Deep Reinforcement Learning Based Resource Allocation in Wireless Networks

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Outline

1. Introduction
2. Radio Resource Management Problem
3. Multi-Agent Deep Reinforcement Learning (DRL) based Solution
4. Full-buffer Simulations
5. Traffic Simulations
6. Conclusion and future work

AI for Wireless:

- Data-driven, model-free AI for wireless can learn sophisticated strategies to enhance the network performance by processing limited previous data.
- The industry is very interested in AI based wireless resource management.

Progress:

- Power Control:
  Multi-Agent Deep Reinforcement Learning for Dynamic Power Allocation in Wireless Networks (IEEE JSAC 2019)
  - Adding Mobility:
    Deep Actor-Critic Learning for Distributed Power Control in Wireless Mobile Networks (Asilomar 2020)
- Joint Spectrum and Power Allocation:
  Deep Reinforcement Learning for Joint Spectrum and Power Allocation in Cellular Networks (submitted to Globecom 2021)
- Both Varying Traffic and Channel Conditions
  Traffic-driven Radio Resource Management via Deep Reinforcement Learning (to be submitted)

System Model:

- N links, K cells, SISO, M subbands.
- $\mathcal{K} = \{1, \ldots, K\}$, $\mathcal{N} = \{1, \ldots, N\}$, and $\mathcal{M} = \{1, \ldots, M\}$
- If link n's user is inside cell k, its associated base station $b_n \in \mathcal{K}$ is at the center of cell k.
- Base station b_n transmits to user n over m in time slot t with $p_{n,m}^{(t)} \geq 0$.
- The power constraint restricts the total transmit power on subband m:

$$\sum_{n \in \mathcal{N} : b_n = k} p_{n,m}^{(t)} \leq P_{\max}, \forall k, \forall m.$$

Link Model:

- $g^{(t)}_{b_n \rightarrow n,m}$: direct channel gain.
- $g^{(t)}_{b_j \rightarrow n,m}$: interfering channel gain.
- Spectral efficiency:

$$C^{(t)}_{n,m}\left(\boldsymbol{p}^{(t)}_m\right) = \log\left(1 + \frac{g^{(t)}_{b_n \rightarrow n,m} p^{(t)}_{n,m}}{\sum_{j \in \mathcal{N}, j \neq n} g^{(t)}_{b_j \rightarrow n,m} p^{(t)}_{j,m} + \sigma^2}\right),$$

where $\boldsymbol{p}^{(t)}_m = \left[p^{(t)}_{1,m}, p^{(t)}_{2,m}, \ldots, p^{(t)}_{N,m}\right]^{\mathsf{T}}$.

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$$C^{(t)}_n = \sum_{m \in \mathcal{M}} C^{(t)}_{n,m}\left(\boldsymbol{p}^{(t)}_m\right).$$

Traffic Model:

- Each link has a queue.
- $N_n^{(t)}$ is link n's queue length in bits at the beginning of time slot t.
- W : total bandwidth.
- T : time slot duration.
- $A_n^{(t)}$: newly arrived packets.
- $$N_n^{(t)} = \max\left(N_n^{(t-1)} - C_n^{(t-1)}WT, 0\right) + A_n^{(t)}L,$$

Channel Variations:

The downlink channel gain:

$$g^{(t)}_{b_n\to n,m} = \beta_{b_n\to n}\left|R^{(t)}_{b_n\to n,m}\right|^2, \quad t = 1, 2, \dots ,$$

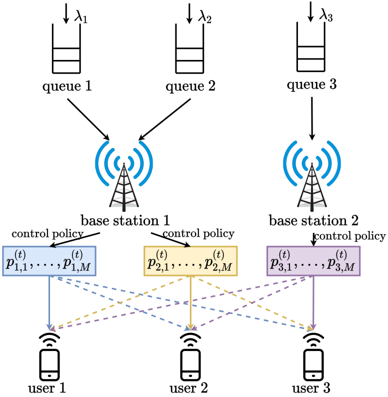
where

- $\beta_{b_n\to n} \geq 0$ is the large-scale fading that includes path loss and log-normal shadowing. It is same across all subbands.
- $R^{(t)}_{b_n\to n,m}$ is the small-scale fading. It is is frequency selective and modeled by Jakes' Model:

$$R^{(t)}_{b_n\to n,m} = \rho R^{(t-1)}_{b_n\to n,m} + \sqrt{1-\rho^2}e^{(t)}_{b_n\to n,m},$$

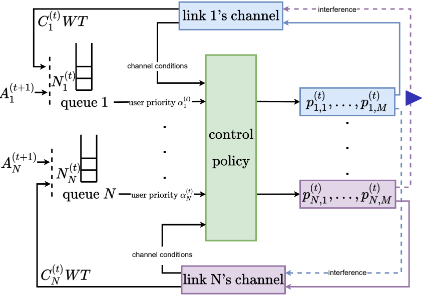
where $\rho = J_0(2\pi f_d T)$, $R^{(0)}_{b_n\to n,m} \sim \mathcal{CN}(0,1)$, and $e^{(1)}_{b_n\to n,m}, e^{(2)}_{b_n\to n,m}, \dots$ consists of i.i.d. CSCG random variables with unit variance.

The Fundamental Problem:

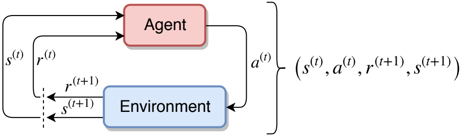


- A control policy that maps traffic & channel conditions to physical layer allocations.
- The long-term utility of user n, U_n, should reflect the average packet delay.
- The fundamental problem becomes finding an optimal control policy that maximizes $U = \sum_{n \in \mathcal{N}} U_n$.

The Fundamental Problem and Reinforcement Learning



- Model-free reinforcement learning learns directly from trial-and-error-interactions:



- The policy $\pi(a|s)$ denotes the probability of taking action a conditioned on the current state being s. The Q-function:

$$Q^\pi(s,a) = \mathbb{E}_\pi \left[R^{(t)} \middle| s^{(t)} = s, a^{(t)} = a \right]$$

where $R^{(t)} = \sum_{\tau=0}^{\infty} \gamma^\tau r^{(t+\tau+1)}$ and $\gamma \in (0,1]$.
- For radio resource management, $r^{(t+1)}$ can be thought as $-\sum_{n \in \mathcal{N}} N_n^{(t+1)}$.

Deep Q-learning algorithm

- indirectly optimize agent performance by learning a value function.
- Use a deep Q-network (DQN) parameterized by $\boldsymbol{\psi}$ to represent the Q-function values $q(\cdot, \cdot; \boldsymbol{\psi})$
- It is an off-policy learning that stores experiences in a memory $\mathcal{D}$.
- $\boldsymbol{\psi}$ is updated using a stochastic gradient descent algorithm by

$$\nabla_{\boldsymbol{\psi}} \frac{1}{|\mathcal{B}|} \sum_{(s,a,r',s') \in \mathcal{B}} \left(y(r', s') - q\left(s, a; \boldsymbol{\psi}\right)\right)^2,$$

where the target is $y(r', s') = r' + \gamma \max_{a'} q\left(s', a'; \boldsymbol{\psi}_{\text{target}}\right).$

Conventional Divide-and-Conquer Solution

- Non-negative user weights (priorities), $\alpha_n^{(t)}, \forall n \in \mathcal{N}$, are used to separate the network layer problem and the physical layer problem:

$$\begin{aligned} \underset{\boldsymbol{p}^{(t)}}{\text{maximize}} \quad & \sum_{n=1}^{N} \alpha_n^{(t)} \sum_{m \in \mathcal{M}} C_{n,m}^{(t)} \left(\boldsymbol{p}_m^{(t)}\right) \\ \text{subject to} \quad & p_{n,m}^{(t)} \geq 0, \forall n \in \mathcal{N}, \, m \in \mathcal{M}, \\ & \sum_{j \in \mathcal{N}_k} p_{j,m}^{(t)} \leq P_{\max}, \forall\, k \in \mathcal{K}, \, m \in \mathcal{M}. \end{aligned}$$

- Proportionally fair scheduling: Recall [Tse and Viswanath '05]:

$$\alpha_n^{(t+1)} = 1/\bar{C}_n^{(t)},$$

where $\bar{C}_n^{(t)} = \beta \cdot C_n^{(t)} + (1-\beta)\bar{C}_n^{(t-1)}$ with $\beta \in (0, 1]$.
This scheme maximizes:

$$\sum_{n \in \mathcal{N}} \log \bar{C}_n^{(t)}.$$

Existing Solutions:

- Conventional Optimization Based:
  - Weighted MMSE (WMMSE) [Shi, Razaviyayn, Luo, and He '11]
  - Fractional programming (FP) [Shen and Yu '18]
  - State of the art when
    - a mathematically tractable accurate system model is available;
    - full channel state information (CSI) is available;
    - iterations converge instantly (for time-varying channels);
    - no network backhaul latency (for time-varying channels).
- Deep Learning Based Solution: [Sun, Chen, Shi, Hong, Fu, and Sidiropoulos '17] proposed a centralized supervised learning scheme;
  - Trains a faster deep neural network (DNN) to approximate WMMSE;
  - Achieves 90% or higher of the sum-rate achieved by WMMSE.

Literature on reinforcement learning for power control:

- [Bennis and Niyato '10] and [Simsek, Czylwik, Galindo-Serrano, and Giupponi '11] used classical Q-learning to reduce the interference in LTE-Femtocells.
- [Amiri, Mehrpouyan, Fridman, Mallik, Nallanathan, and Matolak '18] have used cooperative Q-learning to increase QoS of users in femtocells without considering channel variations.
- [Xu, Wang, Tang, Wang, and Gursoy '17] proposed a centralized deep reinforcement learning approach.
- [Calabrese, Wang, Ghadimi, Peters, and Soldati '17] proposed a similar distributively executed framework to us by using deep Q-learning. No channel variations.
- [Liang, Ye, and Li '19] applied deep Q-learning to minimize V2V links' interference to V2I links, channel variations are simulated by Jakes fading model similar to us.

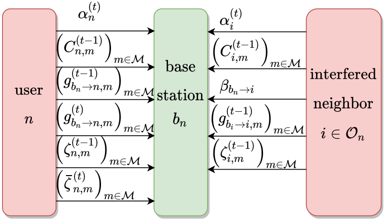
Our main contributions:

- Time varying traffic and channel conditions;
- Practicality constraints on measurements;
- Assume information exchange only between nearby links (delays);
- Distributively executed resource allocation;
- Flexible Objective: The agents collaboratively maximize a quality of service (QoS) objective over their local environment, that can be
  - the average packet delay, or
  - the sum rate, or
  - a proportionally fair throughput, or
  - anything else specified by the network layer.

Distributed Execution

- Centralized vs Distributed Execution:
  - × A centralized single learning agent that outputs joint actions by observing the complete environment state.
  - ✓ Multiple learning agents that output their own action by observing local environment.
- The environment transition is no longer stationary as other agents in the system update their policies/behaviors simultaneously. Multi-agent learning schemes have good empirical performance, but no theoretical guarantee.
- A global DQN is trained by the experiences of all agents.
- Training is centralized to ease implementation and to improve stability.

Preliminaries: Local Information & Aggregates



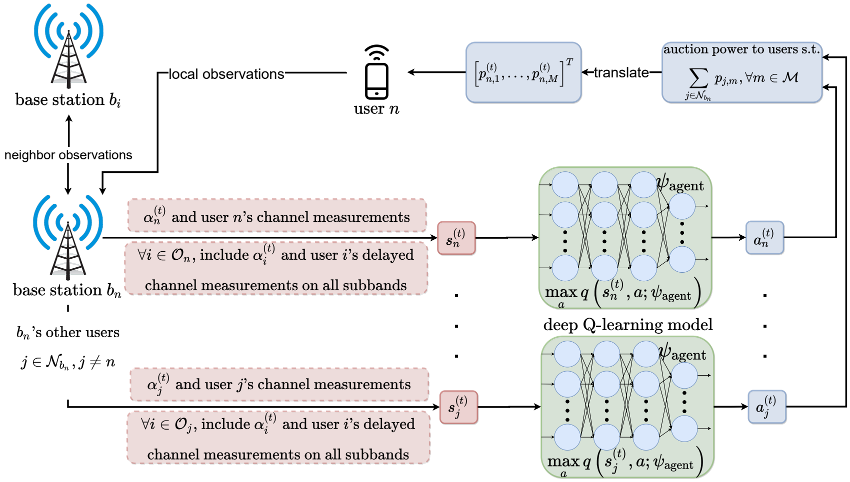
- Neighborhood set of n, $\mathcal{O}_n$, is the set of c receivers with largest $\beta_{b_n\to i}$.
- The aggregated interference at user n on subband m in time slot $t-1$:

$$\zeta_{n,m}^{(t-1)} = \sum_{j\in\mathcal{N},j\neq n} g_{b_j\to n,m}^{(t-1)} p_{j,m}^{(t-1)} + \sigma^2.$$

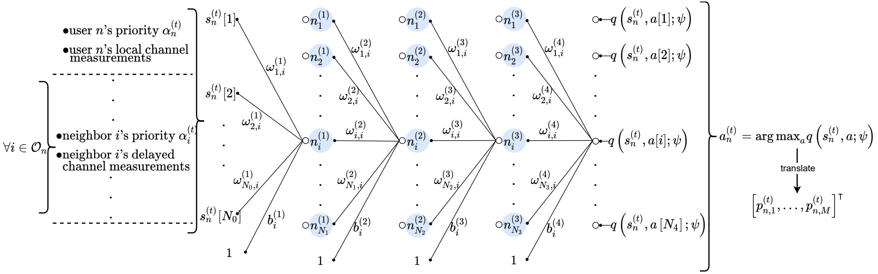
- The aggregated interference at the end of time slot $t-1$ with updated channel gains but with power allocation during $t-1$:

$$\bar{\zeta}_{n,m}^{(t)} = \sum_{j\in\mathcal{N},j\neq n} g_{b_j\to n,m}^{(t)} p_{j,m}^{(t-1)} + \sigma^2.$$

Proposed Distributed Execution Framework



Local State Set Design and The Policy



- Local state of agent n, $s_n^{(t)}$, is composed of:
  1. priority of user n, $\alpha_n^{(t)}$;
  2. most-recent channel measurements of user n;
  3. priorities and delayed channel measurements of all neighbors $\in \mathcal{O}_n$.

Local State / priority of user n

- Traffic-Aware Scheduling: $\alpha_n^{(t)}$ has two entries:
  1. total number of packets waiting in link n's queue;
  2. the rate estimate of link n for time slot t,

$$\bar{\lambda}_n^{(t)} = \frac{\sum_{\tau} \xi^{\tau} A_n^{(t-\tau)}}{\sum_{\tau=1}^{T_{\mathrm{r}}} \xi^{\tau}},$$

- Proportionally fair scheduling: $\alpha_n^{(t)} = 1/\bar{C}_n^{(t-1)}$.

Local State / most-recent channel measurements of user n

- M feature subgroups corresponding to M subbands.
- For subband m, reserve 6 entries:
  - $C_{n,m}^{(t-1)}$;
  - $p_{n,m}^{(t-1)}$;
  - last two measurements of the direct channel gains, $g_{b_n \rightarrow n,m}^{(t)}$ and $g_{b_n \rightarrow n,m}^{(t-1)}$;
  - last two aggregated interference measurements, $\bar{\zeta}_{n,m}^{(t)}$ and $\zeta_{n,m}^{(t-1)}$.

Local State / priorities and delayed CSI of neighbors

- For each neighbor $i \in \mathcal{O}_n$:
- neighbor i's priority: $\alpha_i^{(t)}$;
- neighbor i's significance $\beta_{b_n \to i}$;
- for subband m, 3 entries for neighbor i's delayed channel measurements:
  1. $C_{i,m}^{(t-1)}$;
  2. link i's direct channel gain, $g_{b_i \to i,m}^{(t-1)}$;
  3. most-recent aggregated interference measurement of user i that is available at base station b_n, $\zeta_{i,m}^{(t-1)}$.

Action Set

- Allowed actions on subband m:

$$\mathcal{A}_m = \left\{ 0, P_{\min}, P_{\min} \left(\frac{P_{\max}}{P_{\min}} \right)^{\frac{1}{|\mathcal{A}_m|-2}}, \ldots, P_{\max} \right\},$$

where $P_{\min}$ is the minimum positive transmit power level.

- The action space of agent n:

$$\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_M.$$

Reward function / Local Objective

- We enable collaboration by including signal from neighbors to agent's reward,

$$r^{(t+1)}_{\text{local objective,n}} = \pi_n^{(t)} + \sum_{i \in \mathcal{O}_n} \pi_i^{(t)},$$

where $\pi_n^{(t)}$ is agent n's direct contribution.

- For the traffic-aware scheduling, let:

$$\pi_n^{(t)} = -\max\left(N_n^{(t)} - C_n^{(t)} WT, 0\right).$$

- Alternatively, to maximize weighted sum-rate, let:

$$\pi_n^{(t)} = \alpha_n^{(t)} C_n^{(t)}.$$

Reward function / Externalities

- Ideally, we would use a reward function with externalities

$$r^{(t+1)}_{\text{externalities,n}} = \pi^{(t)}_n - \sum_{i \in \mathcal{O}_n} \pi^{(t)}_{n \to i},$$

where $\pi^{(t)}_{n \to i}$ is the externality from link n to neighbor i.
- The externality computation would require individual interfering channel gains from base station b_n to neighbor i, i.e., $g^{(t)}_{b_n \to i}$, $\forall i \in \mathcal{O}_n$.
- For example, for weighted sum-rate maximization,in time slot t

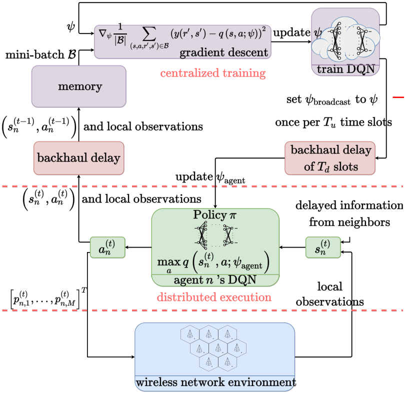
$$\pi^{(t)}_{n \to i} = \alpha^{(t)}_i \left(C^{(t)}_{i \backslash n} - C^{(t)}_i \right),$$

where $C^{(t)}_{i \backslash n}$ is the spectral efficiency of neighbor i without the interference from link n: $C^{(t)}_{i \backslash n} = \sum_{m=1}^{M} \log \left(1 + \frac{g^{(t)}_{b_i \to i,m} p^{(t)}_{i,m}}{\zeta^{(t)}_{i,m} - g^{(t)}_{b_n \to i,m} p^{(t)}_{n,m}} \right)$.

Episodic Training Scheme with Varying Traffic Load

- Goal is to train a single policy to handle various traffic load conditions in the execution stage without further adjustment on the policy.
- The proposed episodic training scheme is composed of multiple consecutive episodes with each episode having a random wireless network initialization and an average arrival rate (traffic load) λ_{avg}.
- Inside each episode, training is structured as a series of interactions between two algorithms namely "Distributed exection" and "Centralized Training". These interactions occur on a time scale of 1 time slot.
- Training samples a mini-batch from global memory $\mathcal{D}_{\text{g}}$ and experience-replay memory $\mathcal{D}$ of current episode.
- At the end of each time slot, training checks for the queue stability.
- If queues remain stable for $T_{\max}$ time slots, training moves to next episode. If resulting average delay is converged, λ_{avg} is increased by λ_{inc}.

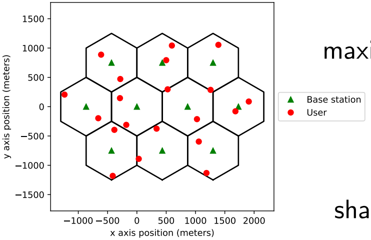
Centralized training and distributed execution framework:



1: **Centralized training** $(\psi, \psi_{\textbf{broadcast}}, \mathcal{D}_{\textbf{g}}, \mathcal{D})$**:**
2: Sample $\mathcal{B}$ from the experiences in $\mathcal{D}_{\text{g}}$ and $\mathcal{D}$.
3: Update ψ using a gradient descent step.
4: If it has been T_u since last policy broadcast, update $\psi_{\text{broadcast}}$ by ψ to update ψ_{agent}.
Output: Updated ψ, $\psi_{\text{broadcast}}$, ψ_{agent}.

1: **Parameters:** ϵ-greedy algorithm's ϵ.
2: **Distributed exec.** $(\psi_{\textbf{agent}})$ at time slot t:
3: **for** agent $n = 1, 2, \dots, N$ **do**
4: Agent n observes its current local state $s_n^{(t)}$;
5: sets $a_n^{(t)} = \arg\max_a q(s_n^{(t)}, a; \psi_{\text{agent}})$.
6: If $t \mod N = n - 1$, set $a_n^{(t)}$ to a random action with a probability of ϵ.
7: Translate action to $[p_{n,1}^{(t)}, \dots, p_{n,M}^{(t)}]^\intercal$, after auction at base station b_n.
8: **end for**
Output: $p_m^{(t)} \forall m \in \mathcal{M}$ & $\left(s_n^{(t)}, a_n^{(t)}\right) \forall n \in \mathcal{N}$.

Simulation Setup



maximum transmit power $P_{\max}$	38 dBm
total bandwidth	10 MHz
slot duration T	20 ms
traffic pattern	full-buffer
path loss (in dB)	$120.9 + 37.6 \log_{10}(d)$
shadowing standard deviation	8 dB
AWGN power	-114 dBm

- DQN:
  - 3 hidden layers of 200, 100, and 50 neurons, respectively;
  - Fully connected; the activation function is $\tanh(\,)$;
  - Limited to 5 neighbors;
  - Limited to 10 discrete power levels.

DQN training

- The trainer broadcasts the new parameters once every 100 slots; these parameters are available at the agents after 50 slots; minimum required downlink/uplink capacity for all backhaul links is about 1 Mbps.
- $\mathcal{D}$ stores 1,000 most recent experiences from each link;
- Use RMSProp to train with a random mini-batch of 256 experiences.
- The proposed algorithms:
  1. Matched DQN – train and test on same deployment.
  2. Unmatched DQN – trained for a different network (different device locations and fading)
- Benchmark allocations:
  1. WMMSE (genie-aided with full instantaneous CSI)
  2. FP (genie-aided with full instantaneous CSI)
  3. centralized (FP with delayed full CSI)
  4. full-power (or max-power) allocation.

Sum-rate maximization: scalability

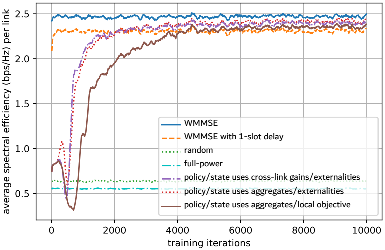
1 user per cell, M=1 subband, $R = 500$ m, $f_d = 10$ Hz.
(cross-link CSI is available to the DQN.)

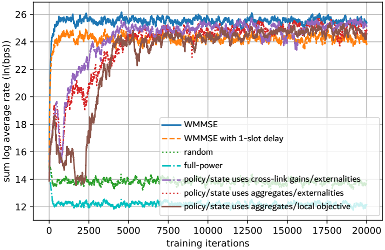
	average sum-rate in bps/Hz per link					
	DQN		benchmark power allocations			
N (links)	matched	unmatched	WMMSE	FP	central	full-power
19	2.78	2.50	2.66	2.58	2.44	1.37
50	2.28	1.99	2.17	2.13	2.00	1.02
100	1.92	1.68	1.90	1.88	1.74	0.89

- Each link determines its action within 0.3 ms.
- A single batch takes up to 17 ms (without GPU).
- FP requires about 15 ms to converge for $n = 19$ links, but with $n = 100$ links this becomes 35 ms.
- WMMSE converges slightly slower than the FP algorithm.

cross-link CSI vs aggregates

N = 20 links, K = 10 cells, M=1 subband, R = 500 m, f_d = 10 Hz.



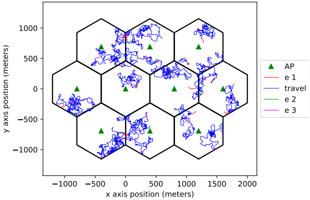


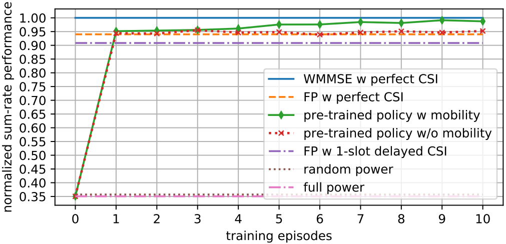
(left) sum-rate maximization; (right) proportionally fair scheduling.

	Average sum-rate performance in bps/Hz per link.				without aggregates.	
(cells,links)	DQN trained for (10,20)	WMMSE	FP	FP w delay	random	full
(10,20)	2.59; 99.2% of WMMSE	2.61	2.45	2.37	0.93	0.91
(20,60)	1.58; 94.0% of WMMSE	1.68	1.59	1.50	0.37	0.35
(20,100)	1.14; 92.7% of WMMSE	1.23	1.15	1.09	0.18	0.17

Extension # 1 / Mobile Users & Continuous Action Space

- Replace deep Q-learning by a deep actor-critic learning algorithm called deep deterministic policy gradient (DDPG) for continuous action space.
- Haas mobility model: travel between training episodes.



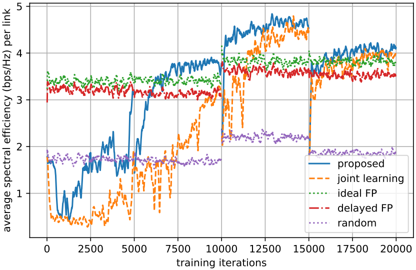


- Policy better experiences various device positions and interference conditions with mobility, so the performance consistently increases.

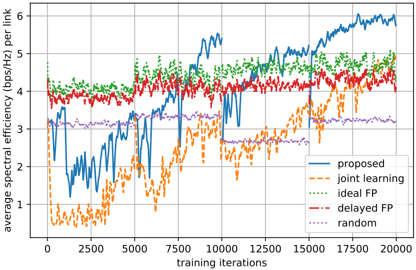
Extension # 2 / Subband Selection & Power Control.

- A link can be active on a single subband at a time with $p_{j,m}^{(t)} \leq P_{\max}$.
- [Tan, Zhang, and Liang '19] proposed an FP based solution for joint subband selection and power allocation.
- Joint DRL scheme's action set is the Cartesian product of available subbands and quantized transmit power levels.
- The computational complexity of FP and the action set complexity of joint DRL do not scale well for a large number of subbands.
- We propose a two-layer learning scheme, where
  - the top layer does discrete subband scheduling by deep Q-learning,
  - the bottom layer is responsible for continuous power allocation at the physical layer by DDPG

Extension # 2 / Simulation results / Training convergence



$M = 4$ subbands, $(K, N) = (5, 20)$.

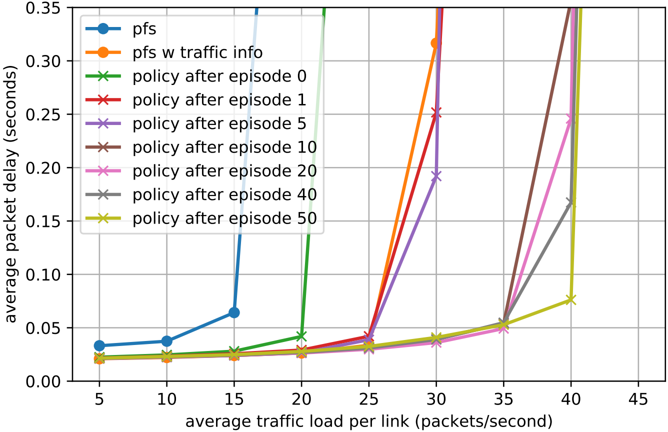


$M = 10$ subbands, $(K, N) = (10, 50)$.

Benchmarks:

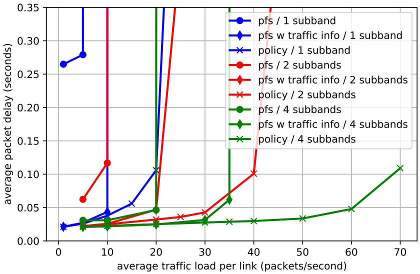
- Benchmarks:
  1. pfs: WMMSE (centralized and genie-aided with full instantaneous CSI) with user priorities adjusted to achieve proportional fairness.
  2. pfs with traffic information: WMMSE that enhances pfs' user priority assignment by also setting user priority to zero if user's queue is empty.

Testing the policy along the episodic training. $M = 1$.

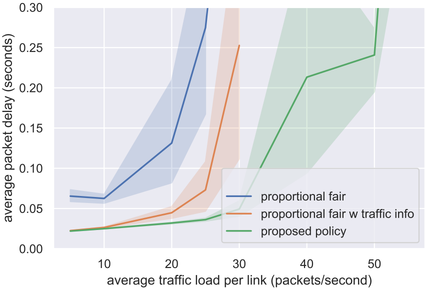


Policy is trained on $N = 5$ users on $K = 5$ cells, and tested on a larger deployment with $N = 20$ users on $K = 20$ cells.

Testing the policy on multiple subbands and seeds.

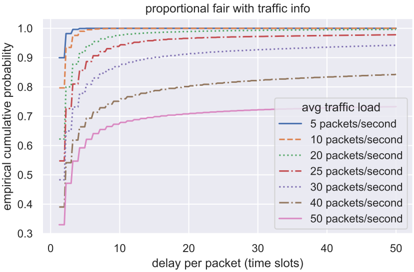


Test a converged policy on a $(N = 20 \text{ users}, K = 10 \text{ cells})$ scenario for total number of subbands $M \in \{1, 2, 4\}$.

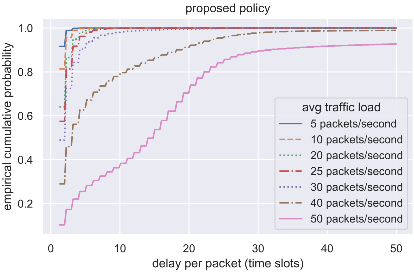


Testing a pre-trained policy on 10 different testing seeds. $N = 20$ links, $K = 10$ cells, $M = 2$ subbands.

CDF of all packet delays $(N, K, M) = (20, 10, 2)$.



proportional fair with traffic info.



proposed policy.

Summary

- A new distributed dynamic spectrum and power allocation algorithm based on deep reinforcement learning.
- The policy successfully maps traffic and channel states to physical resource allocations.
- User priorities connect physical layer resource management with network layer. Policy can achieve any traffic related network objective with a suitably designed reward function.
- Policy works well with delayed CSI and mismatched parameters.
- No need to produce a large amount of training data.
- In certain scenarios, the performance exceeds that of state-of-the-art algorithms WMMSE and FP. The distributed solution scales well.
- Available repositories:
  - `https://github.com/sinannasir/Power-Control-asilomar`
  - `https://github.com/sinannasir/Spectrum-Power-Allocation`

Future work on additional features:

- Multiple-input multiple-output (MIMO) beamforming: The challenge is the additional state-action complexity. Solution may involve a more sample-efficient DRL algorithm and a better neural network architecture or compressed parameters to reduce the complexity.
- User association: The distributed execution scheme needs to be modified. If user associations are not pre-determined, the agents should work above the base stations.

- **Thank you for your time, questions?**

Deep Q-learning algorithm

- Use a deep Q-network (DQN) parameterized by $\boldsymbol{\psi}$ to represent the Q-function values $q(\cdot, \cdot; \boldsymbol{\psi})$
- The optimal Q-function satisfies:
$$Q^{\pi^*}(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s' \in S} \mathcal{P}^{a}_{ss'} \max_{a'} Q^{\pi^*}(s',a'),$$
where $\mathcal{R}(s,a) = \mathbb{E}\left[r^{(t+1)} \middle| s^{(t)} = s, a^{(t)} = a\right]$.
- It is an off-policy learning that stores experiences in a memory $\mathcal{D}$.
- For training, the mean-squared Bellman loss is defined as
$$L\left(\boldsymbol{\psi}, \mathcal{D}\right) = \mathbb{E}_{(s,a,r',s') \sim \mathcal{D}}\left[\left(y(r',s') - q\left(s,a;\boldsymbol{\psi}\right)\right)^2\right],$$
where the target is $y(r',s') = r' + \gamma \max_{a'} q\left(s',a';\boldsymbol{\psi}_{\text{target}}\right)$.
- $\boldsymbol{\psi}$ is updated using a stochastic gradient descent algorithm by
$$\nabla_{\boldsymbol{\psi}} \frac{1}{|\mathcal{B}|} \sum_{(s,a,r',s') \in \mathcal{B}} \left(y(r',s') - q\left(s,a;\boldsymbol{\psi}\right)\right)^2,$$
where the target is $y(r',s') = r' + \gamma \max_{a'} q\left(s',a';\boldsymbol{\psi}_{\text{target}}\right)$.

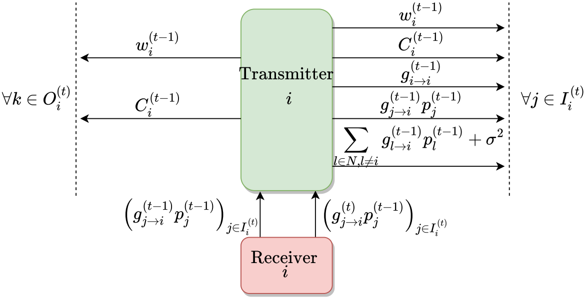
Local Information and Neighborhood Set

- *Interferer set* $I_n^{(t)}$: transmitters that cause interference at receiver n;

$$I_n^{(t)} = \left\{ i \in \mathcal{N}, i \neq n \middle| g_{i \to n}^{(t-1)} p_i^{(t-1)} > \eta\sigma^2 \right\}.$$

- *Interfered set*: $O_n^{(t)}$: links that suffer from transmitter n.

$$O_n^{(t)} = \left\{ k \in \mathcal{N}, k \neq n \middle| g_{n \to k}^{(t-1)} p_n^{(t-1)} > \eta\sigma^2 \right\}.$$



Preliminary for state set

- Regulated interferer and interfered neighborhood sets $\left(\bar{I}_n^{(t)}, \bar{O}_n^{(t)}\right)$.
- We set $\left|\bar{I}_n^{(t)}\right| = \left|\bar{O}_n^{(t)}\right| = c$.
  - Pick c-most significant interferer and interfered neighbors with following criteria:
    - the current received power from interferer $i \in I_n^{(t)}$ at receiver n,
    - the share of agent n on the interference at receiver $k \in O_n^{(t)}$.
  - If necessary, append virtual noise agents with an arbitrary negative weight and spectral efficiency. A virtual noise agent has zero downlink and interfering channel gains.

States

1. Local Information (7 inputs to DQN):

$$p_n^{(t-1)},\ 1/w_n^{(t)},\ C_n^{(t-1)},\ g_{n\to n}^{(t)},\ g_{n\to n}^{(t-1)},$$
$$\sum_{j\in N, j\neq n} g_{j\to n}^{(t)} p_j^{(t-1)} + \sigma^2,\ \sum_{j\in N, j\neq n} g_{j\to n}^{(t-1)} p_j^{(t-2)} + \sigma^2$$

2. From interfering neighbors (3 inputs each):

$$c \text{ interferers of current time slot: } g_{i\to n}^{(t)} p_i^{(t-1)},\ 1/w_i^{(t-1)},\ C_i^{(t-1)}, \quad \forall i \in \bar{I}_n^{(t)}$$

$$c \text{ interferers from history: } g_{i'\to n}^{(t-1)} p_{i'}^{(t-2)},\ 1/w_{i'}^{(t-2)},\ C_{i'}^{(t-2)}, \quad \forall i' \in \bar{I}_n^{(t-1)}$$

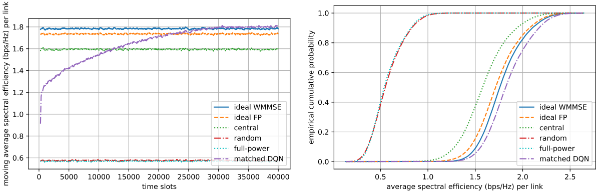
3. From interfered neighbors (4 inputs each):
   t'_n is the last time slot transmitter n was active,

$$g_{k\to k}^{(t-1)},\ 1/w_k^{(t-1)},\ C_k^{(t-1)},\ \frac{g_{n\to k}^{(t'_n)} p_n^{(t'_n)}}{\sum_{j\in N, j\neq k} g_{j\to k}^{(t-1)} p_j^{(t-1)} + \sigma^2}, \quad \forall k \in \bar{O}_n^{(t'_n)}.$$

Sum-rate maximization: multiple links per cell (IMAC)

Constraint $\sum_{j\in\mathcal{N}_k} p_{j,m}^{(t)} \leq P_{\max}$ becomes $p_{j,m}^{(t)} \leq P_{\max}$
$K = 19$ cells, M=1 subband, $R = 500$ m, $f_d = 10$ Hz.
(cross-link CSI is available to the DQN.)

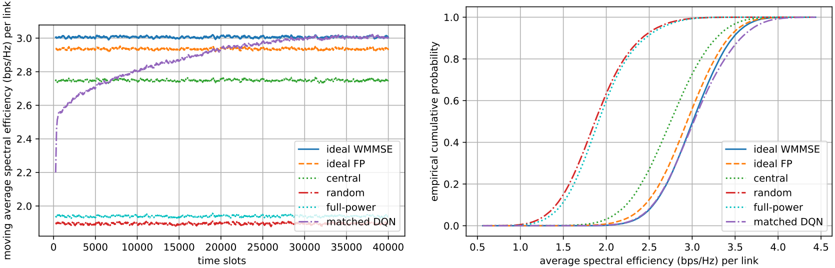
	average sum-rate in bps/Hz per link					
	DQN		benchmark power allocations			
links per cell	matched	unmatched	WMMSE	FP	central	full-power
2	1.84	1.58	1.78	1.74	1.59	0.57
4	1.25	1.06	1.24	1.22	1.10	0.25
random (1–4)	1.61	1.37	1.57	1.53	1.40	0.44



2 links per cell; (left) training (moving average of previous 250 slots); (right) testing.

Sum-rate maximization

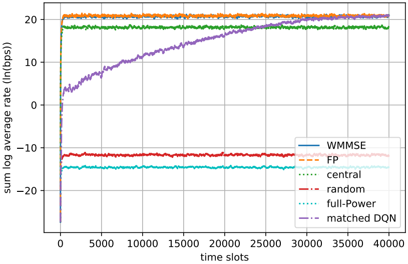
$N = 19$ links, $K = 19$ cells, M=1 subband, $R = 100$ m, $f_d = 10$ Hz. (cross-link CSI is available to the DQN.)

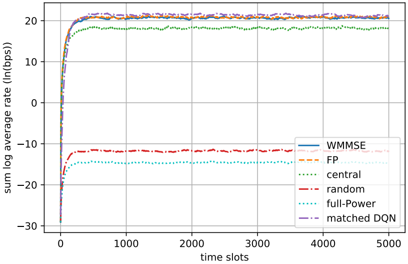


(left) training (moving average of previous 250 slots); (right) testing.

Proportionally fair scheduling

$N = 19$ links, $K = 19$ cells, M=1 subband, $R = 500$ m, $f_d = 10$ Hz.
(cross-link CSI is available to the DQN.)





(left) training; (right) testing.

Continuous Action Space

- [Men, Chen, Wu, and Cheng '19] showed that quantizing the action space with a logarithmic step size gives better outcomes than that of a linear step size for a different channel model.
- They proposed to replace deep Q-learning scheme by a deep actor-critic learning scheme called deep deterministic policy gradient (DDPG).
- Actor-critic learning trains an action-value function using a critic network, defined by ϕ;
- and uses this function estimate to train a policy parameterized by an actor network, defined by $\boldsymbol{\theta}$.
- Actor-critic learning is
  - as sample efficient as value based methods, and
  - as direct as policy based methods.

Actor-critic learning (deep deterministic policy gradient)

- The action is determined by $a = \mu(s; \boldsymbol{\theta})$ with policy parameters being $\boldsymbol{\theta}$.
- For exploration, a noise term can be added on the action values.
- The target policy μ^* satisfies the Bellman property:

$$Q^{\mu^*}(s,a) = \mathcal{R}(s,a) + \gamma \sum_{s' \in S} \mathcal{P}^a_{ss'} Q^{\mu^*}(s', \mu^*(a')),$$

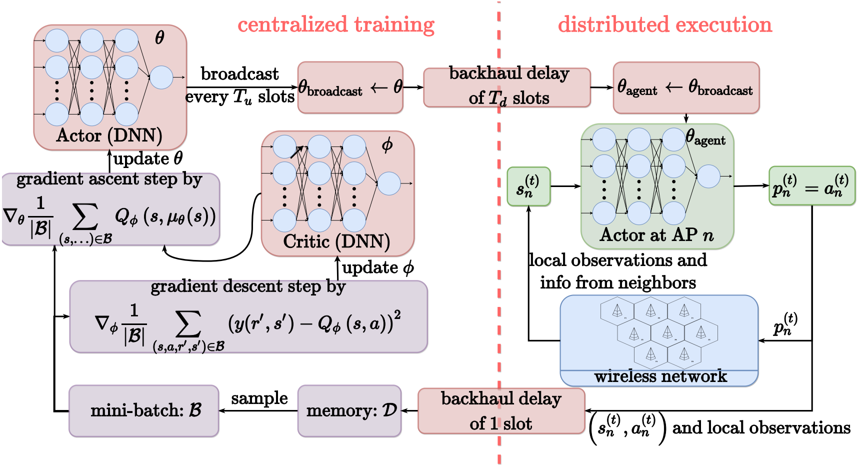
- Critic network is updated by

$$\nabla_{\boldsymbol{\phi}} \frac{1}{|\mathcal{B}|} \sum_{(s,a,r',s') \in \mathcal{B}} \left(y_{\text{critic}}(r', s') - q\left(s, a; \boldsymbol{\phi}\right)\right)^2,$$

  where $y_{\text{critic}}(r', s') = r' + \gamma q\left(s', \mu(s'; \boldsymbol{\theta}); \boldsymbol{\phi}_{\text{target}}\right)$.
- $q(s, a; \boldsymbol{\phi})$ is differentiable with respect to continuous action.
- The policy parameters are updated by the following gradient:

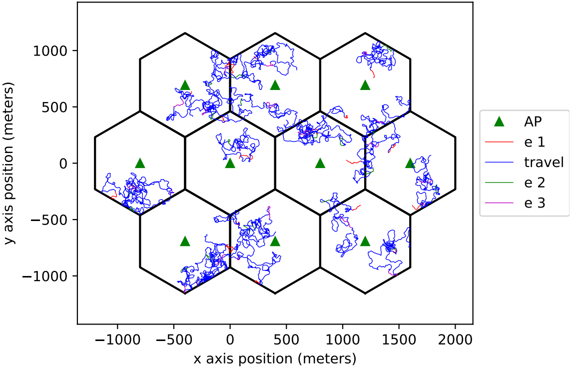
$$\nabla_{\boldsymbol{\theta}} \frac{1}{|\mathcal{B}|} \sum_{(s,\dots) \in \mathcal{B}} q\left(s, \mu(s; \boldsymbol{\theta}); \boldsymbol{\phi}\right).$$

DDPG based centralized training and distributed execution



Mobile Users / Training episodes and traveling

- Steady channel may cause overfitting to a certain network deployment.
- Haas mobility model: travel between training episodes.



- Correlation in Jakes model becomes $\rho_n^{(t)} = J_0(2\pi f_{d,n}^{(t)} T)$, $f_{d,n}^{(t)} = v_n^{(t)} f_c / c$;
- large scale-fading also varies with $\rho_{\mathrm{s},n}^{(t)} = e^{\frac{\Delta \mathbf{x}_n^{(t)}}{d_{\mathrm{cor}}}}$

Problem Formulation

- If link n selects subband m , we have $\alpha_{n,m}^{(t)} = 1$ and $\alpha_{n,j}^{(t)} = 0, \forall j \neq m$.
- SINR at receiver n on subband m in time slot t:

$$\gamma_{n,m}^{(t)} = \frac{\alpha_{n,m}^{(t)} g_{n \to n,m}^{(t)} p_n^{(t)}}{\sum_{l \neq n} \alpha_{l,m}^{(t)} g_{l \to n,m}^{(t)} p_l^{(t)} + \sigma^2},$$

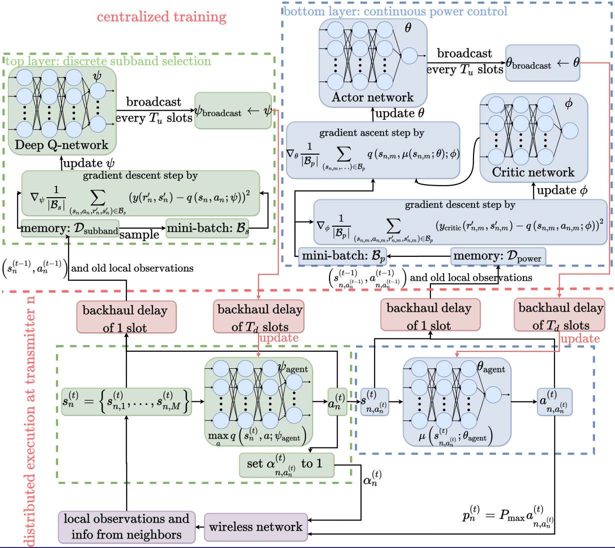
- Spectral efficiency:

$$C_n^{(t)} = \sum_{m=1}^{M} C_{n,m}^{(t)} = \sum_{m=1}^{M} \log\left(1 + \gamma_{n,m}^{(t)}\right).$$

- Let $\boldsymbol{\alpha}^{(t)} = \left[\alpha_{1,1}^{(t)}, \alpha_{1,2}^{(t)}, \dots, \alpha_{N,M}^{(t)}\right]^{\intercal}$ and $\boldsymbol{p}^{(t)} = \left[p_1^{(t)}, \dots, p_N^{(t)}\right]^{\intercal}$, the optimization problem in slot t:

$$\boxed{\begin{aligned} \underset{\boldsymbol{p}^{(t)}, \boldsymbol{\alpha}^{(t)}}{\text{maximize}} \quad & \sum_{n=1}^{N} C_n^{(t)} \\ \text{subject to} \quad & 0 \leq p_n^{(t)} \leq P_{\max}, \forall n \in \mathcal{N}, \\ & \alpha_{n,m}^{(t)} \in \{0,1\}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \\ & \sum_{m \in \mathcal{M}} \alpha_{n,m}^{(t)}, \forall n \in \mathcal{N}, \end{aligned}}$$

DDPG based centralized training and distributed execution



Extension # 2 / Simulation results / Testing performance

(K, N) (cells, links)	M subbands	average sum-rate performance in bps/Hz per link: reinforcement learning proposed	joint	other schemes: ideal FP	delayed FP	random	output layer size: reinforcement learning proposed	joint	average iterations FP
$(5, 20)$	1	1.51	1.50	1.58	1.46	0.41	1 + 1	10	70.30
	2	2.63	2.64	2.66	2.46	0.99	2 + 1	20	102.08
	4	4.57	4.38	3.81	3.57	2.12	4 + 1	40	122.15
$(10, 50)$	1	1.26	1.26	1.31	1.21	0.25	1 + 1	10	72.83
	2	2.08	2.10	2.08	1.92	0.59	2 + 1	20	96.32
	4	3.34	3.34	2.90	2.68	1.31	4 + 1	40	185.93
	5	3.79	3.76	3.18	2.94	1.64	5 + 1	50	206.38
	10	5.71	4.41	4.44	4.08	2.99	10 + 1	100	287.70

- Results show that a pretrained policy is still usable on new deployments and the proposed approach is better scalable than the benchmarks.

Pseudo-code for distributed execution.

Parameters: ϵ-greedy algorithm's ϵ.
Inputs: Deep Q-network parameters at agents ψ_{agent}.
Distributed execution $(\boldsymbol{\psi_{\text{agent}}})$ for time slot t:
for agent $n = 1, 2, \ldots, N$ **do**
 Agent n observes its local environment and uses information from its neighbors to form its current local state $s_n^{(t)}$.
 Agent sets its current action to $a_n^{(t)} = \arg\max_a q\left(s_n^{(t)}, a; \psi_{\text{agent}}\right)$ using deep Q-network with parameters ψ_{agent}.
 If index n is divisible by $t \mod N$, apply ϵ-greedy strategy for exploration during training and agent replaces $a_n^{(t)}$ with a random action with a probability of ϵ.
 Agent translates its action to its allocation decision, i.e., $\left[p_{n,1}^{(t)}, \ldots, p_{n,M}^{(t)}\right]^{\mathsf{T}}$, after power auction at base station b_n.
end for

Output: $\boldsymbol{p}_m^{(t)}$, $\forall m \in \mathcal{M}$, and state-action pairs $\left(s_n^{(t)}, a_n^{(t)}\right) \forall n \in \mathcal{N}$.

Pseudo-code for centralized training.

Parameters: Learning rate λ_{lr}.

Inputs:

Deep Q-network parameters ψ, $\psi_{\mathrm{broadcast}}$, ψ_{agent}.

Global memory $\mathcal{D}_{\mathrm{g}}$ & experience-replay memory of the current episode $\mathcal{D}$.

Centralized training $(\psi, \psi_{\mathbf{broadcast}}, \psi_{\mathbf{agent}}, \mathcal{D}_{\mathbf{g}}, \mathcal{D})$**:**

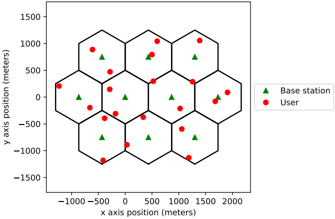
Randomly sample a mini-batch $\mathcal{B}$ from the experiences in $\mathcal{D}_{\mathrm{g}}$ and $\mathcal{D}$.

Update the parameters ψ using a gradient descent step with learning rate equal to λ_{lr} and the gradient $\nabla_{\boldsymbol{\psi}} \frac{1}{|\mathcal{B}|} \sum_{(s,a,r',s') \in \mathcal{B}} \left(y(r', s') - q\left(s, a; \boldsymbol{\psi}\right)\right)^2$.

If it has been T_u since last policy broadcast, update $\psi_{\mathrm{broadcast}}$ by ψ and initiate a broadcast process which will take T_d time slots. At the end of the broadcast process, ψ_{agent} will be set to $\psi_{\mathrm{broadcast}}$.

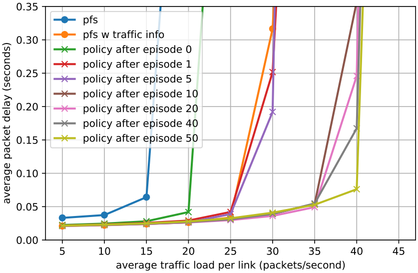
Output: Updated deep Q-network parameters ψ, $\psi_{\mathrm{broadcast}}$, ψ_{agent}.

Simulation Setup

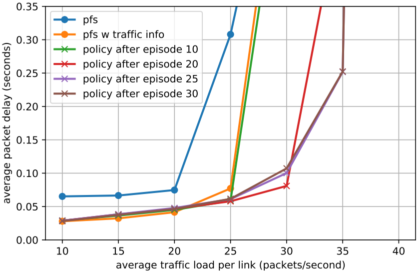


maximum transmit power $P_{\max}$	23 dBm
subband bandwidth	10 MHz
number of subbands	1 to 4
slot duration T	20 ms
traffic arrivals	Poisson arrivals / 500 Kbits
path loss (in dB)	$120.9 + 37.6 \log_{10}(d)$
shadowing standard deviation	8 dB
AWGN power	-114 dBm
maximum Doppler frequency	10 Hz

Testing the policy along the episodic training. $M = 1$.

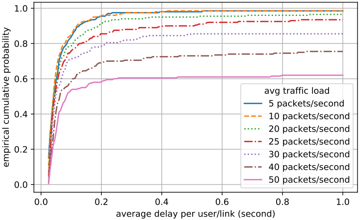


Policy is trained on $N = 5$ users on $K = 5$ cells, and tested on a larger deployment with $N = 20$ users on $K = 20$ cells.

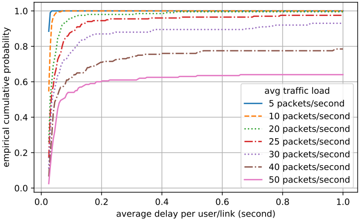


Policy is trained and tested on $N = 10$ users on $K = 5$ cells.

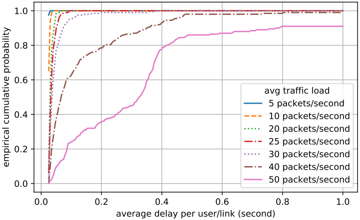
CDF of average user delay $(N, K, M) = (20, 10, 2)$.



(a) proportional fair



(b) proportional fair with traffic info



(c) proposed policy

Some other side problems:

- Better and easily tunable training and exploration schemes to better adapt to the environment non-stationarity of the multi-agent setting.
- We simplified the state set design, but its design can be improved by analyzing the hidden-layer weights of a trained policy that uses global CSI and picking the environment features that impact the decision strategy most strongly.