Dealing with Limited Backhaul Capacity in Millimeter-Wave Systems: A Deep Reinforcement Learning Approach

Mingjie Feng and Shiwen Mao

With limited backhaul capacity and highly dynamic data rates of users, how to allocate backhaul resource to each user remains a challenge for mmWave systems. The authors present a deep reinforcement learning (DRL) approach to address this challenge. By learning the blockage pattern, the system dynamics can be captured and predicted, resulting in efficient utilization of backhaul resource.

Abstract

Millimeter-wave (mmWave) communication is a key technology of fifth generation wireless systems to achieve the expected 1000× data rate. With large bandwidth at the mmWave band, the link capacity between users and base stations (BSs) can be much higher compared to sub-6 GHz wireless systems. Meanwhile, due to the high cost of infrastructure upgrade, it would be difficult for operators to drastically enhance the capacity of backhaul links between mmWave BSs and the core network. As a result, the data rate provided by backhaul may not be sufficient to support all mmWave links; hence, the backhaul connection becomes the new bottleneck. On the other hand, as mmWave channels are subject to random blockage, the data rates of mmWave users significantly vary over time. With limited backhaul capacity and highly dynamic data rates of users, how to allocate backhaul resource to each user remains a challenge for mmWave systems. In this article, we present a deep reinforcement learning (DRL) approach to address this challenge. By learning the blockage pattern, the system dynamics can be captured and predicted, resulting in efficient utilization of backhaul resource. We begin with a discussion on DRL and its application in wireless systems. We then investigate the problem of backhaul resource allocation and present the DRL-based solution. Finally, we discuss open problems for future research and conclude this article.

Introduction

With the explosion of smart devices and data-intensive wireless applications, the demand for high data rate services has drastically increased in recent years. To meet such demand, the fifth generation (5G) cellular network is under intensive research from both industry and academia. According to a recent report, the 5G networks are expected to support massive connections with minimum data rate of 100 Mb/s and peak data rate higher than 10 Gb/s [1]. To achieve this goal, several technologies are considered as candidates for 5G systems, including millimeter-wave (mmWave) communications, massive multiple-input multiple-output (MIMO), and small cell. By operating at mmWave band with large bandwidth, an mmWave system can significantly elevate the data rate performance to the multi-gigabits-per-second level.

As the data rates of links between an mmWave base station (BS) and users are greatly enhanced, the capacity of backhaul link between the BS and the core network becomes relatively limited, posting a new challenge to mmWave cellular networks. Compared to a Long Term Evolution (LTE) system with typical cell throughput less than 150 Mb/s [2], the cell throughput of an mmWave system can be greater than 1.5 Gb/s [3], which is comparable to the data rate of a current backhaul link. As a result, the backhaul links in mmWave cellular networks are expected to achieve much higher data rates compared to current cellular networks. In current LTE networks, the configuration of a backhaul link is to support peak cell throughput. However, this may not be feasible in mmWave networks. Due to cost concerns, it is unlikely for operators to upgrade existing infrastructure to drastically enhance capacity of wired backhauls. In the case of wireless backhaul (e.g., mmWave-based wireless backhaul or free space optical), although the cost can be reduced, the challenge brought by limited backhaul capacity remains. On one hand, the capacity of wireless backhaul link is shared by multiple BS-user links. On the other hand, the backhaul links are likely to experience higher propagation loss than the BS-user links.

The tension caused by limited backhaul capacity may be aggravated in the future as the data rate of mmWave links is expected to keep increasing. For example, high resolution 360° virtual reality (VR) requires data rate on the order of 1 Gb/s and latency of 1 ms. Based on a prediction in [1], the 5G mmWave networks need to support 50 Gb/s data rate by 2024. In addition, due to the expected dense deployment of mmWave BSs [4], a large number of backhaul connections, which can be wired or wireless, will coexist. As a result, the achievable data rate of each backhaul link will be limited, which may be caused by resource sharing, mutual interference, potential congestion, or increased overhead [5]. Therefore, unlike traditional cellular networks (from 1G to 4G) in which the wireless transmission between BS and user is the bottleneck, the backhaul becomes a potential bottleneck in mmWave systems. Although some

Digital Object Identifier: 10.1109/MCOM.2019.1800565

The authors are with Auburn University.

field tests have been performed to demonstrate the potential of mmWave cellular systems such as in [3], these tests are not based on actual cellular networks. Thus, the impact of limited backhaul capacity has not been tested and verified, which requires further investigation. The challenge of the possible bottleneck at backhaul has been observed in the context of ultra-dense small cell deployment [4], in which the large number of small cells put pressure on the backhaul links. Compared to the case of network desification, the bottleneck challenge in an mmWave system is caused by the significantly increased data rate of mmWave transmissions.

On the other hand, due to the short wavelength of mmWave communications, the transmissions between BS and users are subject to random blockage. As a result, the data rate of each user is highly dynamic. In contrast, the data rate of a backhaul link is much more stable since it is implement by wired connection or line of sight (LoS) wireless connection. Therefore, the BS-UE link is characterized by high data rate and unstable connection, while the backhaul link is characterized by relatively limited data rate and stable connection, as shown in Fig. 1. To balance this mismatch and enhance the system performance, efficient backhaul resource allocation to each user is necessary. For example, when a user switches from LoS transmission to non-LoS (NLoS) or experiences an outage, less resource shoud be allocated to this user. However, such adaptive control cannot be implemented by traditional resource allocation schemes due to the varying system dynamics. To perform efficient scheduling, a BS needs to predict possible blockage and estimate the data rate of each user based on the current channel state information (CSI). Then it makes a decision on the backhaul resource allocation and sends a request to the core network. This way, the backhaul scheduling can be performed in a timely manner that captures the blockage pattern.

Deep reinforcement learning (DRL) is a new paradigm for intelligent decision making [6], which can be implemented by TensorFlow and Keras. Combining reinforcement learning and the DNN, a DRL agent interacts with the environment and learns the pattern of a Markov decision process (MDP) through training experience. Specifically, a DRL agent employs a deep neural network (DNN) to approximate the Q-values, where the Q-values are defined by discounted cumulative rewards that can be obtained by taking different actions under certain system states. Then the agent makes optimal decisions based on the estimated Q-values. Compared to other machine learning approaches, DRL is model-free and does not require data samples from an external supervisor. Due to these benefits, the application of DRL in wireless networks has drawn growing attention recently. In this article, we apply DRL to deal with the challenge of limited backhaul capacity in mmWave networks. By learning the blockage pattern based on the CSI of mmWave users, a BS decides the resource allocation of the backhaul link with the objective of maximizing the sum utility of all users.

In the remainder of this article, we first introduce the background of DRL and review its recent applications in wireless systems. Then we present a DRL-based approach for backhaul resource allocation. Finally, we discuss open research problems and conclude this article.

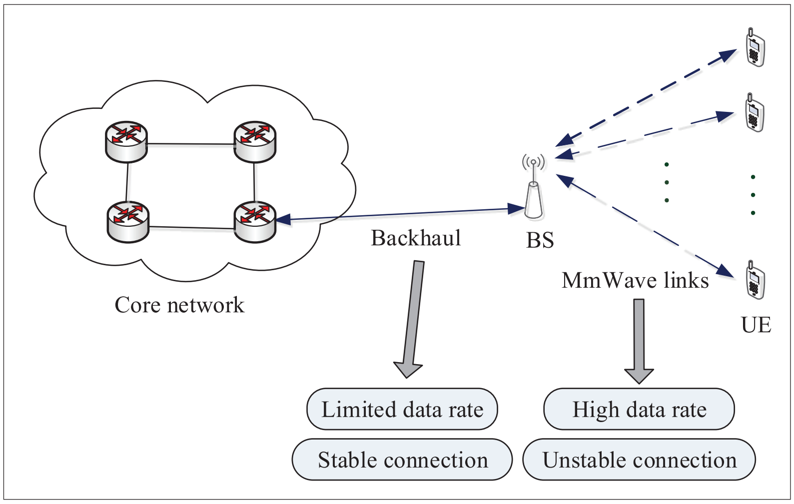

Figure 1. System model of an mmWave system with limited backhaul capacity.

Deep Reinforcement Learning for Wireless Systems

Preliminaries of Deep Reinforcement Learning

A reinforcement learning (RL) agent aims to learn from the environment and take action to maximize the long-term cumulative reward. The environment is modeled as an MDP with a state space, and an RL agent can take actions from a certain action space. The agent interacts with the environment by taking actions, observing the reward and system state transition, and updating its knowledge about the environment. The objective of an RL algorithm is to find the optimal policy, which determines the strategy of taking actions under certain system states. Specifically, a policy is defined by the probabilities of taking different actions under a certain state at a current time instant. In general, a policy is in a stochastic form to enable exploration over different actions. To find the optimal policy, the key component is to determine the value of each state-action function, also known as Q-function. Q-function indicates the expected long-term cumulative rewards that can be obtained if the agent takes different actions under different states. In particular, a Q-function has two parts: one is the instant reward obtained by taking an action under a certain state; the other is the consequent future rewards, which are impacted by the probabilistic system transitions. The details of Q-function can be found in [6]. With Q-functions, an MDP is solved when the optimal policy that maximizes the values of Q-functions (Q-values) is found.

A common RL technique for solving an MDP is Q-learning, which uses an empirical iterative approach to update Q-values. In particular, an agent interacts with the environment by taking actions and obtaining rewards, and then updates the Q-values with the newly observed instant reward.

RL has been applied in decision making problems of mmWave networks such as in [7]. However, in large-scale systems with large numbers of states and actions, the traditional Q-learn-

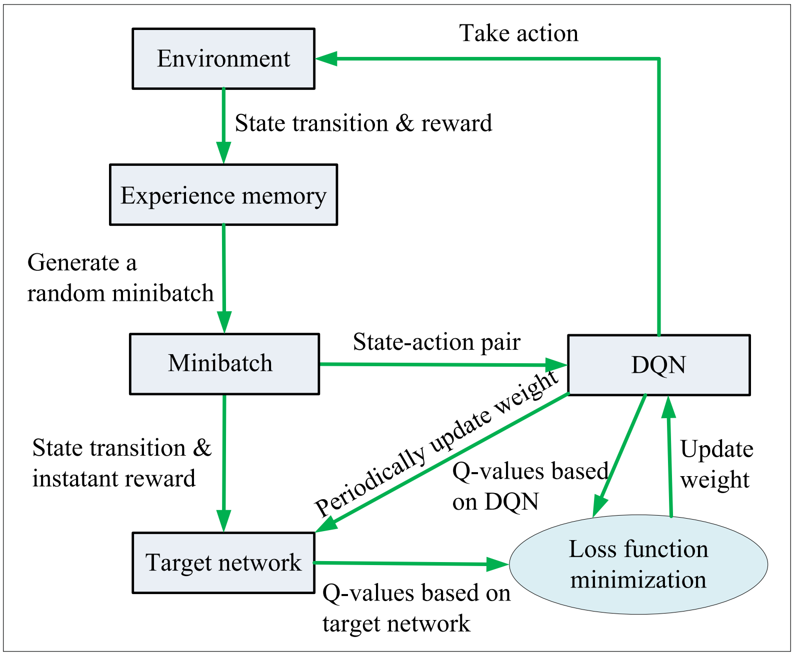

Figure 2. Framework of the DRL approach in [6].

ing approach becomes infeasible since a table is required to store all the Q-values. In addition, traditional Q-learning needs to visit and evaluate every state-action pair, resulting in huge complexity and slow convergence. An effective approach to deal with such challenge is to use a neural network (NN) to approximate the Q-values, where each Q-value is a function of state, action, and the weights of the NN. By training an NN with sampled data, the NN can map the inputs of state-action pairs to their corresponding Q-values. However, a direct application of NN in Q-learning may lead to unstable or even diverge results due to the correlations between training samples and the correlations between Q-values and target values [6].

To reduce such correlations, a DRL approach was proposed in [6], in which a DNN is used to approximate the Q-value, yielding a deep Q-network (DQN). In the DRL approach presented in [6], the agent first explores the environment by randomly taking actions and stores the experience in a target network. A set of experience includes the current state, action, instant reward, and new state. Then a mechanism called *experience replay* is used, where the data are randomly sampled in minibatches from the target network to break the correlation in a sequence of observation. With samples from the target network, the weights of the DQN are updated by minimizing the mean square error of Q-functions between the DQN and the target network. Then a stochastic gradient descent approach is used to obtain the weights of the DQN. To reduce the correlation between the DQN and the target network, the target network is updated less frequently. After the training of the DQN, the agent then takes action based on the estimated Q-values. The general framework of the DRL approach in [6] is shown in Fig. 2.

Applications in Wireless Networks

In the design of wireless networks, a major challenge is to solve the formulated combinatorial problems. While exhaustive search is infeasible due to the prohibitive complexity, existing solutions typically rely on network information exchange, which yields a trade-off between overhead and performance. For DRL approaches, the network optimization is based on trial and error, which do not require explicit or instantaneous network information. In particular, a DRL algorithm is model-free, which does not require explicit knowledge on the inter-dependent patterns of different nodes. In addition, with extensive offline training, a DRL agent is able to predict the system dynamics, which enables timely scheduling. Thus, compared to traditional approaches, DRL-based schemes have the potential to achieve better performance with reduced online overhead.

Due to this promising prospect, DRL algorithms have been recently considered in several wireless networks to perform intelligent decision making [8–13]. In [8], DRL is used to estimate the availability of cache and select a proper set of users for interference alignment. In [9, 10, 13], the problem of multi-channel access is considered in which each user observes the channel dynamics from history and estimates the possible actions of other users, then determines its channel access strategy. In [11], DRL is used to predict the quality of service (QoS) that can obtained when handing over a UE to another BS, resulting in an efficient handover process. In [12], continuous actions and states are considered so that DQN-based DRL cannot be applied. The deep deterministic policy gradient (DDPG), which is based on an actor-critic framework, was employed to address the continuous space control problem. The general idea is to parameterize the Q-functions and derive the optimal values of parameters through a policy gradient. In [10, 11, 13], the problems are formulated as multi-agent control with interactions among agents. As a result, experience replay for a single agent cannot be applied in such scenarios. To take the inter-agent impact into account, long short-term memory (LSTM) is used to generate target values. The key aspects of system models in recent works are summarized in Table 1.

DRL-Based Backhaul Resource Allocation

System Model

We consider an mmWave BS serving multiple user equipments (UEs). Each user has three link states: LoS, NLoS, and outage. The link state of each user follows a Markov process with steady state probabilities given in [3]. We assume that the BS can estimate the link state of each user through the statistics of user signals. The BS can also measure the *achievable* data rate of the mmWave link of each user via uplink signals.

We assume the backhaul resource is divided into multiple orthogonal blocks. The number of resource blocks is larger than the number of UEs. Each block can be a period of time or a range of wavelengths. We assume that each block has a fixed capacity, and each UE can be allocated multiple blocks. Then the backhaul capacity allocated to a user is proportional to the number of allocated blocks. As a result, the *actual* data rate of a user is the minimum of its backhaul capacity and its achievable data rate of the mmWave link.

	Application	State	Action	Reward	Learning objective
[8]	Cache-based interference alignment	Channel power gain	User selection for interference alignment	Network throughput	Channel dynamics and cache availability
[9]	Multi-channel access	Channel state: good/bad	Channel selection of each user	Number of successful transmissions	Channel availability
[10]	Resource management in LTE-Unlicensed	Current channel usage pattern	Channel access probability	Total throughput on selected channels	Channel access patterns of other users
[11]	Handover control in ultra-dense network	Signal qualities from different BSs	BS selection	Weighed sum of data and rate handover energy	Prediction for channel qualities from different BSs
[12]	Traffic allocation in multihop network	Throughput and delay of each session	Traffic split ratio	Total utility (weighted sum of throughput and delay)	Learn traffic pattern from experience
[13]	Multi-channel random access	Channel access of other users	Channel access strategy	Number of successful transmissions	Probabilities of success transmission over multi-channel

Table 1. Applications of DRL in different wireless networks.

DRL Framework

The proposed DRL-based approach employs a DQN to find the resource allocation strategy under different system states. The key component of system state is the achievable data rate of each UE. We also include the link states of all UEs as part of the system states, since they affect the future data rates. Then the system state is used as input to the DQN. The action taken by the agent indicates the backhaul capacity allocation (i.e., the number of blocks allocated to each user). The action space consists of all feasible resource allocation, which includes multiple combinations of integers. For each combination, the sum of all integers equals the number of blocks. To achieve good system performance as well as guarantee fairness, we define the utility of each user to be a concave function of its data rate. Then the system reward is set as the sum of utilities of all users. The architecture of the DQN is shown in Fig. 3. The input includes the link state and achievable data rate information of each user. The output presents the approximated Q-values, and there are several hidden layers between the input and output layers.

The training procedure of the DQN is the same as the one in [6], which uses experience replay to reduce the correlation between training samples, as shown in Fig. 2. With the DQN, the agent at the BS observes the current data rates and link states of all users and obtains the Q-values of taking different actions (i.e., selecting different resource allocation strategies). Then the agent takes an action according to a probabilistic greedy approach to achieve an exploitation-exploration trade-off. Specifically, the agent selects the action with the maximum Q-value with a certain probability and randomly selects an action otherwise.

Illustrative Example

We evaluate the performance of the DRL-based approach with simulations. We consider an mmWave cell with a coverage radius of 100 m; users are randomly distributed in the cell. The probabilities of a user in different link states are functions of the distance between the user and the BS. The probabilities under outage, LoS, and NLoS are given in [3], which are the steady state probabilities of the Markov process of link state.

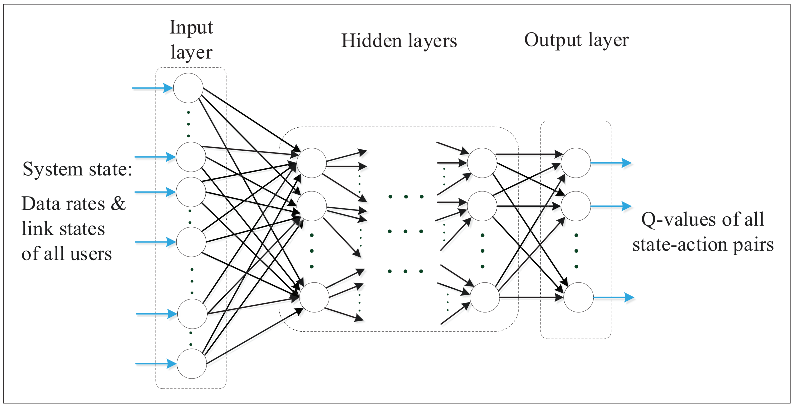

Figure 3. Architecture of the DQN for backhaul resource allocation.

We employ the channel model of 73 GHz band in [3], where NLoS links experience higher path loss than LoS links. The system bandwidth is 1 GHz, and the transmit powers of BS and UEs are 30 dBm and 20 dBm, respectively. The backhaul capacity is 10 Gb/s; the backhaul resource is divided into 20 resource blocks. There are two hidden layers in the DQN, and we use ReLu as the activation function. We consider two DRL-based schemes, namely DRL-1 and DRL-2, with reward functions given as the sum of logarithmic data rate and the sum of square root of data rate, respectively. With the logarithmic utility function, DRL-1 achieves proportional fairness. Compared to DRL-1, DRL-2 is more efficiency-prone with a worse fairness. Two benchmark schemes are considered for comparison: a myopic scheme and the equal allocation scheme. For the myopic scheme, the backhaul resource allocation is based on the current data rates of mmWave links, without considering the future change of link states.

Figure 4 shows the sum rate performance under different numbers of users. As the number of users increases, the sum rates of all schemes grow at reduced rates, showing that the system performance is limited by the backhaul capacity. The proposed DRL-based schemes outperform the other ones, and the performance gap gets larger when the number of users increases. This is because the BS is able to predict the variation of link state and allocate the resource based on long-term consideration. Then the backhaul resource can be efficiently utilized, and this

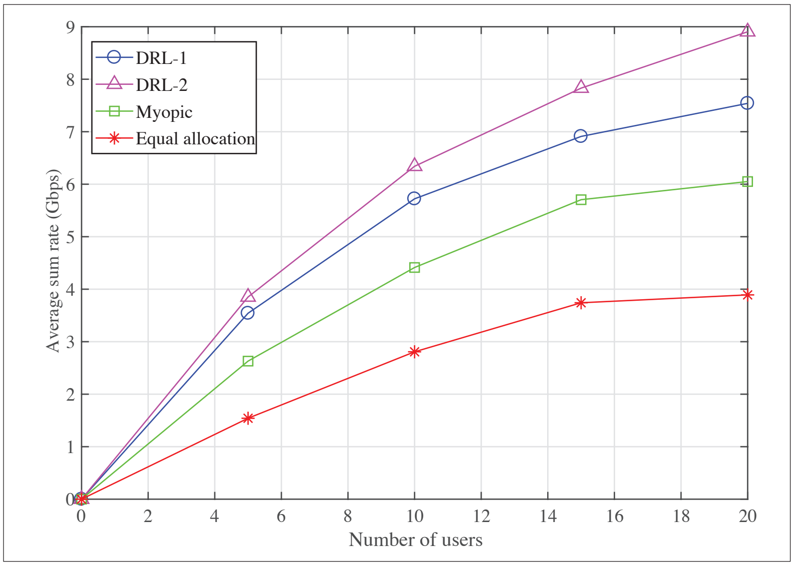

Figure 4. Sum rate performance of different schemes vs. the number of users.

advantage becomes more significant when the number of users is large. Compared to DRL-1, DRL-2 achieves higher data rate since its utility and reward functions are set to prioritize efficiency over fairness.

The performance under different values of the blockage coefficient is shown in Fig. 5. The blockage coefficient is defined in [3], which indicates the likelihood that a user will experience blockage. From Fig. 5, we can see that when the blockage coefficient is small, the performance of the myopic scheme is close to the proposed DRL-based schemes, since the ratio of users under blockage is small and the data rates of mmWave links are relatively stable. However, when the number of users increases, the performance gap between the proposed schemes and the myopic scheme is increased, showing that DRL-based scheduling is effective in capturing the system dynamics and making intelligent decisions from the perspective of long-term benefit.

Open Problems and Future Research

Joint Optimization of Backhaul and MmWave Links

The DRL based backhaul resource allocation presented earlier is based on the given achievable rate of each user. To mitigate the pressure caused by limited backhaul capacity, the design of BS-UE links can also be considered. The design of resource allocation in LTE systems with limited backhaul capacity was studied in [14]. In mmWave systems, the data rate of each mmWave link can be adjusted through precoding design. Considering the channel characteristics of different users, a joint consideration of backhaul resource allocation and precoding can provide a better solution to balance the tension between limited backhaul and increased mmWave data rate demand.

Dynamic Backhaul Capacity

In our model, we assume fixed capacity for backhaul, which corresponds to the case of wired backhaul or LoS mmWave backhaul with highly stable data rate. However, in a practical system with wireless backhaul, the data rate of backhaul would vary over time. Thus, it is necessary for the agent to learn such dynamics as well, and more sophisticated design is required based on the proposed framework.

Multi-Cell Scenario

Capacity Allocation Among Different Backhauls: The design described earlier is based on a single-cell scenario. From the perspective of multi-cell, the capacity allocated to each backhaul can be optimized to further enhance the system performance. For example, an mmWave BS with heavy traffic and high aggregated data rate requirement can share more capacity from the core network. However, load balancing and capacity allocation require coordination between different BSs, and efficient design is required. In addition, how to address the scalability issue is another challenge. Capacity allocation among different backhauls for load balancing has been investigated in other wireless networks, such as in heterogeneous cloud radio access networks [15]. Due to the dynamic nature of mmWave communications, the varying capacity requirement of each backhaul needs to be learned to enable effective scheduling.

Adaptive User Association: To mitigate the pressure of limited backhaul, an effective approach is to perform load balancing. For a BS with large deficit in backhaul capacity, some of the users served by the BS can be handed over to neighboring BSs to reduce the traffic demand on this BS. Thus, traffic-aware user association is another design factor that can be considered for better system performance.

Heterogeneous Network

In a heterogeneous network, the traffic of small cells is transmitted to a macrocell via backhaul connections and then forwarded to the core network via the backhaul of the macrocell. Then the backhaul resource allocation becomes a two-tier problem, which requires more complicated design. In addition, similar to the multi-cell case, the capacity allocation for different small cell backhaul links and adaptive user association are important design issues that should be jointly considered with backhaul resource allocation.

Caching Assisted System

BS caching (e.g., femtocaching) was recently proposed as an effective approach to enhance the data rate of users. By downloading popular contents in advance and storing them at local BSs, the files requested by users are directly transmitted from local BSs. While the primary goal of caching is to increase the capacity of BS-user links and reduce delay, it is also a good solution to the limited backhaul capacity challenge. When the traffic load of an mmWave BS is low, it can request popular files from the core network. When the traffic load is increased, the popular files at the BS can be used to satisfy the demand of some users. As a result, the backhaul capacitiy is mainly used to satisfy the instantaneous demands from users, thus mitigating the traffic burden at the backhaul. Under the caching architecture, the key design issue is the selection of popular contents. With limited storage, it is necessary to learn the patterns of users' preference and blockage. For example, when a user is under frequent blockage, caching and storing the content of this user would lead to underutilization. However, if the content requested by the user is also frequently requested by other users, the utilization would be improved. Thus, the agent needs to learn multiple patterns to derive an efficient caching strategy.

Performance-Complexity Trade-off

In the system model discussed above, we assume the backhaul resource is divided into M blocks. To improve resource utilization and enhance the system performance, a larger value of M is desirable. However, this results in increased dimensions of both action and state spaces. Thus, an adaptive selection of M that achieves a good trade-off between complexity and performance is another design issue.

Conclusion

In this article, we address the challenge of limited backhaul capacity in mmWave networks with a DRL-based approach. We first overview the background of DRL and its applications in wireless networks. Then we present a DRL-based approach to enable efficient backhaul resource allocation, and show the effectiveness through an illustrative example. We then discuss the future research problems and conclude this article.

Acknowledgment

This work was supported in part by the NSF under Grant CNS-1702957 and by the Wireless Engineering Research and Engineering Center at Auburn University.

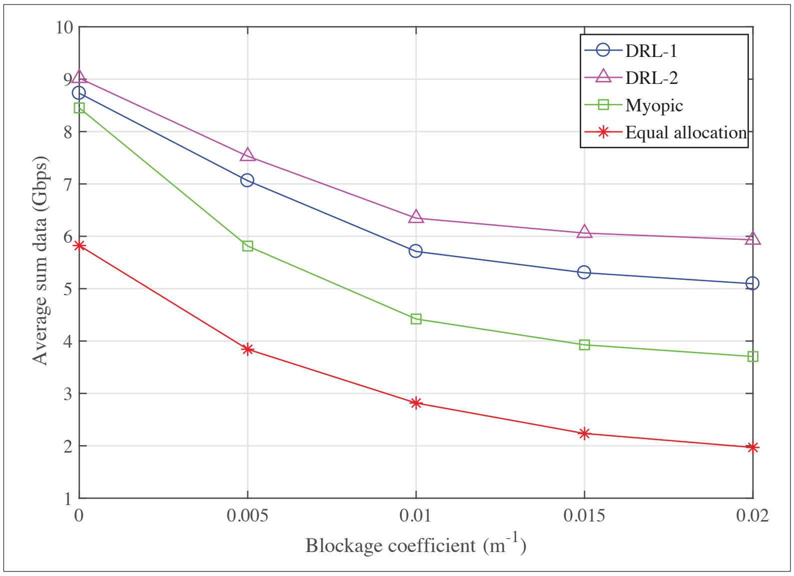

Figure 5. Performance of different schemes vs. blockage coefficient a_{out}.

References

[1] A. Ghosh, "5G mmWave Revolution and New Radio"; https://5g.ieee.org/images/files/pdf/5GmmWave_Webinar_IEEE_Nokia_09_20_2017_final.pdf.

[2] P. Croy, "LTE Backhaul Requirements: A Reality Check," white paper; www.portals.aviatnetworks.com/exLink.asp?9826636OQ63H29I38061128.

[3] M. R. Akdeniz *et al.*, "Millimeter Wave Channel Modeling and Cellular Capacity Evaluation," *IEEE JSAC*, vol. 32, no. 6, June 2014, pp. 1164–79.

[4] X. Ge *et al.*, "5G Ultra-Dense Cellular Networks," *IEEE Wireless Commun.*, vol. 23, no. 1, Feb. 2016, pp. 72–79.

[5] M. Feng, S. Mao, and T. Jiang, "Joint Frame Design, Resource Allocation and User Association for Massive MIMO Heterogeneous Networks with Wireless Backhaul," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, Mar. 2018, pp. 1937–50.

[6] V. Mnih *et al.*, "Human-Level Control Through Deep Reinforcement Learning," *Nature*, vol. 518, no. 7540, Feb. 2015, pp. 529–33.

[7] M. Mezzavilla *et al.*, "An MDP Model for Optimal Handover Decisions in mmWave Cellular Networks," *Proc. IEEE EuCNC '16*, Athens, Greece, June 2016, pp. 100–05.

[8] Y. He *et al.*, "Deep-Reinforcement-Learning-Based Optimization for Cache-Enabled Opportunistic Interference Alignment Wireless Networks," *IEEE Trans. Vehic. Tech.*, vol. 66, no. 11, Nov. 2017, pp. 10433–445.

[9] S. Wang *et al.*, "Deep Reinforcement Learning for Dynamic Multichannel Access in Wireless Networks," *IEEE Trans. Cognitive Commun. and Net.*, vol. 4, no. 2, June 2018, pp. 257–65.

[10] U. Challita, L. Dong, and W. Saad, "Proactive Resource Management for LTE in Unlicensed Spectrum: A Deep Learning Perspective," *IEEE Trans. Wireless Commun.*, vol. 17, no. 7, July 2018, pp. 4674–89.

[11] Z. Wang *et al.*, "Handover Control in Wireless Systems Via Asynchronous Multi-User Deep Reinforcement Learning," *IEEE Internet of Things*. DOI: 10.1109/JIOT.2018.2848295.

[12] Z. Xu, *et al.*, "Experience-Driven Networking: A Deep Reinforcement Learning Based Approach," *Proc. IEEE INFOCOM' 18*, Honolulu, HI, Apr. 2018.

[13] O. Naparstek and K. Cohen, "Deep Multi-User Reinforcement Learning for Dynamic Spectrum Access in Multichannel Wireless Networks," *Proc. IEEE GLOBECOM '17*, Singapore, Dec. 2017.

[14] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-Efficient Resource Allocation in Multi-Cell OFDMA Systems with Limited Backhaul Capacity," *IEEE Trans. Wireless Commun.*, vol. 11, no. 10, Oct. 2012, pp. 3618–31.

[15] C. Ran, S. Wang, and C. Wang, "Balancing Backhaul Load in Heterogeneous Cloud Radio Access Networks," *IEEE Wireless Commun.*, vol. 22, no. 3, June 2015, pp. 42–48.

Biographies

Mingjie Feng [S'15] (mzf0022@auburn.edu) received his Ph.D. degree in electrical and computer engineering from Auburn University, Alabama, in 2018. He received his Bachelor's and Master's degrees from the School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan, China, in 2010 and 2013, respectively. He is currently a postdoctoral research associate in the Department of Electrical and Computer Engineering at the University of Arizona. In 2013, he was a visiting student in the Department of Computer Science and Engineering, Hong Kong University of Science and Technology. His research interests include mmWave communication, massive MIMO, cognitive radio networks, heterogeneous networks, and full-duplex communication. He is a recipient of a Woltosz Fellowship at Auburn University.

Shiwen Mao [S'99, M'04, SM'09, F'19] (smao@ieee.org) received his Ph.D. in ECE from Polytechnic University, Brooklyn, New York, in 2004. He is the Samuel Ginn Distinguished Professor and Director of the Wireless Engineering Research and Education Center at Auburn University. His research interests include wireless networks and multimedia communications. He is a Distinguished Speaker of the IEEE Vehicular Technology Society. He received the 2017 IEEE ComSoc ITC Outstanding Service Award, the 2015 IEEE ComSoc TC-CSR Distinguished Service Award, the 2013 IEEE ComSoc MMTC Outstanding Leadership Award, and the NSF CAREER Award in 2010. He is a co-recipient of the IEEE ComSoc MMTC Best Conference Paper Award in 2018, the Best Demo Award from IEEE SECON 2017, Best Paper Awards from IEEE GLOBECOM 2016 and 2015, IEEE WCNC 2015, and IEEE ICC 2013, and the 2004 IEEE Communications Society Leonard G. Abraham Prize in the Field of Communications Systems.