Stability Analysis of Communication System Under Certain Session Arrival Rate

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Abstract. The transmit rate of backbone network is much more fast than that of the edge network. In the edge wireless communication, transmitter often need select one channel from time-varying ones. Due to unknown statistics of time-varying channel, 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 can evaluate the effectiveness of scheduling policy. However, because the different arrival rates of backbone network and edge network in real commercial network, the traffic model affects the measurement in different way. In this paper, considering the difference between backbone networks transmit rate and edge network transmit rate, we adopt session arrival model to observe the relationship between arrival rate, channel service rate, queue length and queue regret is analyzed in the simulation.

Keywords: Queue regret · Scheduling policy · Wireless communication

1 Introduction

The transmit rate of edge wireless network has been significantly improved. However, the capacity of backbone network is still far more than that of access network. To let the edge network works in a more efficient way, 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 evaluate these new scheduling strategies, traffic reconstruction is important. Many researches focus on the edge network traffic [15–17] and core network traffic [18–20]. The traffic models are different for different network area [21]. Because of the traffic complexity caused by mobile users' behavior some AI-based approaches are designed to build the traffic model [3, 22, 23]. The traffic models have been used to improve the quality of service [24–27], quality of end user experience [28–31] and spectral efficiency [32–34]. However, most researches only concern about the short term performance index. The system's regret index is defined to measure the system stability [35]. In this paper, we investigate how the network traffic affects the regret index. The regret compares the backlog of real learning controller

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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 [36]. Some practical policies have been studied for a long time to deal these problems [37]. To project a perfect service rate observation in busy time under fixed arrival rate, the boundary of regret is obtained [38].

For most wireless communication situations, the channel state is stable in short term. Therefore, transmitter could observe these 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. Some policies suggest that observe the candidate channels in busy period. This might raise the observation cost, but is help to do decision.

In this paper, we consider a more real environment. In the simulation, we consider the session arrival rate. Because the backbone network transmit packets far faster than that of edge network, when a session arrives the edge network at a time slot it contains several packets. For edge network, if the channel is available it only treat one packet each time slot. Through analyzing the record of queue length and queue regret, the relationship between arrival rate, service rate, queue length and queue regret is explored in our simulation.

The paper is divided as six sections. In the second section, we give the related work about queue regret problem. The system model based on session arrival rate is given in the third section. 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

The queue regret problem belongs to the traditional bandit problem. In the multi-armed bandit problem, a fixed limited set of resources need to be allocated between alternative choices in a way that maximizes their expected gain [37]. For each choice, the stochastic properties are unknown at the time of allocation and the allocation must be made under observation. As time passes, we can better understand the choices. In this classic reinforcement learning problem the solution must deal with the exploration-exploitation tradeoff dilemma. Therefore, this multi-armed bandit problem also falls into a lot of stochastic scheduling.

A good scheduling policy is proven to be able to maximize the rate of offered service to the queue in a queuing system. 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 [35]. Those researches mainly consider the packet arrival rate. The main issue in this research is to observe how the session arrival rate affects the regret.

3 System Model

In this regret problem, the capacity of channel is referred to as service rate of server, and the system consists of a single queue and N servers. Controller schedules the servers over discrete time slots $t = 0, 1, 2\ldots$ Sessions arrive to the queue as a Bernoulli process, $A(t)$, with rate $\lambda \in (0, 1]$. We set one session contains L packets. Therefore the packet arrival rate should be $\lambda \cdot L$. 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, and the transmitter treats at most one packet in a time slot. The arrival process and server processes are arbitrarily assumed to be independent. In L time scale, if $\mu_i > \lambda \cdot L$ the system is referred to as stabilizing; otherwise, it is referred to as non-stabilizing.

The controller must select one of the N servers to provide service at the time slot when the queue is non-empty. We set 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 [20]:

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

where $(x)^+$ denote the maximum value of x and 0. The queue length is assumed as 0 initially. The controller do not know the values of $D^i(t)$ prior to making its decision $u(t)$. The controller need to select the channel based on observed maximum expected throughout

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

to provide transmit service. In this paper, the controller does not a priori know the values of μ_i and must therefore use observations of $D(t)$ to obtain i^*. We assume that the controller can observe $D(t)$ at all time slots, 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 [35]:

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

The π is scheduling policy; the assumption implies that $R^{\pi}(T)$ is monotonically with a high probability. Note that the service rate is a probability; the best channel might perform worse than other channel.

4 Queue Regret Analysis

In the stabilizing scenarios, the controller has enough idle periods to observe the service rate of each channel, especially in this session scenario. Based on plenty of observations the controller can select the best channel whose service rate is higher than packet arrival rate that is product of session arrival rate and the number of packets in sessions, the queue regret is expected to stop increasing after initial phase. In the non-stabilizing scenarios, the queue length is expected to increase sharply. Because many packets arrive at same time slot, the queue will keep a backlogged situation for a long time. We concern the relationship between the blogged queue length, the regret, the session arrival and the service rate.

For instance, the controller selects a channel with service rate μ_i. With a long busy period, the observation value of μ_i will approach the real value. If another channel with service rate μ_j with $\mu_j > \mu_i$, the controller only keep use ith channel while the observation value of μ_j is less thanμ_i. This possibility can be written as:

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

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 μ_j. Therefore, the possibility of controller changing channel would increase as the value of $\mu_j - \mu_i$ increase. This implies the queue regret has still chance to keep a low value within a long time busy period. The session arrival model means the longer continue idle time and the longer continue busy time. We would investigate how the size of session affects the performance of controller.

5 Simulation and Results

5.1 Algorithm

The simulation algorithm is shown in Fig. 1. The algorithm observes the service rates of candidate channels uses in idle period. In the busy period, the controller only observes the service rate of selected channel. The algorithm is presented as followed:

```
Step1    While (number of time slots > 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        If (the channel works)
Step10         Queue's length --;
Step11       End if
Step12       Update service rate of the selected server
Step13     End if
Step14     Decide whether new session arrive according to arrival rate
Step15     If (new session arrives)
Step16       Queue's length += number of packets in session
Step17     End if
Step18     Number of time slots --
Step19   End while
```

Fig. 1. Simulation algorithm.

Table 1. Simulation parameters.

Parameter name	Value of parameter in small session	Value of parameter in big session
Number of slots	15000 for each test	15000 for each test
Service rates	0.3, 0.325, 0.35, 0.375, 0.4	0.3, 0.325, 0.35, 0.375, 0.4
Arrival rates	0.02–0.05, increase 0.01 each test	0.002–0.005, increase 0.01 each test
Packets in session	10	100

5.2 Simulation Parameters

Two simulations are carried out. The simulation parameters are listed in Table 1.

In these two simulations, we have 5 candidate channels with a service rate range from 0.3 to 0.4 respectively. The arrival rates increase 0.001 and 0.0001 for each test from 0.02 to 0.05 and 0.002 to 0.005 for the two simulations respectively. Therefore, there are 31 tests in each simulation. And each test last 15000 time slots under the fixed session rates. The queue length and queue regret is recorded for each time slot.

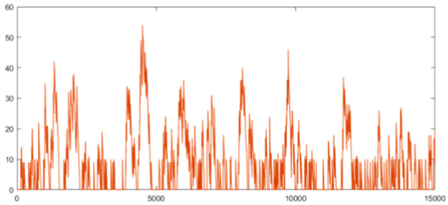
5.3 Simulation Results

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

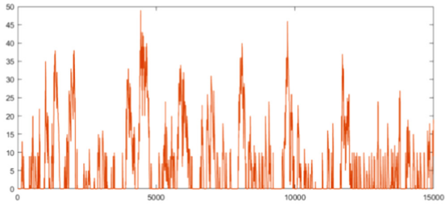
Figure 2 shows the simulation results while the system changes from stable to non-stable. The results shows that the queue lengths and queue regrets are stable while the stable situation in which the arrival rate is lower than all service rates. As expected, the queue regrets increase as the queue length increase while the packet 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. And the fluctuation is high in this session model since the queue length increase sharply at one time slot.

In another simulation, we let the session consist of more packets. The simulation results are shown in Fig. 4 and Fig. 5.

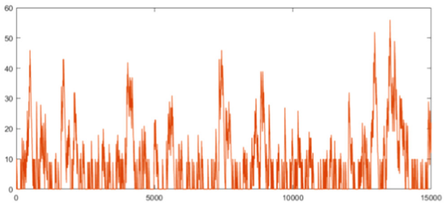
In Fig. 4, the simulation results shows that the queue lengths and queue regrets are stable even if the arrival rate is higher than some low service rates of candidate channels. And the queue regrets also increase as the queue length increase while the arrival rate is approach the lowest service rate. 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. In these two simulations, the small session has higher arrival rate and the big session has lower arrival rate. Therefore, for a long term, the numbers of arrival packets of these two simulations are more likely same. Although these two simulations' packet arrival rates are same, this big session regret fluctuation is higher than that of small session regret, since the queue suddenly increases within big session model.



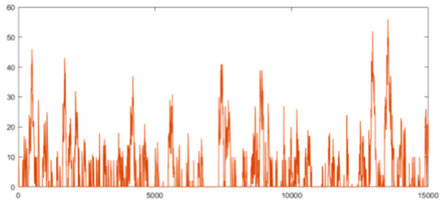
(a1) queue length with 0.02 arrival rate



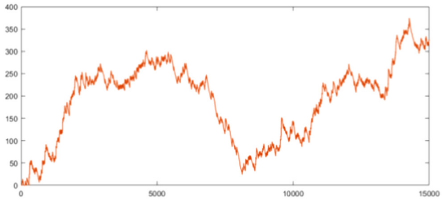
(a2) queue regret with 0.02 arrival rate



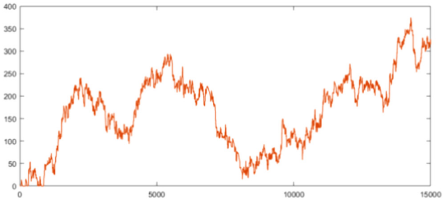
(b1) queue length with 0.025 arrival rate



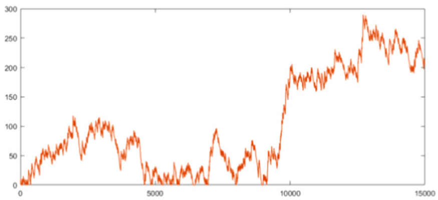
(b2) queue regret with 0.025 arrival rate



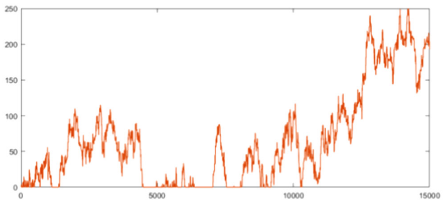
(c1) queue length with 0.03 arrival rate



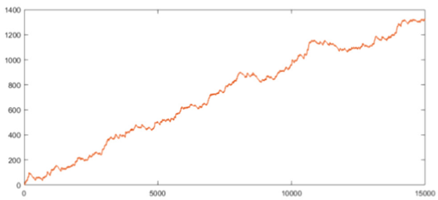
(c2) queue regret with 0.03 arrival rate



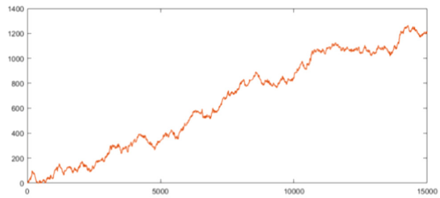
(d1) queue length with 0.035 arrival rate



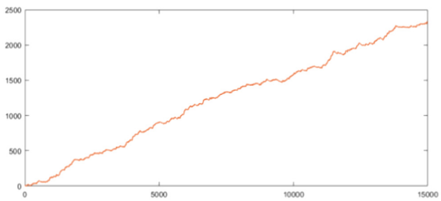
(d2) queue regret with 0.035 arrival rate



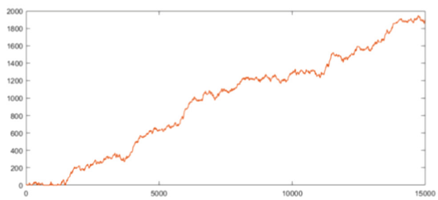
(e1) queue length with 0.04 arrival rate



(e2) queue regret with 0.04 arrival rate

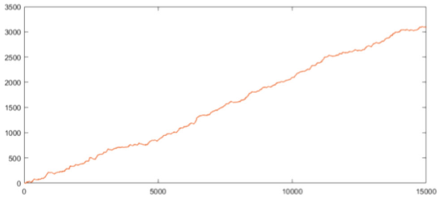


(f1) queue length with 0.045 arrival rate

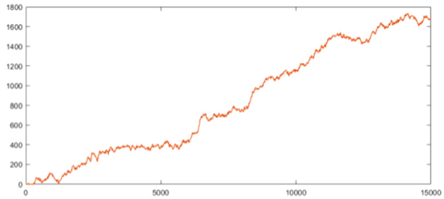


(f2) queue regret with 0.045 arrival rate

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

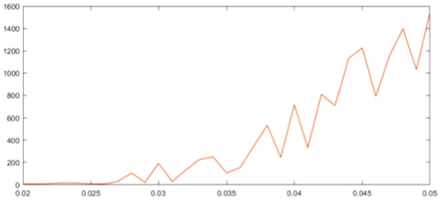


(g1) queue length with 0.05 arrival rate

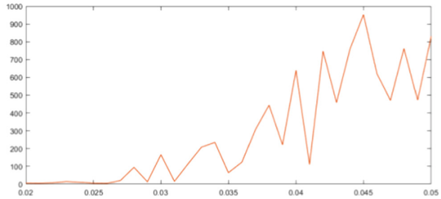


(g2) queue regret with 0.05 arrival rate

Fig. 2. (*continued*)



(a) Average queue length

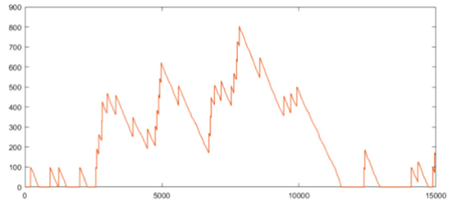


(b) average queue regret

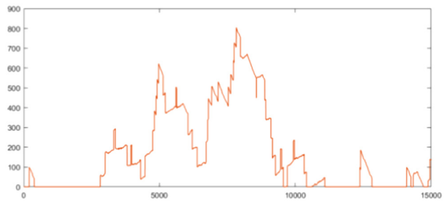
Fig. 3. Average queue length and queue regret over 15000 time slots at each test in big session simulation (horizontal axis unit is arrival rate, vertical axis units are queue length and queue regret respectively)

5.4 Analysis

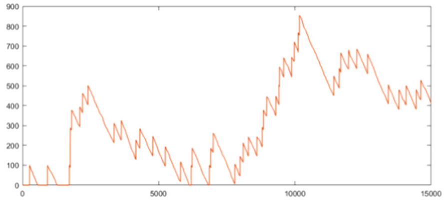
Note that if the queue is non-empty the controller has less chance to observe and update other candidate channels in our scheduling policy. The high session arrival rate dose not leads to rise of queue regret. From record data analysis, we found that if a very low service rate channel is selected in 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. In this session model, the bigger session causes the higher fluctuation of regret and queue length, therefore it is difficult to describe the envelop.



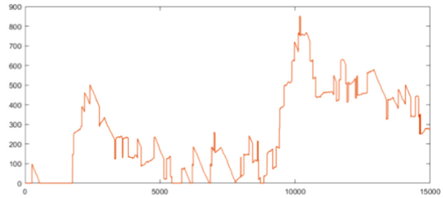
(a1) queue length with 0.002 arrival rate



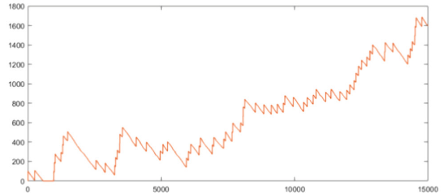
(a2) queue regret with 0.002 arrival rate



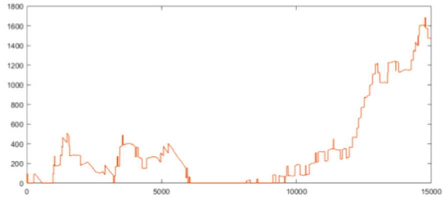
(b1) queue length with 0.0025 arrival rate



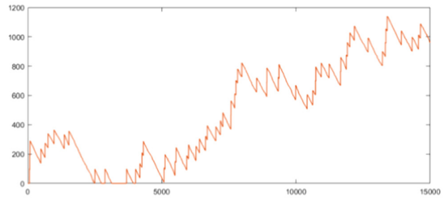
(b2) queue regret with 0.0025 arrival rate



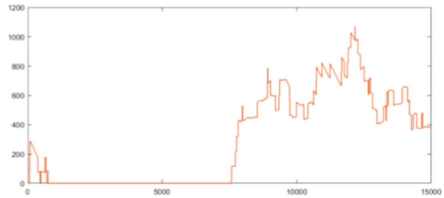
(c1) queue length with 0.003 arrival rate



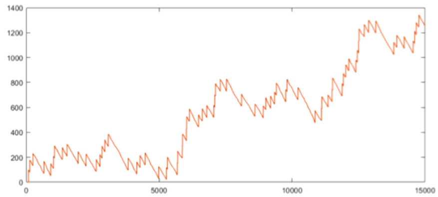
(c2) queue regret with 0.003 arrival rate



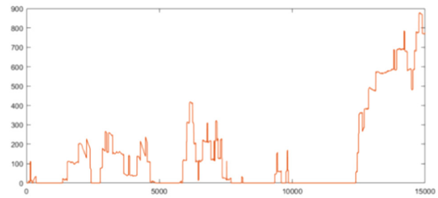
(d1) queue length with 0.0035 arrival rate



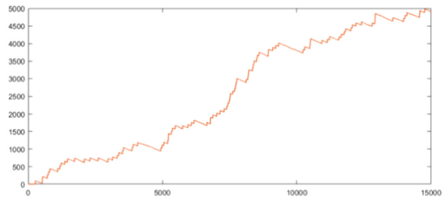
(d2) queue regret with 0.0035 arrival rate



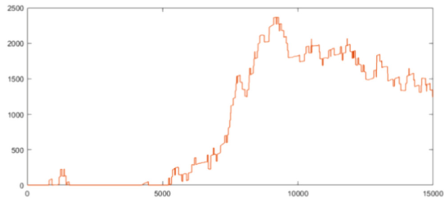
(e1) queue length with 0.004 arrival rate



(e2) queue regret with 0.004 arrival rate

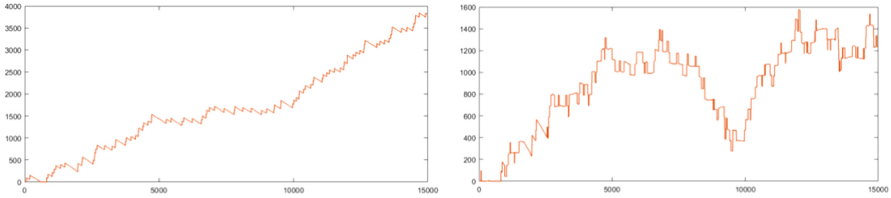


(f1) queue length with 0.0045 arrival rate



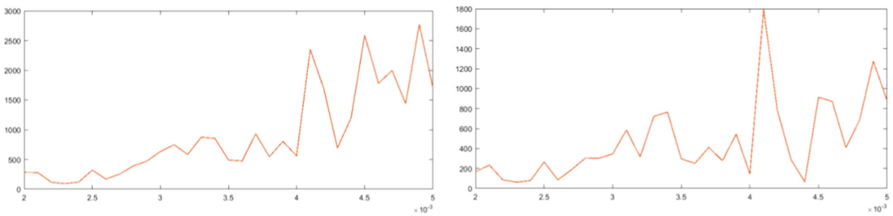
(f2) queue regret with 0.0045 arrival rate

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



(g1) queue length with 0.005 arrival rate (g2) queue regret with 0.005 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 big session simulation (horizontal axis unit is arrival rate, vertical axis units are queue length and queue regret respectively)

6 Conclusion

We propose a session arrival model to describe the edge network, session arrival rate, which contains several packets. In the simulation, 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 compared to the service rates. The queue regret does not increase as the queue length increase. This means that the controller can make right decision with high session arrival rate. Even in these non-stabilizing scenarios, the queue regret have no an increasing trend. In busy period. This is because the controller is able to observe the selected channel and have chance to change choice in busy period. Comparing two different sizes of sessions, we can conclude that the bigger session brings higher fluctuation of system performance.

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References

1. Zhang, K., Chen, L., An, Y., et al.: A QoE test system for vehicular voice cloud services. Mob. Netw. Appl. (2019). https://doi.org/10.1007/s11036-019-01415-3
2. Wang, F., Jiang, D., Qi, S.: An adaptive routing algorithm for integrated information networks. China Commun. **7**(1), 196–207 (2019)

3. Huo, L., Jiang, D., Lv, Z., et al.: An intelligent optimization-based traffic information acquirement approach to software-defined networking. Comput. Intell. **36**, 1–21 (2019)
4. Chen, L., Jiang, D., Bao, R., Xiong, J., Liu, F., Bei, L.: MIMO scheduling effectiveness analysis for bursty data service from view of QoE. Chin. J. Electron. **26**(5), 1079–1085 (2017)
5. Jiang, D., Wang, Y., Lv, Z., et al.: Big data analysis-based network behavior insight of cellular networks for industry 4.0 applications. IEEE Trans. Ind. Inf. **16**(2), 1310–1320 (2020)
6. Jiang, D., Huo, L., Song, H.: Rethinking behaviors and activities of base stations in mobile cellular networks based on big data analysis. IEEE Trans. Netw. Sci. Eng. **1**(1), 1–12 (2018)
7. Chen, L., et al.: A lightweight end-side user experience data collection system for quality evaluation of multimedia communications. IEEE Access **6**(1), 15408–15419 (2018)
8. Chen, L., Zhang, L.: Spectral efficiency analysis for massive MIMO system under QoS constraint: an effective capacity perspective. Mob. Netw. Appl. (2020). https://doi.org/10.1007/s11036-019-01414-4
9. Wang, F., Jiang, D., Qi, S., et al.: A dynamic resource scheduling scheme in edge computing satellite networks. Mob. Netw. Appl. (2019)
10. Jiang, D., Huo, L., Lv, Z., et al.: A joint multi-criteria utility-based network selection approach for vehicle-to-infrastructure networking. IEEE Trans. Intell. Transp. Syst. **19**(10), 3305–3319 (2018)
11. Jiang, D., Zhang, P., Lv, Z., et al.: Energy-efficient multi-constraint routing algorithm with load balancing for smart city applications. IEEE Internet Things J. **3**(6), 1437–1447 (2016)
12. Jiang, D., Li, W., Lv, H.: An energy-efficient cooperative multicast routing in multi-hop wireless networks for smart medical applications. Neurocomputing **220**(2017), 160–169 (2017)
13. Jiang, D., Wang, Y., Lv, Z., et al.: Intelligent optimization-based reliable energy-efficient networking in cloud services for IIoT networks. IEEE J. Selected Areas Commun. (2019)
14. Shahini, A., Kiani, A., Ansari, N.: Energy efficient resource allocation in EH-Enabled CR networks for IoT. IEEE Internet Things J. **6**(2), 3186–3193 (2019)
15. Jiang, D., Wang, W., Shi, L., et al.: A compressive sensing-based approach to end-to-end network traffic reconstruction. IEEE Trans. Netw. Sci. Eng. **5**(3), 1–2 (2018)
16. Zeng, Y., Qi, Z., Chen, W. Huang, Y.: TEST: an end-to-end network traffic classification system with spatio-temporal features extraction. In: 2019 IEEE International Conference on Smart Cloud (SmartCloud), Tokyo, Japan, pp. 131–136 (2019)
17. Qi, S., Jiang, D., Huo, L.: A prediction approach to end-to-end traffic in space information networks. Mob. Netw. Appl. (2019)
18. Kim, E., Choi, Y.: Traffic monitoring system for 5G core network. In: 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN), Zagreb, Croatia, pp. 671–673 (2019).
19. Wang, Y., Jiang, D., Huo, L., et al.: A new traffic prediction algorithm to software defined networking. Mob. Netw. Appl. (2019)
20. Jiang, D., Huo, L., Li, Y.: Fine-granularity inference and estimations to network traffic for SDN. Plos One **13**(5), 1–23 (2018)
21. Wang, X., et al.: The joint optimization of online traffic matrix measurement and traffic engineering for software-defined networks. IEEE/ACM Trans. Netw. **28**(1), 234–247 (2020)
22. Gu, Y., Lu, W., Xu, X., Qin, L., Shao, Z., Zhang, H.: An improved bayesian combination model for short-term traffic prediction with deep learning. IEEE Trans. Intell. Transp. Syst. **21**(3), 1332–1342 (2020)
23. Huo, L., Jiang, D., Qi, S., et al.: An AI-based adaptive cognitive modeling and measurement method of network traffic for EIS. Mob. Netw. Appl. (2019)
24. Aung, S.T., Thein, T.: Internet traffic categories demand prediction to support dynamic QoS. In: 2020 5th International Conference on Computer and Communication Systems (ICCCS), Shanghai, China, pp. 650–654 (2020)

25. Attia, M.B., Nguyen, K.K., Cheriet, M.: Dynamic QoS-aware scheduling for concurrent traffic in smart home. IEEE Internet Things J. **7**(6), 5412–5425 (2020)
26. Lemeshko, O., Yeremenko, O., Yevdokymenko, M., Hailan, A.M.: Tensor based load balancing under self-similar traffic properties with guaranteed QoS. In: 2020 IEEE 15th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET), Lviv-Slavske, Ukraine, pp. 293–297 (2020)
27. Ren, S., Tang, G.: A reactive traffic flow estimation in software defined networks. In: 2020 5th International Conference on Computer and Communication Systems (ICCCS), Shanghai, China, pp. 585–588 (2020)
28. Mangla, T., Halepovic, E., Ammar, M., Zegura, E.: Using session modeling to estimate HTTP-based video QoE metrics from encrypted network traffic. IEEE Trans. Netw. Serv. Manage. **16**(3), 1086–1099 (2019)
29. Tian, F., Yu, Y., Li, D., Cui, J., Dong, Y.: QoE optimization for traffic offloading from LTE to WiFi. In: 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), Osaka, Japan, pp. 115–116 (2019)
30. Tang, S., Li, C., Qin, X., Wei, G.: Traffic classification for mobile video streaming using dynamic warping network. In: 2019 28th Wireless and Optical Communications Conference (WOCC), Beijing, China, pp. 1–5 (2019)
31. Bao, R., Chen, L., Cui, P.: User behavior and user experience analysis for social network services. Wirel. Netw. (2020). https://doi.org/10.1007/s11276-019-02233-x
32. Oszmianski, J., Safjan, K., Dottling, M., Bohdanowicz, A.: Impact of traffic modeling and scheduling on delay and spectral efficiency of the WINNER system. In: VTC Spring 2008 - IEEE Vehicular Technology Conference, Singapore, pp. 2661–2665 (2008)
33. Zhao, G., Chen, S., Zhao, L., Hanzo, L.: Energy-spectral-efficiency analysis and optimization of heterogeneous cellular networks: a large-scale user-behavior perspective. IEEE Trans. Veh. Technol. **67**(5), 4098–4112 (2018)
34. Zhao, G., Chen, S., Qi, L., Zhao, L., Hanzo, L.: Mobile-traffic-aware offloading for energy- and spectral-efficient large-scale D2D-enabled cellular networks. IEEE Trans. Wirel. Commun. **18**(6), 3251–3264 (2019)
35. Stahlbuhk, T., Shrader, B., Modiano, E.: Learning aloglrithms for mining queue length regret. In: 2018 IEEE International Symposium on Information (2018)
36. Bubeck, S., Cesa-Bianchi, N.: Regret analysis of stochastic and nonstochastic multi-armed bandit problems. Found. Trends Mach. Learn. **5**(1), 1–122 (2012)
37. Auer, P., Cesa-Bianchi, N., Fischer, P.: Finite-time analysis of the multiarmed bandit problem. Mach. Learn. **47**(2–3), 235–256 (2002)
38. Krishnasamy, S., et al.: Regret of queueing bandits. In: Proceedings of Neural Information Processing Systems, pp. 1669–1677 (2016)