DEEP REINFORCEMENT LEARNING FOR WIRELESS SCHEDULING WITH MULTICLASS SERVICES

Apostolos Avranas, Marios Kountouris  
EURECOM

Philippe Ciblat  
Télécom Paris, Institut Polytechnique de Paris

{apostolos.avranas, marios.kountouris}@eurecom.fr, philippe.ciblat@telecom-paris.fr

ABSTRACT

In this paper, we investigate the problem of scheduling and resource allocation over a time varying set of clients with heterogeneous demands. In this context, a service provider has to schedule traffic destined to users with different classes of requirements and to allocate bandwidth resources over time as a means to efficiently satisfy service demands within a limited time horizon. This is a highly intricate problem, in particular in wireless communication systems, and solutions may involve tools stemming from diverse fields, including combinatorics and constrained optimization. Although recent work has successfully proposed solutions based on Deep Reinforcement Learning (DRL), the challenging setting of heterogeneous user traffic and demands has not been addressed. We propose a deep deterministic policy gradient algorithm that combines state-of-the-art techniques, namely Distributional RL and Deep Sets, to train a model for heterogeneous traffic scheduling. We test on diverse scenarios with different time dependence dynamics, users’ requirements, and resources available, demonstrating consistent results using both synthetic and real data. We evaluate the algorithm on a wireless communication setting using both synthetic and real data and show significant gains in terms of Quality of Service (QoS) defined by the classes, against state-of-the-art conventional algorithms from combinatorics, optimization and scheduling metric (e.g., Knapsack, Integer Linear Programming, Frank-Wolfe, Exponential Rule).

1 INTRODUCTION

User scheduling, i.e., which user to serve, and the associated resource allocation, i.e., which resources to assign to scheduled users, are two long-standing and relevant fundamental problems, in particular in mobile communications. There is a plethora of new Internet applications with very diverse requirements in terms of Quality of Service (QoS). Some applications require the transmission of a large amount of data without any strict deadline, whereas some other, usually mission-critical, applications are time-sensitive and a small amount of data has to be reliably received within a stringent latency constraint. The increased heterogeneity in users’ traffic and the diverse QoS requirements complicates substantially the provisioning of high fidelity, personalized service of guaranteed QoS. The objective of this work is to design a system architecture and an algorithm, take as inputs the specific constraints of the traffic/service class each user belongs to and and schedules users for service allocating the resources required in order to maximize the number of satisfied users.

The problem considered here is hard to solve due to at least two main technical challenges. First, with the exception of few special cases, there is no simple closed-form expression for the problem and a fortiori for its solution. Second, the problem solving algorithm has to be scalable with the number of active users. Existing approaches rely on combinatorial methods or suboptimal solutions, which seem to work satisfactorily in specific scenarios, failing though to perform well when the number of active users becomes large. This motivates the quest for alternative solutions. In this paper, we propose to resort to Deep Reinforcement Learning (DRL) to tackle this challenging problem.

In the context of DRL, we propose to combine together several ingredients in order to solve the heterogeneous scheduling and dynamic resource allocation problems. In particular, we leverage the
theory of Deep Sets to design permutation equivariant and invariant models, as a means to address the scalability issue. That way, the number of active users can be increased without having to increase the number of parameters. Furthermore, we improve the stability of the learning by using distributional reinforcement learning and combining it in a novel way with a Dueling Networks architecture. Additionally, we show that reward normalization can further speed up the learning. Finally, the proposed DRL-based algorithm is compared with conventional approaches based on combinatorial or suboptimal optimization methods. In particular, we compare our performance in terms of QoS provisioning and user satisfaction with that of Frank-Wolfe algorithm, knapsack, integer linear programming, and exponential scheduling rule. Our experiments and simulation results using both synthetic and real data clearly show that our DRL method significantly outperforms conventional state-of-the-art algorithms.

2 RELATED WORK

The scheduling problem is a well known problem appearing in various fields and as technologies progress and more people want to take advantage of the new services, how to schedule them in an efficient way becomes more intricate. This is exactly the case in wireless communication systems. Researchers are resorting to new methods, such as deep reinforcement learning, which have shown impressive results [Mnih et al., 2015; Silver et al., 2016]. For example in [Chinchali et al., 2018] they perform scheduling on a cellular level using Deep Reinforcement learning (DRL). Also ideas using DRL in a distributed way to perform dynamic power allocation has appeared in [Naparstek & Cohen, 2018; Nasir & Guo, 2019]. Nevertheless, to the best of our knowledge, the problem of scheduling on traffic of users with heterogeneous performance requirements has not been appropriately addressed. To solve this hard problem, one can resort to distributional Reinforcement Learning researched in [Jaquette, 1973] and followed by [Dabney et al., 2018a;b] in order to have richer representations of the environment thus obtaining better solutions. Also techniques like noisy network for better explorations [Fortunato et al., 2018] or architectures such as dueling networks [Wang et al., 2016] have greatly improved the stability of the trained models. Finally, recent work [Zaheer et al., 2017] managed to simplify and improve neural network models when permutation invariance properties apply. We combine those ideas with a deep deterministic policy gradient method [Lillicrap et al., 2016] to reach a very efficient scheduling algorithm.

3 HETEROGENEOUS SCHEDULING AND RESOURCE ALLOCATION

3.1 PROBLEM DEFINITION

The problem we consider here involves a system in which a set of randomly arriving users communicate over a time varying wireless channel with a base station (BS) (service provider). We consider the challenging setting where users belong to different service classes with heterogeneous requirements and demands. Users request that their traffic is served according to QoS requirements imposed by the service class they belong to. Each class specifies the amount of data to be delivered, the maximum tolerable latency, and the “importance/priority” of each user. At each time step, a centralized scheduler (at the BS) takes as input the (time varying) set of active users belonging to different service classes and has to decide (i) which user to serve, and (ii) how to allocate the limited communication resources per time step, in order to maximize the long-term “importance” weighted sum of satisfied users. A user is considered to be satisfied whenever it has successfully received its requested data within the maximum tolerable latency as specified by its service class.

The complicated, innately combinatorial problem of scheduling and resource allocation is exacerbated by communicating over wireless fading channels, which introduce additional uncertainty due to time-varying, random link quality. The scheduler cannot exclude the possibility of a bad connection (i.e., low channel strength and link quality), which in turn could render data transmission unsuccessful. To mitigate that effect, some protocols leverage channel state information (CSI) at the transmitter, i.e., the scheduler at the BS knows in advance the link quality and adapts the resources allocated, to the instantaneous channel conditions. We consider the following two extreme cases of channel knowledge: (i) full-CSI, in which perfect (instantaneous, error free) CSI is provided to the scheduler enabling accurate estimation of exact resources each user requires; (ii) no-CSI, in which the scheduler is completely agnostic to the channel quality. In case of unsuccessful and/or erroneous
data reception, we employ a simple retransmission protocol (HARQ-type I), according to which the erroneously decoded packet is completely disregarded and the user will receive its data on a future retransmission. In other words, the data required by a user should be transmitted in its entirety, all in one go, and multiple transmission trials are allowed until the data is successfully received (decoded). We consider the following widely employed model for the channel dynamics: the quality of a wireless channel/link depends on the distance of the user from the serving BS and evolves in a Markovian way from the link/channel quality realization of the previous time step [Jakes & Cox (1994)]. The mathematical description of the traffic generator model and the associated channel dynamics is provided in the appendix A.

To gain further insight into the problem, we draw the following analogy. Consider a server having a water pitcher that is full at every time step and has to distribute water across a set of people. Every person has a glass and is satisfied only if its glass is filled (or overfilled) at any time instant prior to a maximum waiting time. As mentioned before, in this work we consider a simple retransmission protocol (HARQ-type I), which in our analogy means that the server cannot fill a glass by pouring water little by little using many rounds. If a glass is not completely filled with water at a time step, it will be emptied and the server has to retry. The wireless communication setting introduces the additional complication that the volumes of the glasses are not actually fixed but fluctuate (due to the randomness of the connection/link quality of each user). In the full-CSI case, the server could know at every time step the volume of each glass and therefore the exact amount of resources required to fill them. In sharp contrast, in the no-CSI case, the server can only have a rough estimate of the volume, mainly using the amount of data requested and the distance between the user and the BS.

3.1.1 MDP Formulation and State Representation

The aforementioned scheduling and resource allocation problem can be modeled as a Markov Decision Process (MDP) (Bellman, 1957) \( (\mathcal{S}, \mathcal{A}, R, P, \gamma) \), where \( \mathcal{S} \) is the state space of the environment (described briefly below and in detail in appendix A.2), and \( \mathcal{A} \) is the action space, i.e., the set of all feasible allocations in our case. After action \( a_t \in \mathcal{A} \) at state \( s_t \in \mathcal{S} \), a reward \( r_t \sim R(\cdot|s_t, a_t) \) is obtained and the next state follows the probability \( s_{t+1} \sim P(\cdot|s_t, a_t) \). The discount factor is \( \gamma \in [0, 1) \).

Under a fixed policy \( \pi : \mathcal{S} \rightarrow \mathcal{A} \), the return is a random variable defined as \( Z_\pi = \sum_{t=0}^{\infty} \gamma^t r_{t+i} \) representing the discounted sum of rewards when a trajectory of states is taken following the policy \( \pi \). An agent (scheduler) ideally aims to find the optimal policy \( \pi^* \) maximizing the mean reward \( \mathbb{E}_\pi[Z^\pi] \).

We assume maximum \( K \) active users per time step and a set of classes \( \mathcal{C} \). Every user belongs to a class \( c \in \mathcal{C} \), which determines the requested data size \( D_c \), the maximum number \( L_c \) of time slots user is eager to wait, and its importance \( \alpha_c \), i.e., an index allowing the scheduler to prioritize certain service classes having privileged contracts (e.g., SLAs - service level agreements). A new user \( u \) arrives at time \( t_0 \) at a random location in space and the probability to belong to class \( c \) is \( p_c \). After \( L_c \) time steps a new user may (or may not) arrive. Throughout its lifespan \( t \in [t_0, t_0+L_c-1] \), the user’s signal quality fluctuates due to the small-scale fading \( h_{u,t} \), which follows a Markovian model (see 2) in appendix A.2.2. This makes that the data rate that can be provided also fluctuates. The maximum data rate at time \( t \) is calculated here using Shannon’s capacity formula, i.e., \( R_{u,t} = w_{u,t} \log_2(1 + \kappa_u |h_{u,t}|^2) \) bit/s, where \( w_{u,t} \) is the bandwidth of the channel, \( \kappa_u \) is a value depending on the distance of the user to the BS (pathloss) and the transmit power. User \( c \) is satisfied if at any time slot \( t \) of its lifespan, it is allocated bandwidth \( w_{u,t} \) such that \( R_{u,t} > D_c \). The total bandwidth (resources) is \( W \) and the BS/scheduler allocates it at every time slot over the set of currently active users \( U_t^{\text{act}} \). Evidently, \( \sum_{u \in U_t^{\text{act}}} w_{u,t} \leq W \quad \forall t \). Let \( l_{u,t} \leq L_c \) be the number of time slots a yet unsatisfied user \( u \) is eager to wait (i.e. \( u \in U_t^{\text{act}} \)) and \( \mathbb{I} \{ \cdot \} \) denote the indicator function; the MDP is then described as

\[
\begin{align*}
\text{State: } & s_t = \{ \forall u \in U_t^{\text{act}} : D_c, L_u, a_u, \kappa_u, l_{u,t}, h_{u,t} \} \\
\text{Action: } & a_t = \{ \forall u \in U_t^{\text{act}} : w_{u,t} \} \\
\text{Reward: } & r_t = \sum_{u \in U_t^{\text{act}}} \alpha_u \mathbb{I} \{ R_{u,t} > D_u \}.
\end{align*}
\]

As said before, the problem considered here can be formulated as an MDP problem due to the Markovian traffic generation and the time evolution of channels \( h_{u,t} \). In the full-CSI case, the
We now explain the architecture of the model $\pi$ another NN $s$ with $t$ return (conditioned again on the action at $Z$).

Set $u,t \subseteq s$ is a part of the state, leading to a Partially Observable MDP (POMDP) [Astrom 1965]. A way to reduce a POMDP to an MDP is by substituting the states with the “belief” of the states [Kaelbling et al. 1998] of the value of $s_t$. Another way is to use the complete history $\{o_0, a_0, a_1, \ldots, a_{t-1}, o_{t-1}\}$ and notice that only the most recent part is relevant. Note that users that have already left the system do not affect in any way how the channels of the current user will evolve or the generation of future users. Therefore, we can only consider the scheduling and allocation history of only the currently active users. So if $w_{u,t} = (w_{u,t_0}, w_{u,t_0+1}, \ldots, w_{u,t})$ the scheduling history of $u$ then the input of the actor is $\{\forall u \in U^\text{act} : D_u, u_t, a_u, \kappa_u, l_{u,t}, w_{u,t}\}$.

### 3.2 Deep Reinforcement Learning Approach

Deep reinforcement learning (DRL) has shown great potential to solve various large MDP optimization problems, mainly in cases where the environment is close to deterministic imposed by game rules (Atari, Chess, Go [Mnih et al., 2015; Silver et al., 2017, 2016]) or physical laws (robotics and physics tasks [Kober et al., 2013; Lillicrap et al., 2015]). A relevant question here is whether we can develop DRL algorithms that cope successfully with environments exhibiting stochasticity of high variance, as the one in our case due to stochastic channel dynamics and heterogeneous traffic. Otherwise stated, would DRL still provide gains when it is impossible to accurately predict the number of active users, their service demands, and their channel/link characteristics even after few steps? Recent work from other fields, such as finance and transportation [Nazari et al., 2018; Charpentier et al., 2020], applying DRL to similar high volatility and random dynamic problems are indeed encouraging.

#### 3.2.1 Policy Network

Our objective is to build a scheduler that can handle a large number of users $K$, even in the order of hundreds, in which case the action space becomes infeasibly large for a conventional Deep Q-Learning Network (DQN) approach. For that, we employ a Deep Deterministic Policy Gradient (DDPG) method [Lillicrap et al., 2016], with which we aim at training a policy $\pi_\theta : S \rightarrow A$ modeled as a Neural Network (NN) with parameters $\theta$. Moreover, we require that our method works in both full-CSI and no-C SI cases with minor - if any - modifications. With full-C SI, the exact amount of required resources (bandwidth) per user is known, so the (discrete) action boils down to just select the subset of user to satisfy. In the no-C SI case, the action is continuous since on top of selecting the users, the scheduler has to decide on the portion of resources each user takes. Those portions are exactly the output of $\pi_\theta$ in the no-C SI case, whereas with full-C SI, a continuous relaxation is performed and the scheduler provides the value (related to importance) per resources. That way, a user ranking is obtained, which allows the scheduler to proceed sequentially: the scheduler serves (satisfies) as many of the most “valuable” (highest rank) users as possible subject to available resources. This discrepancy in the output process is the only minor difference in the considered model between full-C SI and no-C SI.

Set $Z^\pi(s_t, a_t) = r_t + Z^\pi_{t+1}$, with $r_t \sim R(\cdot|s_t, a_t)$ being the return whenever at $t$ the state is $s_t$ and action $a_t$ is taken followed by policy $\pi$. Let $Q^\pi(s_t, a_t) = \mathbb{E}[Z^\pi(s_t, a_t)]$ be the expected return (conditioned again on the action at $s_t$ is $a_t$). Then, the objective of the agent is to maximize $J(\theta) = \mathbb{E}_{s_{t_0} \sim \rho_{s_{t_0}}^0, s \sim \rho_{s_t}^0} [Q^\pi(s_t, \pi_\theta(s_{t_0}))]$, with $\rho_{s_{t_0}}^0$ being the probability of the initial state $s_{t_0}$ at time $t_0$. The gradient can be written (Silver et al. 2014),

$$\nabla_\theta J(\theta) = \mathbb{E}_{s_{t_0} \sim \rho_{s_{t_0}}^0, s \sim \rho_{s_t}^0} [\nabla_\theta \pi_\theta(s) \nabla_a Q^\pi(s, a)|a = \pi_\theta(s)],$$

with $\rho_{s_{t_0}}^0$ the discounted state (improper) distribution defined as $\rho_{s_{t_0}}^\pi(s) = \sum_{i=0}^{\infty} \gamma^i \mathbb{P}(s_{t+i} = s|s_{t_0}, \pi_\theta)$. In practice $\rho_{s_{t_0}}^\pi$ is approximated by the (proper) distribution $\rho_{s_{t_0}}^\pi(s) := \sum_{i=0}^{\infty} \mathbb{P}(s_{t+i} = s|s_{t_0}, \pi_\theta)$. To compute the gradient, the function $Q^\pi(s, a)$ is needed, which is approximated by another NN $Q^\psi(s, a)$, named value network, described in the next subsection.

We now explain the architecture of the model $\pi_\theta$. The policy falls in a category of permutation equivariant functions meaning that permuting the users should only result in permuting likewise

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1The continuous relaxation is also mandatory for a DDPG approach to work so that the gradients can pass from the value network.
the resource allocation. In [Zeheer et al. 2017] necessary and sufficient conditions are shown for permutation equivariance in neural networks; their model is adopted here with minor changes. At first, the characteristics $x_i \in \mathbb{R}^{N_u}; i \in \{1, \ldots, K\}$ of each (active) user are processed individually by the same function $\phi_{\text{user}}: \mathbb{R}^{N_u} \rightarrow \mathbb{R}^{H_u}$ modeled as a two layer fully connected network. Then all those features per user are aggregated with the permutation equivariant $f_\sigma: \mathbb{R}^{K \times H} \rightarrow \mathbb{R}^{K \times H'}$ of $H' / H'$ input/output channels:

$$f_\sigma(x) = \sigma(x\Lambda + 11^T \Gamma), \quad 1 \in [1, \ldots, 1] \in \mathbb{R}^K, \quad \Lambda, \Gamma \in \mathbb{R}^{H \times H'}$$

and $\sigma(\cdot)$ an element wise non-linear function. We stack two of those, one $f_{\text{relu}}: \mathbb{R}^{K \times H_u} \rightarrow \mathbb{R}^{K \times H_u'}$ with $\sigma(\cdot)$ being the $\text{relu}(x) = \max(0, x)$ and a second $f_{\text{linear}}: \mathbb{R}^{K \times H_u} \rightarrow \mathbb{R}^{K \times 1}$ without any non-linearity $\sigma(\cdot)$. In addition to preserving the desirable permutation equivariance property, this structure also brings a significant parameter reduction, since an increase in the number of users does not necessitate additional parameters with bigger network prone to overfitting traps.

Before the final non-linearity, which is a smooth approximation of $\text{relu}(x)$, namely $\text{softplus}(x) = \log(1 + e^x)$ that restricts the output to be positive, there is a crucial normalization step $x \rightarrow \frac{x - \mu}{\beta} / \|x\|_2$ with $x \in \mathbb{R}^K \| \cdot \|_2$ being the $\ell_2$ norm. Before explaining the cruciality of that step, we first need to clarify the meaning of the output. If $y \in \mathbb{R}^K$ is the output, its interpretation in the no-CSI case is straightforward, since it gives the portions of the total resources $W$ allocated to each user (i.e., $y_i / W$ is allocated to $i$-th user). For full-CSI, the output indicates the exact bandwidth each user needs; allocating either more or less bandwidth (due to HARQ-I) would lead to resource wastage. Outputting a binary decision, i.e., indicating which users to satisfy per time slot, would ruin the differentiability, which is a mandatory property for DDPG to work. For that, the policy outputs instead a continuous relaxation by assigning a (positive real) value to each user, denoting how advantageous the policy believes is to allocate resource to that user. This results in a user ranking, which allows us to allocate resources accordingly to the rank as long as the total resource constraint is not violated.

Coming back to the normalization step, consider the full-CSI case. Without that step, the value network perceives that the higher the value assigned to a user, the more probable is to get resources, thus to be satisfied and take reward, leading to a pointless unceasing increase of every user’s value. However, by subtracting the mean value, whenever the value of a user increases, the value of the rest decreases, hence bringing the notion of limited total resources. In the no-CSI case, there is an additional benefit. There is an extra final operation, i.e., $x \rightarrow \frac{x}{\|x\|_1}$, see Figure 2, so as to signify portions (of the total bandwidth) adding up to 1. Having done the normalization step previously (dividing by $\|x\|_2$), helps keeping the denominator $\|x\|_1$ stable.

A final note regards the exploration. The output has to satisfy properties, such as positive symmetry and/or adding to one, which makes the common approach of adding noise on the actions rather cumbersome. An easy way out is through noisy networks [Fortunato et al. 2018], which introduce noise to the weights of a layer, resulting to changed decisions for the policy network. The original approach considers the variance of the noise to be learnable; we keep it constant though since it has provided better results. The noise is added at $\phi_{\text{users}}$ parameters, resulting to altered output features per user and therefore different allocations.

3.2.2 Value Network

As mentioned previously $Q^\pi(s, a)$ is used for computing the gradient (3.2.1). However, as this is intractable to compute, a neural network, named value network, is used to approximate it. The value network is employed in the following three ways.

**Expected approach:** A first, common approach is through the Bellman operator

$$\mathcal{T}^\pi Q(s_t, a_t) = \mathbb{E}[R(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim P(s_t, a_t)}[Q(s_{t+1}, \pi(a_{t+1}))]]$$

to minimize the temporal difference error, i.e., the difference between before and after applying the Bellman operator. This leads to the minimization of the loss

$$\mathcal{L}_2(\psi) = \mathbb{E}_{s_t \sim p_{s_0}, a_t \sim p_{a_0}}[(Q^\psi(s, a) - \mathcal{T}^\pi Q^\psi(s, a))^2] \quad \text{[Expected]}$$

where $(\pi_{\theta'}, Q_{\theta'})$ correspond to two separate networks called target policy and target value networks, respectively, used for stabilizing the learning, and are periodically (or gradually) updated as copies of the current actor and value networks.
Distributional approach: Another way is to approximate the distribution instead of only approximating the expected value of the return, as in (Barth-Maron et al. [2018]). Algorithmically, it is impossible to represent the full space of probability distributions with a finite number of parameters, so the value neural network $Z^\psi_{\pi} : S \times A \rightarrow \mathbb{R}^{N_Q}$ must approximate the actual $Z^\pi_\psi$ with a discrete representation. Among many variations (Bellemare et al., 2017; Dabney et al., 2018a), we choose the representation to be a uniform (discrete) probability distribution supported at \{(Z^\psi_i)_{i} | i \in \{1, \cdots, N_Q\}\} where $(Z^\psi_i)_i$ is the $i$-th element of the output. More rigorously, the distribution that the value neural network represents is $\frac{1}{N_Q} \sum_{i=1}^{N_Q} \delta_{(Z^\psi_i)}$, where $\delta_z$ is a Dirac delta function at $z$ (Dabney et al. [2018b]). Minimizing the 1-Wasserstein distance between this (approximated) distribution and the actual one of $Z^\pi_\psi$, can be done by minimizing the quantile regression loss

$$L_1(\psi) = \sum_{i=1}^{N_Q} \mathbb{E}_{s_{t}\sim p_{s_0}, a_{t}\sim p_{a_{t}}^{\pi_\psi}}[f_1(Z - (Z^\psi_i))_i]$$

where $f_1(x) = x(\frac{1}{2N_Q} - 1_{\{x<0\}})$, the distributional Bellman operator is $\mathcal{T}^\pi Z^\psi(s_{t}, a_{t}) \overset{D}{=} R(s_{t}, a_{t}) + \gamma Z^\pi(s_{t+1}, \pi(a_{t}))$, $s_{t+1} \sim P(s_{t}, a_{t})$ and $Z^\pi_\psi$ is the target policy network (defined in the same way as before).

Distributional & Dueling approach: Notice that even though we approximate the distribution of $Z^\pi_\psi(s, a)$, what is actually needed for improving the policy is only its expected value, approximated as $Q^\psi_\psi(s, a) \approx \frac{1}{N_Q} \sum_{i=1}^{N_Q} (Z^\psi_i)_i$. Therefore a natural question arises: why using $Z^\psi_\psi$ instead of following the previous approach, which directly approximates the needed expected value. The justification of this is provided using an analogy. Instead of having a scheduler and its users, consider a teacher and its students. Even though the objective of the teacher is to increase the mean “knowledge” of its students, using the distribution of the capacity/knowledge of the students enables for instance to decide whether to distribute its attention uniformly among students or to focus mostly on a fraction of them.

Intuitively, one expects to observe gains using the distributional RL approach. However, that was not the case at first, the reason being that the number of users and how easily they can be satisfied may vary significantly depending on state $s_{t}$. This increases remarkably the variance $r_t$ and consequently that of $Z^\pi_\psi(s_{t}, a_{t})$. In order to facilitate the approximation, we propose to split it into two parts: one that estimates the mean $Z^\psi_\psi, \text{Mean}$ and one that estimates the shape of the distribution $Z^\psi_\psi, \text{Shape}$. We use a dueling architecture (Wang et al. [2016]) as shown in Figure 2, hence the output becomes $(Z^\psi_i)_i = Z^\psi_\psi, \text{Mean} + (Z^\psi_\psi, \text{Shape})_i - \frac{1}{N_Q} \sum_{i=1}^{N_Q} (Z^\psi_\psi, \text{Shape})_i, \forall i \in \{1, \cdots, N_Q\}$; this effectively pushes $Z^\psi_\psi, \text{Mean}$ to approximate $Q^\pi_\psi$ used for training the policy. To ensure the decomposition of the distribution into shape and mean, we add a loss term $L_{\text{shape}} = \left(\sum_{i=1}^{N_Q} (Z^\psi_\psi, \text{Shape})_i\right)^2$, centering $Z^\psi_\psi, \text{Shape}$ around zero. The total loss function is

$$L_{1+\text{duel}}(\psi) = L_1(\psi) + L_{\text{shape}}(\psi). \quad \text{[Distr. & Dueling]}$$

To further facilitate the estimation of the distribution, the returns are normalized by scaling reward (see 1 in appendix E). As shown in Figure 1 this also brings the mean values around zero, this facilitating both branches of the dueling architecture.

In Figure 3 we provide support for choosing distributional RL. We use the traffic model described in Table 1a showing the two classes of users with different requirements. In Figure 3a (which is the mean taken over five experiments), although all approaches are observed to converge to approximately the same value (without reward normalization), the combination of distributional RL with dueling architecture converges faster. Figures 3b and 3c focus on two (out of the five) experiments,
Figure 2: The Neural Network architecture.

Figure 3: Comparison between distributional and standard (non-distributional) RL approach. We conducted five experiments (with different seeds) for no-CSI using the traffic model of Table 1a, a maximum number of users $K = 75$, and resources (total bandwidth) $W = 5$ MHz. In the first figure, we depict the average over those five experiments; in the other figures, we consider one specific experiment in an attempt to show the inherent ability of distributional RL in dealing with heterogeneous traffic.

showcasing the advantage of using distributional RL. This approach quickly detects the existence of two different services classes with heterogeneous requirements, thus gradually improving the satisfaction rate for both of them. On the other hand, trying only to learn the expected value leads to a training where the performance for one class is improved at the expense of the other. This behavior was apparent in all the experiments. Finally, reward normalization clearly provides further boost in the performance.

A final remark is that the architecture should be designed in a way preserving the permutation invariance. If we associate every user’s characteristics with the resources given by the agent, i.e., the action corresponding to it, then permuting the users and accordingly the resource allocation should not influence the assessment of the success of the agent. To build such an architecture, we adopt the same architecture as in our Policy Network which uses the ideas from DeepSets (Zaheer et al., 2017).

3.3 Benchmarks using conventional approaches

We briefly describe here schedulers that are built upon conventional optimization techniques and algorithms, depending on the type of CSI. We then compare the performance of our DRL algorithm with that of the derived state-of-the-art scheduling approaches.
Table 1: Classes description for two scenarios

(a) Users of equal importance

| Class 1 | Data   | Latency | Imp. | Prob. |
|---------|--------|---------|------|-------|
| Class 1 | 2Kbits | 2       | 1    | 0.3   |
| Class 2 | 16Kbits| 10      | 1    | 0.2   |

(b) Prioritized and normal users

| Class 1 | Data   | Latency | Imp. | Prob. |
|---------|--------|---------|------|-------|
| Class 1+| 2Kbits | 2       | 2    | 0.05  |
| Class 2 | 16Kbits| 10      | 2    | 0.05  |

3.3.1 Full-CSI

For explanation convenience, we use once again the analogy introduced in Section 3.1. With full-CSI the server knows at each time, the volume of the glasses of all active users (people) as well as their importance. Solving the problem myopically, i.e., ignoring the impact on the future steps, leads to a reformulated knapsack problem with the volume of glasses being the weight of the objects, whose value is the importance of its “holder”. The size of the server’s pitcher is the capacity of the knapsack we try to fill with objects so as to maximize the sum of their value. This benchmark is simply referred to as myopic Knapsack. More details are given in appendix B.2.1.

Accounting for the impact on the future becomes highly nontrivial (more details in appendix B.2.2). One way out is to assume that the scheduler acts as an oracle and knows in advance the users that will appear and their channels for the future \( T - 1 \) time steps. In that case, the problem can be written as an Integer Linear Programming and can be solved by standard Branch and Cut approach. We obtain therefore an upper bound which we call oracle ILP. More details in appendix B.2.2.

3.3.2 No-CSI

In the no-CSI case, we may at best learn the channel (usually with autoregression). Using DRL, the dynamics of the environment does not change through training (and testing) and the agent could learn how to react well under those conditions. Therefore, even though it acts in a model-free manner, in a way it can learn the statistics of the problem in hand. For fair comparison, we consider a benchmark that has knowledge of the channel and traffic dynamics statistics. However, multiple local optima may appear when the optimization problem is solved based only on statistical knowledge. The Frank-Wolfe algorithm guarantees reaching to a local optimum, so we run this method \( N_{\text{init}} \) times and select the best local optimum we found. More details in appendix B.1.

4 Experiments

We consider two different scenarios for the generated traffic, described in Table 1. The first scenario consists of two classes, one with users requesting a small amount of data but with a stringent latency constraint (of just two time slots) and one delay-tolerant class requesting a large amount of data. Every class has the same importance, and this is the main difference with the second scenario in which certain users are of higher priority. We note that with equally important users, the scheduler just aims at indiscriminately increasing the satisfaction probability of every user. On the other hand, having users of unequal importance pushes the scheduler to favor specific classes, thus allocating the resources in an unfair manner. Finally, the Prob. column describes the probability with which a user of that class appears in the system at a given time slot (note that they do not add up to one so it is possible that no user appears during some time slots).

4.1 Synthetic Data

The channel dynamics is captured by parameter \( \rho \). For \( \rho = 0 \), the channel evolves in an i.i.d. manner at each time step, thus increasing the future unpredictability and the chances to recover from a bad quality connection link (deep fading). We consider that the distance between users and BS ranges from 0.05 km to 1 km. We keep the power per unit bandwidth equal to \( 1 \mu \text{Watt Hz} \). Additional information related to the communication network setting is provided in appendix C. Hereafter we refer to the DRL approach as “Deep Scheduler”.

In Figures 4a and 4b we showcase the significant performance gains by using the Deep Scheduler in the full-CSI case with a maximum number of \( K = 100 \) users. Our proposed scheduler consistently outperforms the myopic Knapsack approach, which is myopically optimal but solving it is non-
polynomial in time. We observe that the performance of Deep Scheduler is close to optimal, as being very close to the “oracle ILP”, in which the scheduler knows in advance the future and can be considered as upper bound. We want to emphasize that for 95% satisfaction probability, from Figure 4b we have about 13% bandwidth saving against myopic Knapsack, which is followed by a 13% power saving as the power per Hz is kept constant.

In Figures 4c and 4d, we show the results for the no-CSI case with $K = 60$ users. In that case, we know that the Frank-Wolfe (FW) algorithm reaches to a suboptimal solution. For that, we repeatedly run the algorithm with different initialization (for each time step) and select the best outcome among various suboptimal points. This process is unfortunately very slow (see appendix B.1) and becomes slower for increasing $K$. So even if this method could result in considerable performance improvement, especially with high $N_{init}$, for computational complexity reasons, we were obliged to stop at $N_{init} = 20$. Moreover, as $K$ increases, unfortunately so does the number of local optima and that of solutions with poor performance. This is one of the reasons why our Deep Scheduler substantially outperforms the Frank-Wolfe algorithm even at moderate $K = 60$.

Finally, in Figure 4e, we confirm that the Deep Scheduler exhibits consistently high performance even with more service classes of diverse priorities.

4.2 Real Data

To assess the applicability of our algorithm in a more realistic setup, we perform experiments on real data using traces based on real measurements over LTE/4G networks in a city of Belgium (van der Hooft et al., 2016; Mao, 2017). Six different types of transportation (foot, bicycle, bus, tram, train, car) are used and the throughput and the GPS location of a mobile device continuously demanding data are recorded every second. Since the time scale of one second is much larger than the small-scale fading timescale, the measurement is $x_i = \frac{E_h}{W \log_2(1 + |h|^2)}$ for every $i$ sec. The value of $\kappa$, which mainly depends on the user location, can safely be assumed constant within one second. As the measurements’ bandwidth $W$ is not reported, we assume it to be 15 MHz, giving a mean signal-to-noise ratio (SNR) $\approx 6$ dB in an

Table 2: Equal Importance classes

| Class | Data | Lat. | Prob. |
|-------|------|------|-------|
| 1     | 1Kbits | 5msec | 0.2  |
| 2     | 25Kbits | 25msec | 0.3f |
|                | \( \text{N}_{bl} \) (W) | 6 (3MHz)   | 15 (5MHz) | 25 (10MHz) | 50 (15MHz) | 75 (20MHz) |
|----------------|--------------------------|------------|-----------|------------|------------|------------|
| myopic Knap.   |                          | 6.4/48.6%  | 10.2/64.3%| 15.2/84.3% | 17.0/91.2% | 17.6/93.3% |
| Exp. Rule      |                          | 5.9/39.2%  | 8.9/50.4% | 14.0/72.9% | 17.0/90.2% | 18.1/95.8% |
| Deep Sched.    |                          | 6.8/52.6%  | 10.6/67.6%| 15.5/86.9% | 17.2/93.0% | 18.3/96.2% |
| oracle ILP     |                          | 9.0/62.9%  | 14.6/81.8%| 18.6/98.5% | 18.9/98.7% | 19.0/98.9% |

LTE compliant system. This allows us to retrieve \( \kappa \) from measurement \( x_i \). To compute the channel dynamics \( h \), the user speed is required (2) which is estimated using the GPS coordinates from the traces. A user arriving to the system belongs to a class according to Table 2 with its type of transportation chosen randomly; we then sample \( x_i \) from the traces accordingly and we compute the channel dynamics. Finally, until now we assumed that the bandwidth can be split as small as desired; however, in practice the bandwidth is split into \( N_{bl} \) resource blocks and each user is assigned an integer multiple of those. In Table 3 we increase \( N_{bl} \) with the size of the resource block constant to 200kHz. For the full-CSI case, we also compare with the exponential rule (Shakkottai & Stolyar, 2001). This scheduling metric, widely used in practice for packet scheduling in systems with mix of real-time and non real-time traffic, is a generalization of proportional fair scheduler taking into account the latency constraints of each user (explained in appendix D).

5 CONCLUSION

The problem of scheduling and resource allocation of a time varying set of users with heterogeneous traffic and QoS requirements in wireless networks has been investigated here. Leveraging deep reinforcement learning, we have proposed a deep deterministic policy gradient algorithm, which builds upon distributional reinforcement learning and Deep Sets. Our experiments on synthetic and real data in heterogeneous scenarios with different traffic and channel dynamics show that our Deep Scheduler achieves significant gains against state-of-the-art conventional combinatorial optimization methods.

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A PROBLEM SETTING

A.1 TRAFFIC MODEL

We consider a traffic model where users enter and exit the system in a continuous way. Each user belongs to a certain service class, which is characterized by the following attributes:

- Data size $D$: the amount of data the user belonging to that class asks for.
- Maximum Latency $L$: the maximum number of time slots within which the user has to successfully receive its data packets of size $D$, so as to be satisfied.
- Importance $\alpha$: an index allowing the scheduler to prioritize a certain service class, having users with privileged contracts (e.g., high-value SLAs), requesting for better service and higher reliability.
- Arrival probability $p$: the probability a new user belonging to that class arrives in and enters the system.

We denote by $C$ the set of classes; every user entering the system belongs to a class $c \in C$ with probability $p_c$, and is characterized by the tuple $(D_c, L_c, \alpha_c)$. We assume that a maximum number $K$ of users can coexist per time slot. We also assume that a new user appears whenever a previous one has reached the maximum time allowed to be active in the system. For example, if a user appears at time $t=1$, belonging to class $c \in C$ with $L_c = 4$, then even if it successfully receives its requested packet of size $D_c$ at $t=1$, it will remain in the system until a new user belonging to a class $c' \in C$ appears at $t=5$ with probability $p_{c'}$. Therefore, at every time slot, a set of users $U_t$ (with constant cardinality $|U_t| = K$) is observed. Some users belong to set $U_{act} \subseteq U_t$, some users request resources from the BS as being unsatisfied, and some of them have already been satisfied. The assumption of always having $K$ active users is alleviated by adding the null class $c_0$ with $D_{c_0} = 0$, $\alpha_{c_0} = 0$, and $L_{c_0} > 0$. A “user” of the null class is equivalent to that no user has appeared; that way, the number of users could fluctuate over time.

The rationale behind using this traffic model is as follows: (i) it is a traffic model under which users with different stringent data and latency requirements come and go; it is quite generic yet tractable enough to permit to benchmark (this does not apply to DRL since it is model-free) (ii) the traffic remains uninfluenced by the scheduler decisions. On the contrary, under the assumption that
whenever a user is satisfied a new one arrives with some probability per time slot, the scheduler performance has an impact on the traffic statistics since at a given time interval, a scheduler with abundant resources would deal with more users than one with scarce resources. This is because having more resources available implies being able to satisfy users faster resulting in a model that has (statistically) more users appearing.

A.2 Network, Channel, and Rate Model

A.2.1 Network Topology

Users are assumed to be uniformly distributed within two concentric rings of radii \(d_{\text{min}}\) and \(d_{\text{max}} > d_{\text{min}}\). Therefore, the distance of a user from the serving BS is a random variable with a probability density function: \(f_d(d_u) = \frac{2d_u}{d_{\text{max}}^2-d_{\text{min}}^2}, d_u \in [d_{\text{min}}, d_{\text{max}}]\). Furthermore, we assume a low mobility scenario, which implies that there are no significant changes in the received signal power during the time interval users remain active. Consequently, the distances between the users and the BS are kept constant. The main randomness in the link quality (channel strength) is due to small-scale channel variations (fading) as described below.

A.2.2 Channel Model

Multiple users can be served simultaneously; to avoid interference among them, orthogonal frequency bands are assigned to scheduled users. We assume that users experience frequency flat fading, i.e., every user has a constant channel gain during a given time slot and throughout all available frequency bands assigned. Consider that user \(u\) has entered the system at time \(t_0\). Its channel gain at time \(t\) is given by \(g_{u,t} = \frac{C_{pl}|h_{u,t}|^2}{\sigma_n^2}d_u^{-n_{pl}}, \) where \(n_{pl}\) is the pathloss exponent, \(C_{pl}\) is a constant accounting for constant losses and \(\sigma_n^2\) is the noise power spectrum density (in Section 3.1.1 we set \(\kappa_u = \frac{C_{pl}}{\sigma_n^2}d_u^{-n_{pl}}\) for simplicity). The distance \(d_u\) remains constant throughout the lifespan of user \(u\), but there is Rayleigh fading evolving at every time slot according to the following Markovian model

\[
h_{u,t} = \rho h_{u,t-1} + Z
\]

where \(h_{u,t_0} \sim \mathcal{CN}(0,1)\), \(\mathcal{CN}(0, v)\) is a circular complex normal distribution with zero mean and variance \(v\), and \(Z \sim \mathcal{CN}(0, 1 - \rho^2), t > t_0\). The parameter \(\rho = J_0(2\pi f_d T_{\text{slot}}) \in [0, 1]\) (Tan & Beaulieu, 2000) determines the time correlation of the channel, with \(J_0(\cdot)\) denoting the zeroth-order Bessel function of the first kind, \(f_d\) the maximum Doppler frequency (determined by the mobility of the users), and \(T_{\text{slot}}\) the slot duration. If \(\rho = 0\), (high mobility) the user experiences an independent realization of the fading distribution at each time slot (i.i.d. block fading). If \(\rho = 1\) (no mobility), channel attenuation is constant throughout the user’s lifespan (no fading).

A.2.3 Service Rate

We assume ideal link adaptation and capacity-achieving codes so that Shannon’s capacity formula is a valid measure of the service rate. The data rate of user \(u\) at time \(t\) is equal to \(R_{u,t} = w_{u,t} \log_2(1 + g_{u,t}P_{u,t})\), where \(P_{u,t}\) is the transmit energy per channel use or symbol and \(w_{u,t}\) is the bandwidth of the channel assigned. An outage happens when the user’s data requirement is higher than the instantaneous channel capacity. For instance, if we consider transmission at given time \(t_u\) to a user at distance \(d_u\) from the BS, belonging to class \(c \in C\) with resources \((w_{u,t}, P_{u,t})\), then the probability of failing to correctly decode its packet is equals to

\[
P_{u,t}^{\text{fail}}(w_{u,t}, P_{u,t}; d_u) = \mathbb{P}(w_{u,t} \log_2(1 + g_{u,t}P_{u,t}) < D_u|d_u) = \mathbb{P}(|h_{u,t}|^2 < \zeta_u d_u^{n_{pl}}) = 1 - e^{-\zeta_u d_u^{n_{pl}}}
\]
with \( \zeta_{u,t} = \frac{\sigma^2_u}{C_p(t_{u,t})} \). If the user distance from the BS \( d_u \) is not known to the scheduler, the probability of error becomes

\[
P_{u,t}^{fail}(w_{u,t}, P_{u,t}) = \mathbb{P}(w_{u,t} \log_2(1 + g_{u,t}P_{u,t}) < D_u) = \int_{d_{\min}}^{d_{\max}} P_{u,t}^{fail}(w_{u,t}, P_{u,t}; d) f_d(d) \, \mathrm{d}d
\]

\[
= 1 - \frac{\Gamma\left(\frac{2}{n_{pl}}; \zeta_{u,t} D_{\min}^2\right) - \Gamma\left(\frac{2}{n_{pl}}; \zeta_{u,t} D_{\max}^2\right)}{n_{pl} \zeta_{u,t}^2 \frac{D_{\min}^2}{2}}
\]

where \( \Gamma(s, x) = \int_x^{\infty} t^{s-1} e^{-t} \, \mathrm{d}t \) is the upper incomplete gamma function. For exposition convenience, We overload notation by allowing \( x \) in \( D_x, \alpha_x, L_x \) to either denote a class \( x \) or a user \( x \) belonging to a class with those characteristics.

### A.3 Scheduling Procedure

The general objective of the BS is to appropriately and efficiently utilize its energy and bandwidth resources in every time slot in order to satisfy its associated users. We only focus on bandwidth allocation, assuming that a fixed amount of energy is spent per channel use and no power adaptation is performed, i.e., \( P_{u,t} = P, \forall u, t \). If the total bandwidth available at the BS is \( W \), the scheduler aims at finding the \((w_{u_1,t}, w_{u_2,t}, \ldots) \in \mathbb{R}_{\geq 0}^{U_{t,act}}\) with \( u_1, u_2, \ldots \in U_{t,act} \) such that

\[
\sum_{u \in U_{t,act}} w_{u,t} \leq W, \quad \forall t
\]

and at maximizing over a finite time horizon the accumulated reward for every satisfied user, which in turn is described by the following objective "gain-function"

\[
G = \sum_t \sum_{u \in U_{t,act}} \alpha_u \mathbb{1}\{w_{u,t} \log_2(1 + g_{u,t}P) > D_u\}\}
\]

We stress out that a user \( u \) remains on the set \( U_{t,act} \) for a time interval less or equal to its maximum acceptable latency \( L_u \). If not satisfied within that interval, then it does not contribute positively to the objective \( G \).

As implied by (5), the retransmission protocol adopted is Hybrid Automatic Repeat reQuest (HARQ-type I) with rate adaptation. If a user fails to correctly decode its data/packet, then this data/packet is discarded (no buffering at the receiver side) and the user has to wait until the BS sends again this data for another decoding attempt. Finally, we consider two different classes of channel knowledge. In the first case, referred to as full CSI, the exact channel realization \( h_{u,t}, \forall u \in U_{t,act} \) and the location of the users and so \( d_u, \forall u \in U_{t,act} \) are known at each time \( t_c \). In the second case, referred to as no-CSI, the BS/scheduler has no knowledge of the channel, neither its instantaneous realization, nor its (long-term) statistics. We remark here that in order to be able to implement conventional methods, such as Frank-Wolfe algorithm and knapsack, in the no-CSI case, we had to assume some kind partial CSI. Hence, for those methods, we assume that no-CSI refers to knowledge of the statistical properties of channels and locations at current time \( t_c \) and the future. This is not case for our proposed DRL algorithm, which could operate with complete absence of CSI.

### B Scheduling Methods

#### B.1 Frank-Wolfe

In this section, we deal with the case where the scheduler knows all the statistical properties of the system, i.e. channel and traffic. We write the problem in an optimization form on which the Frank-Wolfe method is applied to decide the resource allocation.

Let first concentrate on the case of a single user \( u_0 \) appearing at time \( t_0 \). The current time is \( t_c \in [t_0, t_0 + L_{u_0} - 1] \). We denote by \( w_{u_0,t} = (w_{u_0,t_0}, w_{u_0,t_0+1}, \ldots, w_{u_0,t}) \) the assigned bandwidth from time \( t_0 \) (beginning of transmission for user \( u_0 \)). Additionally, let \( A_{u_0,t} \) be a binary random
variable which if \( A_{u_0,t} = 1 \) then \( u_0 \) is still unsatisfied at the end of time slot \( t \) (after receiving \( w_{u_0,t} \) resources) and \( A_{u_0,t} = 0 \) otherwise. Given that at the beginning of time \( t \) user \( u_0 \) is still unsatisfied and that we know the resource allocation \( w_{u_0,t} \) is scheduled to be done at time \( t \), we define \( \Phi(w_{u_0,t}; d_{u_0}) \) to be the probability that \( w_{u_0,t} \) is still not enough when the location \( d_{u_0} \) is known but the channel \( h_{u_0,t} \) is unknown:

\[
\Phi(w_{u_0,t}; d_{u_0}) = \begin{cases} 
\mathbb{P}(A_{u_0,t} = 1|w_{u_0,t-1}, A_{u_0,t-1} = 1), & t > t_0 \\
\mathbb{P}(A_{u_0,t} = 1|d_{u_0}), & t = t_c = t_0.
\end{cases}
\]

(6)

The average contribution of user \( u_0 \) to the gain function (5) on the time interval \([t_c, t]\) is given by the following equation, derived by applying the chain rule for conditional probability:

\[
g_{u_0}^{[t_c, t]} = g(w_{u_0,t_c}, ..., w_{u_0,t}; d_{u_0}) = \begin{cases} 
0, & \text{if } t_c > t_0 \text{ and } A_{u_0,t_c-1} = 0 \\
\alpha_{u_0} \left(1 - \prod_{j=t_c}^{t} \Phi(w_{u_0,j}; d_{u_0})\right), & \text{else.}
\end{cases}
\]

(7)

Now we consider that the average contribution on the gain function (5) for the the future users following the user \( u_0 \). The next user (if it exists) appears at time \( t_1 = t_0 + L_{u_0} \), and so on. Therefore we consider the users noted as \( u_1, u_2, \ldots \) that will appear at \( t_1 = t_0 + L_{u_0}, t_2 = t_1 + L_{u_1}, \ldots \). We denote that with probabilities \( p_{c_1}, p_{c_2}, \ldots \), they will belong to classes \( c_1, c_2, \ldots \), respectively (and one of these classes may be the null class). These classes will determine the maximum latencies \( L_{u_1}, L_{u_2}, \ldots \) and consequently the time arrivals \( t_1, t_2, \ldots \) all being random variables. As we consider here future users, even their locations are unknown. Consequently we need to average over the locations the equations (6) and (7) to obtain their contribution on the gain function (5). So for \( i \geq 1 \) if \( w_{u_i,t} = (w_{u_i,t_1}, w_{u_i,t_1+1}, \ldots, w_{u_i,t}) \), we have

\[
g_{u_i}^{[t_i, t]} = g(w_{u_i,t_i}, ..., w_{u_i,t}; d_{u_0}) = \alpha_{u_0} \left(1 - \prod_{i=t_i}^{t} \Phi(w_{u_i,i})\right)
\]

(8)

where the contribution looking at time \( t \) with \( t < t_i + L_{u_i} \) starts at time \( t_i \) for user \( u_i \) and where

\[
\Phi(w_{u_i,t}) = \begin{cases} 
\mathbb{P}(A_{u_i,t} = 1|w_{u_i,t-1}, A_{u_i,t-1} = 1), & t > t_i \\
\mathbb{P}(A_{u_i,t} = 1), & t = t_i.
\end{cases}
\]

(9)

Hence, the averaged value of gain function for the sequence of users \( u_0, u_1, \ldots \) (so when one user at most is active per time slot, i.e. \( K = 1 \)) starting at the current time \( t_c \) is:

\[
\mathcal{G}(w_{u_0,t_1}, ..., w_{u_0,t_1-1}, w_{u_1,t_1}, ...,) = \mathcal{G}^{[t_1, t_1-1]}(.; d_{u_0}) + \sum_{c_1 \in C} \left( \underbrace{p_{c_1} \cdot g_{u_1}^{[t_2, t_2-1]}(.;)}_{\text{here}} + \sum_{c_2 \in C} \left( p_{c_2} \cdot g_{u_2}^{[t_3, t_3-1]}(.;) + \sum_{c_3 \in C} (.)\right) \right).
\]

(10)

From (10), we observe a tree structure\(^2\) that when a user vanishes there is a summation over all the possibilities of the classes that the new user can belong to. Therefore a number of branches is equal to the number of possible classes (\(|C|\)). To manage the scalability issue, we cut the tree by considering only \( T \) future time slots and work with the finite horizon \([t_c, t_c + T - 1]\).

Finally, the general case with multiple users served simultaneously (\( K > 1 \)) is easy to be considered by just computing \( K \) "parallel trees". With a slight abuse of notation, we consider that the first subscript of the variables \( w \) now refers to the index of the tree (and implicitly to a specific user). As a consequence, the variables for the scheduled bandwidth resources over an horizon of length \( T \) can be put into the following matrix:

\[
W_{t_c} = \begin{bmatrix}
    w_{1, t_c} & w_{1, t_c+1} & \cdots & w_{1, t_c+T-1} \\
    w_{2, t_c} & w_{2, t_c+1} & \cdots & w_{2, t_c+T-1} \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{K, t_c} & w_{K, t_c+1} & \cdots & w_{K, t_c+T-1}
\end{bmatrix}
\]

\(^2\) A simple way to be computed is recursively
and the average gain for these resources takes the following form:

\[
G(W_{t_c}) = \sum_{k=1}^{K} G(w_{k,t_c}, w_{k,t_c+1}, \ldots, w_{k,t_c+T-1}).
\] (11)

Finally, we arrive at our optimization problem at current time \(t_c\), the solution of which serves as benchmark in the no-CSI case (statistical CSI for the conventional methods):

\[
\max_{W_{t_c} \in \mathbb{R}^{K \times T}_{\geq 0}} G(W_{t_c})
\] (12)

\[
\text{s.t.} \quad \sum_{k=1}^{K} w_{k,t} \leq W, \quad \forall t \in \{t_c, \ldots, t_c+T-1\}.
\] (13)

It can be easily shown that the objective function \(G(\cdot)\) is non-concave with multiple local optimums. In contrast, the constraints given by equation (13) describe a compact and convex domain set which allows the application of so-called Frank-Wolfe algorithm [Frank & Wolfe, 1956]. The idea behind this algorithm is as follows: at each iteration, the algorithm starts from a point and approximates the objective function around it with a linear (first-order) approximation. Then it solves the corresponding Linear Programming problem (LP) to find the best solution which will be the starting point of the next iteration. The procedure terminates when the algorithm converges to a local optimum, i.e., when the objective function does not increase anymore significantly. In order to exhibit a solution close to the global optimum, the algorithm is repeated \(N_{\text{init}}\) times with different randomly chosen initial points. At the end, we peak the best local optimum.

We provide some general remarks:

- The above benchmark procedure takes into account the past through (6) since all the previously allocated resources are involved.
- The procedure at current time \(t_c\) proposes a solution for the scheduler for both the current time \(t_c\) and for the future \([t_c+1, t_c+T-1]\). Nevertheless, as this procedure will be recomputed at time \(t_c+1\) (once the actions proposed for time \(t_c\) is applied and new information about the transmission’s success or failure are available), the actions proposed at time \(t_c\) for time \(t_c+1\) are generally not applied. Obviously we will apply at time \(t_c+1\) the solution advocated by the procedure computed at time \(t_c+1\).
- The Frank-Wolfe method is sublinear but the computation of the objective function (11) and its partial derivatives grow exponentially with \(T\) which leads in practice to a slow and cumbersome method if one wants to account for the impact of distant future (not to mention that to be sure to retrieve a good local optimum we have to repeat the process \(N_{\text{init}}\) times).
- Lastly, the algorithm treats the “mean” case. It does not specify what really happens in the future since it only evaluate what happens in the future on average (for example over every possible class of future user). It would be possible to address for every future scenario differently but by skyrocketing the number of variables and constraints, making the already-slow benchmark procedure slower.

### B.1.1 Calculating the expressions

Hereafter, we concentrate on calculating (6) and (9) for different channel model subcases. The rest of the benchmark procedure is straightforward.

\[
\frac{dP_{\text{fail}}}{dw} = \int_{d_{\text{min}}}^{d_{\text{max}}} \frac{d\xi}{d\zeta} \left( \frac{(d_{\text{max}}^2 - d_{\text{min}}^2)}{2} \right) d\zeta
\]
• **The i.i.d. fading channel case** ($\rho = 0$): It is the simplest subcase since there are no time dependencies on the fading, so equations (4) and (7) become

$$\Phi(w_{u_0,t}; d_{u_0}) = P_{f_{u_0}}(w_{u_0,t}, P; d_{u_0}) \text{ and } \Phi(w_{u,t}, P) = P_{f_{u_0}}(w_{u_0,t}, P), \quad i \geq 1.$$  

We remind the users $u_i$ for $i \geq 1$ follow the user $u_0$, and therefore we average over their unknown locations.

• **The constant fading channel case** ($\rho = 1$): Now the channel is the same for each retransmission on the user. For user $u_0$, the channel is invariant but unknown. Only its location is known. At time $t > t_0$, we have

$$\Phi(w_{u_0,t}; d_{u_0}) = \mathbb{P}(w_{u_0,t} \log(1+g_{u_0} P) < D_{u_0}, w_{u_0,t} \log(1+g_{u_0} P) < D_{u_0}, \forall t' \in [t_0,t-1], d_{u_0}) = \frac{\mathbb{P}(w_{u_0,t} \log(1+g_{u_0} P) < D_{u_0}, \forall t' \in [t_0,t-1]|d_{u_0})}{\mathbb{P}(w_{u_0,t} \log(1+g_{u_0} P) < D_{u_0}, \forall t' \in [0,t-1]|d_{u_0})}.$$  

Therefore we obtain

$$\Phi(w_{u_0,t}; d_{u_0}) = \begin{cases} 1 & \text{if } t > t_0 \\ \frac{\max\{w_{u_0,t}, \max\{w_{u_0,t-1}, P; d_{u_0}\}, P, d_{u_0}\}}{\max\{w_{u_0,t-1}, P; d_{u_0}\}, P, d_{u_0\}} & \text{if } t = t_0. \end{cases}$$  

For the case of the future users ($u_i$ with $i \geq 1$), the equations remain the same with the only change that the location of the users is unknown as well. So in equation (16), we just need to omit the $d_u$ similarly to the i.i.d. case.

• **The general Markovian case** ($\rho \in (0,1)$): Let us focus on the user $u_0$ and we are looking at the time $t = t_0 + 1$. According to [Nuttall 1975](eq: 37), we have:

$$\Phi(w_{u_0,t_0+1}; d_{u_0}) = \int_{x_{u_0}} \int_{x_{u_0}} \mathbb{P}(h_{u_0,t_0+1} = x | y) \mathbb{P}(h_{u_0,t_0} = y) dx dy = 1 - \frac{e^{-x_{u_0}^2} Q_1(\frac{x_{u_0}}{\sigma_R}, \frac{\rho x_{u_0}}{\sigma_R}) - e^{-x_{u_0}^2} Q_1(\frac{\rho x_{u_0}}{\sigma_R}, \frac{x_{u_0}}{\sigma_R})}{2(1-e^{-x_{u_0}^2})}$$  

with $x_{u_0} = \sqrt{\zeta_{u_0,t_0+1}} d_{u_0}^{-n_{ul}}$, $i \in \{0,1\}$ and $Q_M$ be the Marcum Q-function.

For the future users ($u_i$, $i \geq 1$), we have at time $t = t_i + 1$ (we remind that user $u_i$ starts its transmission at time $t_i$):

$$\Phi(w_{u,t_0+1}) = \int_{d_{u_0}} \Phi(w_{u,t_0+1}; d_{u_0}) f_i(d) dd,$$

where $\Phi(w_{u_0,t_0+1}; d_{u_0})$ is given by (17) by replacing $u_0$ with $u_i$. This equation (18) is already intractable whereas we are just focusing on the two first adjacent retransmissions. Obviously, it is even worse if we consider more retransmissions. Therefore the benchmark procedure will be only designed for $\rho = 0$ or $\rho = 1$, even if tested in the general case $\rho \in (0,1)$. More precisely, for any $\rho$, we apply the benchmark procedure designed for either $\rho = 0$ or $\rho = 1$, and keep the best result.

This case is much more complicated due to the correlation between the channel realizations. Actually, at time $t$, the distribution of $h_{u,t}$ given the past (which is not known in practice) is Ricean distributed. More precisely, if the user $u$ is active at $t - 1$ and $t$, we have $\mathbb{P}(|h_{u,t}| = x | h_{u,t-1}) = \text{Rice}(x; v_R = \rho h_{u,t-1}, \sigma_R^2 = \frac{1-\rho^2}{2})$ where $v_R$ and $\sigma_R^2$ are the so-called Ricean parameters.

### B.2 Knapsack and Integer Linear Programming

We consider here the full-CSI case. Let first work on the user $u_0$ at the current time $t_{c}(t_{c} \geq t_0)$ for which both channel $h_{u_0,t_{c}}$ and location $d_{u_0}$ are known. However, future channel realizations in $t > t_c$ are only statistically known. User $u_0$ is not satisfied at time $t$ if and only if (iff) the allocated bandwidth $w_{u_0,t}$ is smaller than the following threshold

$$w_{u_0,t}^b = \frac{D_{u_0}}{\log_2(1+g_{u_0,t} P)}.$$
Consequently, the probability of error for user $u_0$, defined by $[9]$, can be expressed as

$$
\Phi(w_{u_0,t}; d_{u_0}) = \begin{cases} 
\mathbb{P}(w_{u_0,t} < w_{u_0,t}^h | A_{u_0,t-1} = 1, h_{u_0,t}, d_{u_0}), & \text{if } t > t_c \\
1\{w_{u_0,t} < w_{u_0,t}^h\}, & \text{if } t = t_c.
\end{cases}
$$

(19)

We remark that the probabilities are not necessarily continuous due to the indicator function in $[19]$. Consequently, the gain function described in $[11]$ is now non-continuous over the variables $w_{k,t}, \forall k$ (since we know exactly the channel gains at $t_c$ and indicator functions occur at this time), but continuous for $w_{k,t}, t > t_c$ corresponding to the future. To overcome this problem, we split the problem into the following two cases:

- **Immediate horizon ($T = 1$):** we focus only on the current time $t_c$ and the effects on future are ignored. We reach to a Knapsack that is myopically optimal.

- **Finite horizon ($T > 1$):** we take into account the future and we assume that the channel realization and the location at time $t \in [t_c, t_c + T - 1]$ are both known in advance, i.e., when the algorithm is run at time $t_c$. We write the problem as an integer linear programming (ILP) and the algorithm functions as an oracle providing an upper bound.

### B.2.1 IMMEDIATE HORIZON: $T = 1$

In that case, the optimization problem can be entirely recast. The variables to be optimized are $x_{u,t_c}$, which is 1 if user $u$ is active at time $t_c$ or 0 otherwise. The cost in bandwidth is $w_{u,t_c} x_{u,t_c}$, because we assume that if a user is active, then the scheduler provides to it the minimum bandwidth required to send its data with no failure. Then, the contribution in the gain function is $\alpha_u x_{u,t_c}$. Therefore the optimization problem can be written as follows

$$
\max_{x_{u,t_c}} \sum_{u \in U_{t_c}^{act}} \alpha_u x_{u,t_c}
$$

s.t.

$$
\sum_{u \in U_{t_c}^{act}} w_{u,t_c} x_{u,t_c} \leq W
$$

$$
x_{u,t_c} \in \{0, 1\}, \forall u \in U_{t_c}^{act}.
$$

This problem is a Knapsack problem, which corresponds to maximizing the total value by choosing from a set of objects a proper subset. Every object has its value but also a weight that prevents from picking all of them since the total weight of the chosen subset should not overreach the capacity level. It is a well known NP-complete problem with various efficient algorithms for solving it; we used Google’s OR-TOOLS library for that.

### B.2.2 FINITE HORIZON: $T > 1$

As remarked previously, the original problem described by $[19]$ is mixed, i.e., discrete over some variables and continuous over others. One idea is to approximate the indicator function with a continuous function in order to apply the Frank-Wolfe algorithm again as in the no-CSIT (statistical CSI) case. However, we refrain from following this approach for two main reasons: the number of bad local optima would increase and that heavily depends on the choice of the approximating function. Hereafter, we assume that for the future $T - 1$ time slots, the BS knows exactly the amount and the locations of users to appear, as well as the class they will belong and the channel quality they will experience. As a result, the BS acts as an oracle capable to perfectly calibrate the scheduling against future fluctuations. We obtain therefore an upper bound of the performance of our policies.

This problem cannot successfully be linked to a knapsack problem. Let us assume that during the time interval $[t_c, t_c + T - 1]$, the oracle knows a set of $U_{t_c}^T$ users (objects) appear in total. We can think of having $T$ different knapsacks (one for each $t \in [t_c, t_c + T - 1]$ and all of total capacity $W$), and we want to fill them with users from the set $U_{t_c}^T$. The goal is to maximize the overall value of the chosen

---

The form $1\{w > w_{u,t_c}^h\}$ needs to be changed into a continuous function that is equal to 0 when $w < w_{u,t_c}^h$ in order to avoid giving less than $w_{u,t_c}^h$ resources at user $u$; otherwise it goes as fast as possible to 1.
objects, i.e., satisfied users. This corresponds to a “multiple knapsack problem” but with a crucial difference. In contrast to standard “multiple knapsack problems”, the weight of each user/object is time-varying due to channel variability, which also changes the required resources (weight). That means that every object has a different weight depending on the knapsack it will be put in. Even considering $\rho = 1$ (constant channel) does not help much since for some time slots in $[t_c, t_c + T - 1]$ a user can happen to be either “not yet active” or “served thus non-active”. In those time slots, we have to assume a different weight that will be something greater than $W$ so as to make it impossible to fit in the knapsacks corresponding to those time slots. Finally, we address our problem using a more generic (and slower) approach after formulating it as Integer Linear Programming. As mentioned, within the lifespan $t \in I_{t_{ife}} = [\max(t_c, t_u), \min(t_u + L_u - 1, t_c + T - 1)]$ of a user $u \in U_{t_c}^T$, $w_{u,t}^{th}$ is the (accurately predicted by the oracle) required bandwidth to satisfy $u$ at time $t$ given its channel gain $g_{u,t}$. Outside $t \in [t_c, t_c + T - 1]/I_{t_{ife}}$, $w_{u,t}^{th}$ is given a value greater than $W$ so as to prevent any allocation. The formulation is

$$\max_{x_{u,t}} \sum_{u \in U_{t_c}^T} x_{u,t} \quad s.t. \quad \sum_{u \in U_{t_c}^T} w_{u,t}^{th} x_{u,t} \leq W, \quad \forall t \in [t_c, t_c + T - 1]$$

$$\sum_{t = t_c}^{t_c + T - 1} x_{u,t} \leq 1, \quad \forall u \in U_{t_c}^T$$

$$x_{u,t} \in \{0, 1\}, \quad \forall t \in [t_c, t_c + T - 1] \text{ and } \forall u \in U_{t_c}^T.$$ 

To solve this ILP problem for every time step, we use IBM CPLEX Optimization software, which relies on the Branch and Cut algorithm (Mitchell 2002).

C PARAMETERS OF THE SETTING

The distance dependent pathloss at distance $d$, which is related with $\kappa_u$, is set to $120.9 + 37.6 \log_{10} d$ (in dB) which is LTE standard compliant (LTE 2018). In our setting, this translates into a constant loss component $C_{pl} = 10^{-12.09}$ and pathloss exponent $n_{pl} = 3.76$. The noise spectral density is $\sigma_N^2 = -149\text{dBm/Hz}$ (see appendix A.2).

For the DRL model, we softly update the target policy and value network with momentum 0.005. We use replay buffer of capacity 5000 samples. The batch size is set to 64 and the learning rate is equal to 0.001. The discount factor is $\gamma = 0.95$. With constant probability of 0.25 we explore according to what described in 3.2.1. We use $N_Q = 50$ of quantiles to describe the distribution. The $\phi_{user}$ consists of two fully connected layers each of dimensions 10 (50) when synthetic (real) data is used. The input/output channels ratio of both $f_{relu}$ and $f_{linear}$ is 10/10. We remark that the number of parameters is relatively low (around 1000). Increasing this further unavoidably resulted in overfitting due to the high variance of the environment. Moreover, keeping the number of parameters low makes our solution fast and cheap (both in terms of energy and hardware), is particularly important for its practical use in real-world communication systems.

D EXPONENTIAL RULE

The exponential rule (Shakkottai & Stolyar 2001) is a simple scheduling metric, where an index is computed for every user based on an explicit formula. At each time slot, users ($R_t$ in total) are ordered according to their index values and we start serving (satisfying) the ones with the highest rank until resources are finished. Let $w_{u,t}$ be the time slots user $u$ has waited unsatisfied and $l_{u,t}$ be the time slots eager to wait more (therefore $L_u = u + l_u$ is the latency constraint of its class). Let

$$R_{u,t} = \sum_{\tau = t - w_{u,t}} \mathcal{R}_{u,t}$$

the estimated mean rate. Then the index $j_u$ for
user $u$ is given by

$$j_u = \gamma_{u,t} R_{u,t \infty} - \frac{a_{u,t} W_{u,t}}{1 + \sqrt{a_{u,t} W_{u,t}}}$$

with $a_{u,t} W_{u,t} = \frac{1}{K_t} \sum_u a_{u,t} W_{u,t}$, $\gamma_{u,t} = \frac{a_{u,t}}{K_{u,t}}$ and $a_{u,t} = -\log \delta_{u,t}$ with $\delta_u$ being the delay violation probability. We used $\delta = 10^{-2}$ as suggested in their paper [Shakkottai & Stolyar, 2001].

### E Scaling rewards

**Algorithm 1** Reward Scaling

1: procedure INITIALIZE-SCALING
2: \( R_0 \leftarrow 0 \)
3: \( RS = \text{RUNNING STATISTICS}() \quad \triangleright \text{New Class that tracks mean and standard deviation} \)
4: procedure SCALE-OBSERVATION($r_t$)
5: \( R_t \leftarrow \gamma R_{t-1} + r_t \)
6: \( RS = \text{ADD}(RS, R_t) \)
7: return $r_t - \text{MEAN}(RS)$

\( \triangleright \text{STANDARD-DEVIATION}(RS) \)