm{n}}{\mathrm{k}} {\mu_j}^{\mathrm{k}} {\mu_j}^{\mathrm{n-k}}, \tag{4}$$

where the n is the number of controller observing the jth channel in initial phase. We know that the Eq. (4) increase fast when $\mathrm{n} \cdot \mu_i$ approaching to μ_j. Therefore, controller has higher possibility of changing channel as the value of $\mu_j - \mu_i$ increase. This implies the queue regret has chance to keep a low value within a long time busy period.

5 Simulation and Results

5.1 Algorithm

The algorithm we adopt in simulation is shown in Fig. 1. The algorithm uses idle period to observe the service rates of channels. In the busy period, the service rate of selected channel is updated at each time slot. The algorithm is presented as followed:

Step1	While (simulation time > 0)
Step2	If (the queue is empty)
Step3	Select a random channel
Step4	Observe the selected channel
Step5	Update the service rate of observed channel
Step6	else
Step7	Select randomly a channel from the set of servers with highest rate
Step8	Decide whether transmit the packet according to real service rate
Step9	Update service rate of the selected server
Step10	End if
Step11	Simulation time --
Step12	End while

Fig. 1. Simulation algorithm.

5.2 Simulation Parameters

We make two simulations, the simulation parameters are listed in Table 1.

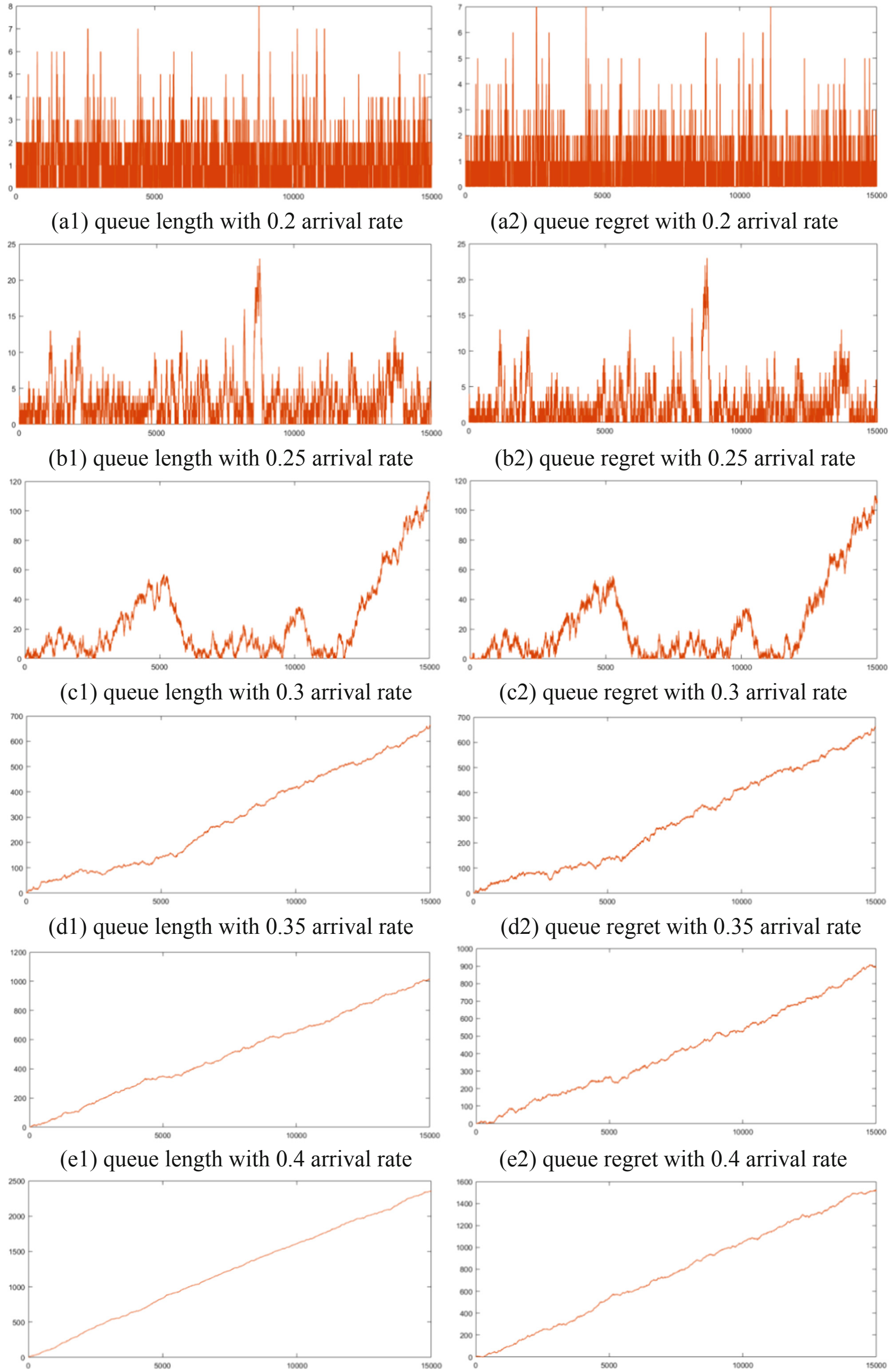
Table 1. Simulation parameters.

Parameter name	Value of parameter in simulation 1	Value of parameter in simulation 2
Number of slots	15000 for each test	15000 for each test
Service rates	0.3, 0.325, 0.35, 0.375, 0.4	0.2, 0.225, 0.25, 0.275, 0.3
Arrival rates	0.2–0.5, increase 0.01 each test	0.2–0.5, increase 0.01 each test

In these two simulations, we have 5 candidate channels with a service rate range from 0.3 to 0.4 and from 0.2 to 0.3 respectively. Both the arrival rates increase 0.01 at each test from 0.2 to 0.5. Therefore, there are 31 tests in each simulation. And each test last 15000 time slots under the fixed arrival rates.

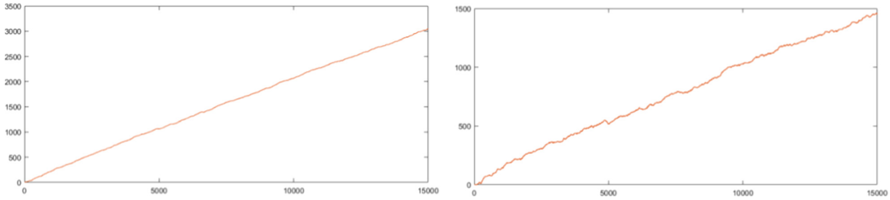
5.3 Simulation Results

The simulation results are shown in Fig. 2 and Fig. 3.



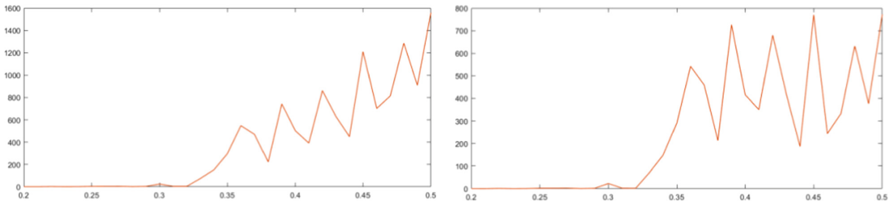
(a1) queue length with 0.2 arrival rate
(a2) queue regret with 0.2 arrival rate
(b1) queue length with 0.25 arrival rate
(b2) queue regret with 0.25 arrival rate
(c1) queue length with 0.3 arrival rate
(c2) queue regret with 0.3 arrival rate
(d1) queue length with 0.35 arrival rate
(d2) queue regret with 0.35 arrival rate
(e1) queue length with 0.4 arrival rate
(e2) queue regret with 0.4 arrival rate
(f1) queue length with 0.45 arrival rate
(f2) queue regret with 0.45 arrival rate

Fig. 2. Slices in Simulation1 (horizontal axis unit is time slot, vertical axis units are queue length and queue regret respectively)



(g1) queue length with 0.5 arrival rate (g2) queue regret with 0.5 arrival rate

Fig. 2. (*continued*)



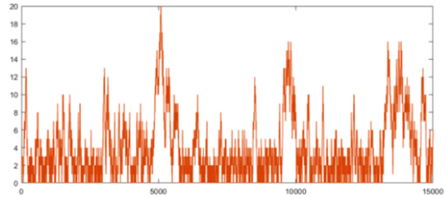
(a) Average queue length (b) average queue regret

Fig. 3. Average queue length and queue regret over 15000 time slots at each test in simulation 1 (horizontal axis unit is arrival rate, vertical axis units are queue length and queue regret respectively).

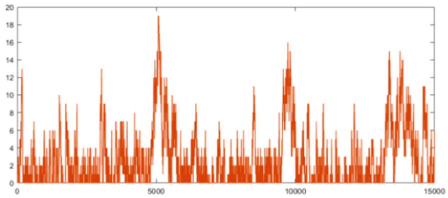
In Fig. 2, the results shows that the queue lengths and queue regrets are stable while the arrival rate is lower than all service rates. And the queue regrets increase as the queue length increase while the arrival rate is approach the lowest service rate. In Fig. 3, the average queue lengths have an increasing trend while the arrival rate surpasses the service rate despite of some fluctuation. However, the queue regrets have no an obviously increasing trend as the arrival rate increases. The fluctuation is caused by randomly channel selection in initial phase when the controller lacks of observation.

The simulation results are shown in Fig. 4 and Fig. 5.

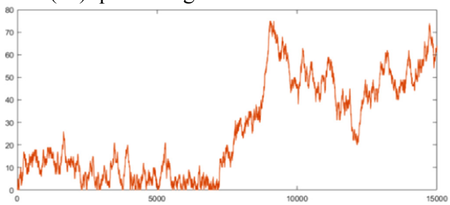
In Fig. 4, the results shows that the queue lengths and queue regrets are stable even if as the arrival rate has surpassed some low service rates of candidate channels. And the queue regrets also increase as the queue length increase while the arrival rate is approach the lowest service rate. In Fig. 5, the average queue lengths have a more obviously increasing trend than that of simulation 1 while the arrival rate surpasses the service rate despite of some fluctuation. However, the queue regrets is very stable as the arrival rate increases. The fluctuation is also caused by randomly channel selection in initial phase when the controller lacks of observation.



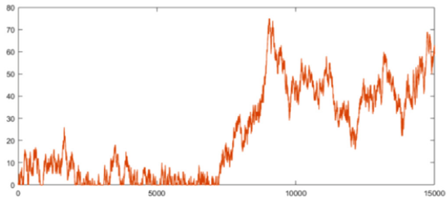
(a1) queue length with 0.2 arrival rate



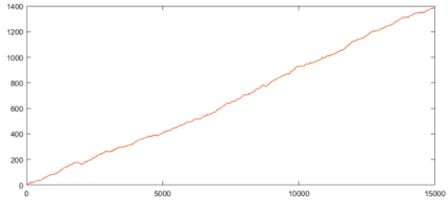
(a2) queue regret with 0.2 arrival rate



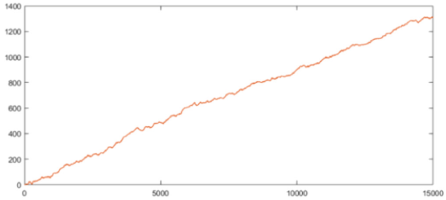
(b1) queue length with 0.25 arrival rate



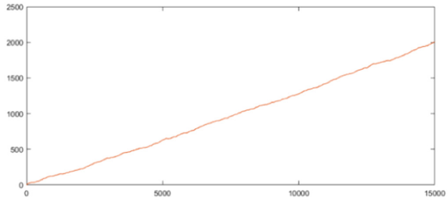
(b2) queue regret with 0.25 arrival rate



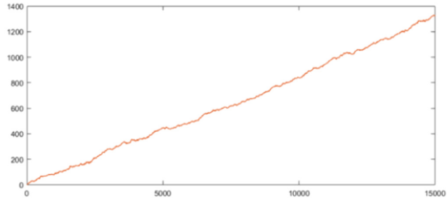
(c1) queue length with 0.3 arrival rate



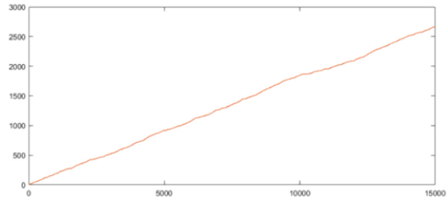
(c2) queue regret with 0.3 arrival rate



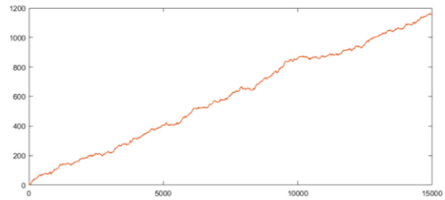
(d1) queue length with 0.35 arrival rate



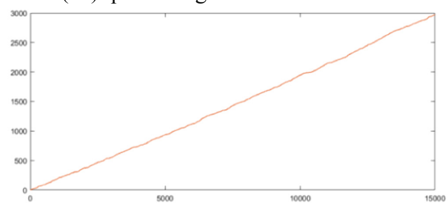
(d2) queue regret with 0.35 arrival rate



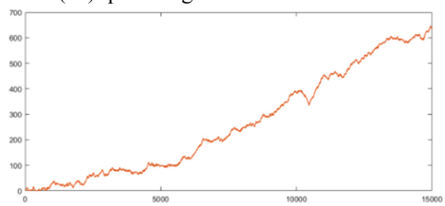
(e1) queue length with 0.4 arrival rate



(e2) queue regret with 0.4 arrival rate

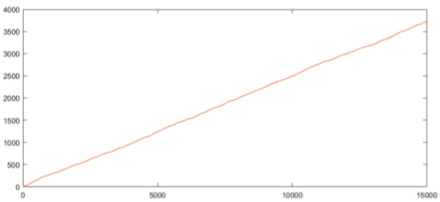


(f1) queue length with 0.45 arrival rate

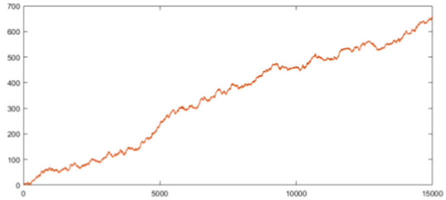


(f2) queue regret with 0.45 arrival rate

Fig. 4. Slices in Simulation2 (horizontal axis unit is time slot, vertical axis units are queue length and queue regret respectively).

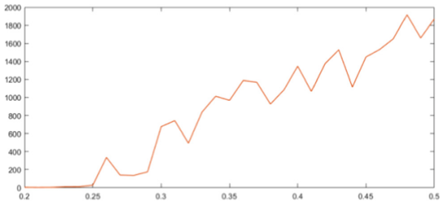


(g1) queue length with 0.5 arrival rate

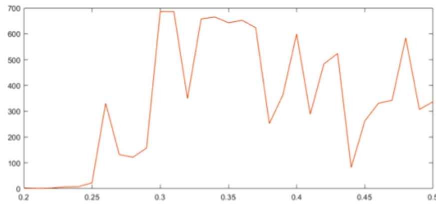


(g2) queue regret with 0.5 arrival rate

Fig. 4. (*continued*)



(a)Average queue length



(b) average queue regret

Fig. 5. Average queue length and queue regret over 15000 time slots at each test in simulation 2 (horizontal axis unit is arrival rate, vertical axis units are queue length and queue regret respectively)

5.4 Analysis

We know that if the queue is non-empty the controller have no chance to observe and update other candidate channels in our scheduling policy. However, the high arrival rate dose not leads to queue regret rise. Through record data analysis, we found that if a very low service rate channel is selected in initial phase because the observation is not enough, the controller can update the service rate of the selected channel. Therefore, the service rate of selected channel will approach the real value. The controller may change the channel with a high possibility.

6 Conclusion

In this paper, we designed a scheduling algorithm to select optimal channel according to observation during idle period. In the simulation, the arrival rate increase from a low level to a high level in which the arrival rate is higher than all available service rates. However, the queue regret does not increase as the queue length increase. However, even in these non-stabilizing scenarios, the queue regret have no an increasing trend. In busy period, the controller could observe the selected channel and have chance to change choice. This implies that the busy period observation is not necessary even in some non-stabilizing scenarios.

Acknowledgements. This work is partly supported by Jiangsu major natural science research project of College and University (No. 19KJA470002) and Jiangsu technology project of Housing and Urban-Rural Development (No. 2019ZD041).

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