A Scheduling Policy for Downlink OFDMA in IEEE 802.11ax with Throughput Constraints

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Abstract—In order to meet the ever-increasing demand for high throughput in WiFi networks, the IEEE 802.11ax (11ax) standard introduces orthogonal frequency division multiple access (OFDMA). In this letter, we address the station-resource unit scheduling problem in downlink OFDMA of 11ax subject to minimum throughput requirements. To deal with the infeasible instances of the constrained problem, we propose a novel scheduling policy based on weighted max-min fairness, which maximizes the minimum fraction between the achievable and minimum required throughputs. Thus, the proposed policy has a well-defined behaviour even when the throughput constraints cannot be fulfilled. Numerical results showcase the merits of our approach over the popular proportional fairness and constrained sum-rate maximization strategies.

Index Terms—IEEE 802.11ax, OFDMA, multi-user scheduling, max-min fairness, Lyapunov optimization.

I. INTRODUCTION

The ever-growing demand for fast and ubiquitous wireless connectivity poses the challenge of delivering high data rates while efficiently managing the scarce radio resources. Orthogonal frequency division multiplexing (OFDM) has become a mainstream transmission method for broadband wireless systems. Additionally, thanks to the independent fading of users’ channels, efficient spectrum utilization can be attained by exploiting multi-user diversity. Specifically, OFDM subcarriers can dynamically be allocated to multiple users according to their instantaneous channel conditions. Therefore, the multiuser version of OFDM, called orthogonal frequency division multiple access (OFDMA), has been recognized as a key technology for next-generation wireless systems.

Towards this direction, the new IEEE 802.11ax (11ax) amendment for high efficiency wireless local area networks (WLANs) employs OFDMA in both downlink (DL) and uplink (UL) directions [1]. Specifically, DL OFDMA is expected to boost DL throughput and alleviate the DL-UL asymmetry problem when the access point (AP) lacks transmission opportunities compared to the stations [2]. The efficiency of the OFDMA transmissions, though, mainly hinges on how the AP selects the stations and allocates the available resources. Therefore, intelligent multi-user scheduling is crucial for attaining the best possible system performance.

The peculiarities of 11ax OFDMA implementation render the scheduling and resource allocation problem different from that in cellular networks. There are few recent works on the OFDMA scheduling problem for 11ax networks. In [3], the authors proposed a framework based on Lyapunov optimization to dynamically adjust the OFDMA transmission duration so that padding overhead is minimized. To do so, they assumed flat fading across the resource units (RUs) and considered fixed RU allocation in conjunction with round-robin user scheduling. The problem of joint user scheduling and RU allocation was firstly studied in [4], [5]. Specifically, D. Bankov et al. proposed a set of multiuser schedulers by formulating the unconstrained utility maximization problem as an assignment problem for the UL. However, they focused on maximizing the utility of instantaneous station rates rather than their long-term throughput. In general, to provide fairness as well as minimum quality-of-service among the stations, many works in the literature proposed to maximize a utility function of the long-term time average rates under minimum average rate requirements (see [6], [7], and references therein).

In this work, we address the throughput-constrained scheduling problem in OFDMA of 11ax. Specifically, we propose a simple yet effective scheduling policy that applies max-min fairness in order to maximize the minimum fraction between the achievable and minimum requested throughputs. Thus, it minimizes the maximum throughput violation for infeasible instances. Numerical simulations show that the proposed policy increases substantially the throughput of the worst-case station, whilst scaling efficiently as the number of stations increases in the network, with respect to existing methods such as proportional fairness and constrained sum-rate maximization.

Notation: $\mathcal{A}$ is a set; $\mathbf{a}$ is a vector; $(\cdot)^+ = \max(\cdot, 0)$; $\max(\mathcal{A})$ denotes the maximum element of set $\mathcal{A}$; and $(\mathcal{A})_{i,j}$ is the $(i,j)$th entry of matrix $\mathcal{A}$.

II. SYSTEM MODEL

A. DL OFDMA Model

Consider the DL of a 11ax network consisting of an AP and a set $\mathcal{K} \triangleq \{1, \ldots, K\}$ of stations. We assume a throughputs
constrained traffic mode\(^1\) where each station \(k\) has a minimum DL throughput requirement denoted by \(r_{k}^{\text{min}}\). To this end, the AP periodically commences a DL OFDMA transmission of duration \(T_{DL}\), as shown in Fig. 1. Specifically, the time axis is divided into scheduling periods of equal duration, with period \(t\) corresponding to the normalized time interval \([t, t+1]\). In each scheduling period, an OFDMA transmission takes place without collisions; if there is an ongoing transmission, the scheduled OFDMA transmission is deferred until the channel is sensed idle. Let \(\mathcal{N} = \{1, \ldots, N\}\) be the set of RUs, with each RU comprising of multiple consecutive subcarriers.\(^2\) The vector of channel gains of station \(k\) over RU \(n\) in period \(t\) is denoted by \(g_{k,n}[t]\). The channel state in scheduling period \(t\) is then defined as \(\mathcal{G}[t] \triangleq \{g_{k,n}[t]\}_{k,n \in \mathcal{N}}\), and is assumed to evolve according to a block-fading process. Thus, \(\mathcal{G}[t]\) remains constant during period \(t\) but is independent and identically distributed across different scheduling periods.

### B. Scheduling Policy

Let \(p_{k,n}[t]\) denote the transmit power assigned to the \(k\)th station over RU \(n\) in scheduling period \(t\). For simplicity, we assume equal power allocation across the \(N\) RUs. Hence, \(p_{k,n}[t] = P_{\text{total}}/N\), where \(P_{\text{total}}\) is the power budget of the AP. The scheduling decisions are then specified by the binary variables \(s_{k,n}[t] \in \{0, 1\}\), with \(s_{k,n}[t] = 1\) if RU \(n\) is assigned to the \(k\)th station, and \(s_{k,n}[t] = 0\) otherwise. A scheduling policy controls the decisions of the AP at each period \(t\), which are given by the matrix \(S[t]\) defined as \((S[t])_{k,n} \triangleq s_{k,n}[t]\).

More particularly, at the beginning of each period \(t\), the AP observes the random channel state \(\mathcal{G}[t]\), and selects \(S[t]\) whose elements satisfy the 11ax RU allocation constraints
\[
\sum_{k=1}^{K} s_{k,n}[t] \leq 1, \quad \forall n \in \mathcal{N}, \quad (1)
\]
\[
\sum_{n=1}^{N} s_{k,n}[t] \leq 1, \quad \forall k \in \mathcal{K}. \quad (2)
\]
Constraint (1) ensures that stations cannot share the same RU, while constraint (2) guarantees that every station is assigned to one RU at most. Finally, the set of all feasible scheduling decisions is defined as
\[
\mathcal{S} \triangleq \{S \in \{0, 1\}^{K \times N} | (1) \quad \text{and} \quad (2)\}. \quad (3)
\]

### C. Rate Allocation and Throughput

For a given channel realization \(g_{k,n}[t]\) and transmit power \(p_{k,n}[t]\), the AP can transmit \(f(p_{k,n}[t], g_{k,n}[t])\) bits per OFDM symbol to station \(k\) over RU \(n\). The function \(f(\cdot, \cdot)\) models the rate selection scheme, and has to conform with the 11ax restriction that a single modulation and coding scheme (MCS) is employed over all the subcarriers of a RU \(^3\). Next, assume there are \(L\) MCSs, and let \(p_{\ell}\) denote the bit rate of MCS \(\ell\).

\(^1\)This is suitable for elastic applications, such as file transfers and Web browsing sessions \((8)\). \(^2\)11ax supports various RU configurations. We focus on a specific configuration for ease of exposition. In the simulation results, we investigate the case of multiple RU patterns as well.

If RU \(n\) consists of \(S_{n}\) data subcarriers and all subcarriers are used for transmission, then the set of achievable bit rates on RU \(n \in \mathcal{N}\) is given by \(\mathcal{R}_{n} = \{S_{n}p_{1}, \ldots, S_{n}p_{L}\}\). The number of bits transmitted to station \(k\) over RU \(n\) during the scheduling period \(t\) is denoted by \(r_{k,n}[t]\), and is calculated as
\[
r_{k,n}[t] = f(p_{k,n}[t], g_{k,n}[t]) \frac{T_{DL}}{T_{\text{OFDM}}}, \quad (4)
\]
where \(T_{\text{OFDM}}\) is the duration of an OFDM symbol, and \(f(p_{k,n}[t], g_{k,n}[t]) \in \mathcal{R}_{n}\). Then, the instantaneous transmission rate \(r_{k}[t]\) associated with the \(k\)th station is given by
\[
r_{k}[t] = \sum_{n=1}^{N} s_{k,n}[t] r_{k,n}[t] \quad \text{(bits/period)}. \quad (5)
\]
Finally, the **throughput** of station \(k\) is defined as the long-term average
\[
\bar{r}_{k} \triangleq \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{r_{k}[t]\}, \quad (6)
\]
where the expectation is taken with respect to the channel realizations as well as the scheduling decisions.

### III. Throughput-Constrained Scheduling

#### A. Problem Description

It is customary to assess the efficacy of a scheduling policy in terms of fairness. This is modeled by a utility function \(U(\cdot)\), which is a concave, continuous and entrywise non-decreasing function of the stations’ throughput. Let \(\bar{r} = (\bar{r}_{1}, \ldots, \bar{r}_{K})\). The throughput-constrained scheduling problem is then formulated as the utility maximization problem \(^9\)
\[
\text{maximize}_{\{S[t] \in \mathcal{S}\}} \quad U(\bar{r}) \quad \text{s.t.} \quad \bar{r}_{k} \geq r_{k}^{\min}, \quad \forall k \in \mathcal{K}. \quad (7)
\]

**Infeasible Instances and Admission Control**: Even though the aforementioned problem can be solved using tools in stochastic network utility optimization, there is no guarantee that (7) is feasible, i.e., the minimum throughput requirements will be fulfilled. This situation can occur when some stations have too week channel conditions, and/or too high throughput requirements. Traditional approaches assume that (7) has a feasible solution, but it might not yield a good performance for infeasible instances. One can deal with the infeasible instances by employing admission control. However, it is not trivial to identify which station to remove from the system in order to turn (7) into a feasible problem.

#### B. Proposed Policy

We present a low-complexity solution to the throughput-constrained scheduling problem (7), which does not depend on admission control and has a well-defined behaviour for infeasible instances. First, let \(\bar{r}^{\pi}\) denote the throughput vector attained by scheduling policy \(\pi\). Then, (7) is feasible whenever a policy \(\pi\) exists with \(\bar{r}_{k}^{\pi} \geq r_{k}^{\min}, \quad \forall k \in \mathcal{K}\). Therefore, we propose to directly maximize the minimum \(\bar{r}_{k}^{\pi}/r_{k}^{\min}\), leading to the optimization problem
\[
\text{maximize}_{\{S[t] \in \mathcal{S}\}} \quad \min_{k \in \mathcal{K}} \left\{ \frac{\bar{r}_{k}}{r_{k}^{\min}} \right\}. \quad (8)
\]
Note that the weighted max-min problem \(\text{(3)}\) admits a well-defined solution. More particularly, if \(\bar{r}_k/r_{1\text{min}} \geq 1, k \in K\), then the policy that solves \(\text{(3)}\) maximizes the minimum surplus \(\bar{r}_k - r_{1\text{min}} \geq 0\). Likewise, if there is at least one station \(k' \in K\) with \(\bar{r}_{k'}/r_{1\text{min}} < 1\), the policy that solves \(\text{(3)}\) minimizes the maximum constraint violation \(r_{1\text{min}} - r_{k'} \geq 0\).

IV. SOLUTION VIA LYAPUNOV OPTIMIZATION

In the sequel, we resort to Lyapunov optimization to derive a near-optimal solution.

**Definition 1.** Let \(U^*\) denote the maximum utility value of \(\text{(3)}\), and \(\bar{r} \triangleq (\bar{r}_1/r_{1\text{min}}, \ldots, \bar{r}_K/r_{1\text{min}})\). A scheduling policy \(\pi\) is said to produce an \(O(\epsilon)\)-optimal solution to \(\text{(3)}\) if \(U(\bar{r}^\pi) \geq U^* - O(\epsilon)\), and all the associated constraints are satisfied.

A. The Transformed Problem

Following the approach in [11, Ch. 5] for solving stochastic network optimization problems, we transform the problem \(\text{(3)}\) into a form involving only time averages rather than time of functions. To this end, let \(\gamma[t] = (\gamma_1[t], \ldots, \gamma_K[t])\) be a vector of auxiliary variables chosen within a set \(\Gamma\). The set \(\Gamma\) must bound both the auxiliary and rate variables, and hence is selected as

\[
\Gamma = \{\gamma \in \mathbb{R}^K | 0 \leq \gamma_k \leq R_{\text{max}}, \forall k \in K\},
\]

where \(R_{\text{max}} = \max(\bigcup_{n=1}^N R_n)\) is the maximum transmission rate over a RU. Now consider the transformed problem:

\[
\begin{align*}
\text{maximize} & \quad \min_{k \in K} \{\gamma_k[t]\} \\
\text{subject to} & \quad \gamma_k \leq \bar{r}_k/r_{1\text{min}}, \quad \forall k \in K.
\end{align*}
\]

The connection between \(\text{(8)}\) and \(\text{(10)}\) is established as follows. Suppose an arbitrary scheduling policy \(\pi\) solves the problem \(\text{(10)}\). The maximum utility value, denoted by \(U(\gamma^\pi)\), is then attained, whilst satisfying all the associated constraints. Because \(U(\cdot)\) is concave, it also holds

\[
\gamma^\pi \leq \bar{r}/r_{1\text{min}} \Rightarrow U(\bar{r}) \geq U(\gamma^\pi) \geq U(\gamma^\pi),
\]

where the last inequality is Jensen’s inequality for concave functions. According to \([11]\), if \(U(\gamma^\pi) \geq U^* - O(\epsilon)\), then \(U(\bar{r}) \geq U^* - O(\epsilon)\) as well, hence yielding the desired result.

Next, we detail the algorithm the produces such a solution.

B. The Drift-Plus-Penalty Algorithm

In Lyapunov optimization, each time average constraint is associated with a virtual queue, and constraint satisfaction is expressed as a queue stability problem. More particularly, for the constraint \(\gamma_k \leq \bar{r}_k/r_{1\text{min}}\), we consider a virtual queue that obeys the recursion

\[
Q_{k}[t+1] = (Q_{k}[t] - r_k[t]/r_{1\text{min}} + \gamma_k[t])^+, \quad (12)
\]

where \(Q[t], r_k[t]/r_{1\text{min}}, \text{ and } \gamma_k[t]\) correspond to the virtual queue size, service rate, and arrival rate for the scheduling period \(t\), respectively. The drift-plus-penalty (DPP) algorithm is described in Algorithm 1 the parameter \(V\) affects the convergence speed and accuracy of the algorithm [11].

### Algorithm 1 Weighted Max-Min Scheduling

For each scheduling period \(t \in \{0, 1, 2, \ldots\}\) do:
1. Observe \(\{Q_{k}[t]\}_{k \in K}\) and the channel state \(G[t]\).
2. Choose \(\gamma(t) \in \Gamma\) such that

\[
\max_{\gamma(t) \in \Gamma} V \min_{k \in K} \{\gamma_k[t]\} - \sum_{k=1}^K Q_k[t] \gamma_k[t].
\]

3. Choose \(S[t] \in \mathcal{S}\) such that

\[
\max \sum_{k=1}^K Q_k[t] r_k[t]/r_{1\text{min}}.
\]

4. Update the virtual queues using (12).

C. Maximization Subproblems

According to Algorithm 1, we can address the weighted max-min problem by solving a set of deterministic subproblems at every scheduling period \(t\). More specifically, the first subproblem regards the auxiliary variables. The optimal auxiliary variables are obtained by observing that

\[
\max_{\gamma(t) \in \Gamma} V \min_{k \in K} \{\gamma_k[t]\} \leq \max_{\gamma(t) \in \Gamma} \gamma_{\text{min}}[t] \left(V - \sum_{k=1}^K Q_k[t]\right), \quad (13)
\]

where \(\gamma_{\text{min}}[t] = \min_{k \in K} \{\gamma_k[t]\}\). Based on (13), it is straightforward to show that

\[
\gamma_k^*[t] = \begin{cases} 
R_{\text{max}}, & \text{if } V > \sum_{k=1}^K Q_k[t] \\
0, & \text{otherwise}
\end{cases}
\]

Next, the maximization subproblem for the scheduling decision \(S[t]\) is recast as

\[
\max_{S[t] \in \mathcal{S}} \sum_{k=1}^K \sum_{n=1}^N s_{k,n,t} \phi_{k,n,t}[t], \quad (14)
\]

where \(\phi_{k,n,t}[t] \triangleq Q_k[t] r_k[t]/r_{1\text{min}}^\gamma_{\text{min}}[t]\). The transmission rate \(r_k[n,t]\) is calculated using (4). The above problem determines the optimal RU assignment for the scheduling period \(t\), and is a classical assignment problem. Hence, it can be solved in \(O(\max(K,N)^3)\) using the Hungarian method [10].

V. PERFORMANCE EVALUATION

In this section, we assess the performance of the proposed scheduling policy. For this purpose, we consider the following benchmark strategies:

- Proportional Fairness (PF): In each period \(t\), the scheduler selects the stations that maximize the instantaneous weighted sum-rate, where the weight associated with station \(k\) is equal to the inverse of the exponential moving average of its throughput [5].
- Ergodic Sum-Rate Maximization (ESRM): We solve the problem in \([7]\) for \(U(\bar{r}) = \sum_{k=1}^K r_k\). Since \(U(\bar{r})\) is a linear function of the rates in ESRM, we have \(U(\bar{r}) = U(\bar{r})\). Therefore, we can readily employ the DPP
algorithm without using auxiliary variables \[11\]. To this end, we have a virtual queue for the minimum throughput constraint \( r_{k,n}^{\text{min}} \geq r_k \), which obeys the recursion
\[
Z_k[t + 1] = (Z_k[t] - r_k[t] + r_{k,n}^{\text{min}}[t])^+, \quad \forall k \in K. \tag{15}
\]
Then, in each period \( t \), the scheduler selects the stations by solving \(14\) for
\[
\phi_{k,n}[t] = V_{\text{ESRM}} r_{k,n}[t] + Z_k[t](r_{k,n}[t] - r_{k,n}^{\text{min}}), \tag{16}
\]
where \( V_{\text{ESRM}} \) denotes the control parameter of the DPP algorithm for the ESRM scheme.

### TABLE I: Main simulation parameters.

| Notation | Description | Value |
|----------|-------------|-------|
| \( f_c \) | Carrier frequency | 5 GHz |
| \( d_{\text{max}} \) | Radius of the WLAN area | 15 m |
| \( P_{\text{total}} \) | Maximum transmit power | 20 dBm |
| \( T_{\text{OFDM}} \) | Duration of OFDM symbol | 16 \( \mu \)s |
| \( T_{\text{DL}} \) | Duration of DL OFDMA transmission | 3.2 ms |

### TABLE II: MCS for the 20 MHz channel \[13\].

| Index | MCS | Minimum SNR (dBm) |
|-------|-----|--------------------|
| 1     | BPSK, 1/2 | -82 |
| 2     | QPSK, 1/2 | -79 |
| 3     | QPSK, 3/4 | -77 |
| 4     | 16-QAM, 1/2 | -74 |
| 5     | 16-QAM, 3/4 | -70 |
| 6     | 64-QAM, 2/3 | -66 |
| 7     | 64-QAM, 3/4 | -65 |
| 8     | 128-QAM, 5/6 | -64 |
| 9     | 256-QAM, 3/4 | -59 |
| 10    | 256-QAM, 5/6 | -57 |

#### A. Simulation Setup

The area of the WLAN is modeled by a circle of radius \( \min d_{\text{max}} \) meters. The AP is located at the center of the circle, and stations are uniformly distributed inside the circle with minimum distance from the AP of 1 meter. The path attenuation is calculated using the 11ax path-loss model for a residential scenario \[14\].

\[
\text{PL}_k = 40.05 + 20 \log_{10}(f_c/2.4) + 20 \log_{10}(\min(d_k, 5)) + 1\{d_k > 5\} \cdot 35 \log_{10}(d_k/5), \quad \text{(dB)}
\]

#### B. Numerical Results

1) Single versus Multiple RU Patterns: We first investigate the benefits of employing multiple RU patterns. We use the minimum throughput achieved by a station as a figure of merit. To this end, we evaluate the empirical cumulative distribution function (CDF) of the minimum throughput for 100 network realizations. Specifically, for each network realization, the minimum throughput is calculated by averaging over 1000 small-scale fading realizations. Regarding the 11ax multiple RU patterns, we consider the following three options:

- \( N_1 = 9 \) RUs with \( S_1 = 24 \) data subcarriers each.
- \( N_2 = 4 \) RUs with \( S_2 = 48 \) data subcarriers each.
- \( N_3 = 2 \) RUs with \( S_3 = 102 \) data subcarriers each.

Fig. 2: Empirical CDF of the minimum throughput for \( K = 12 \) stations: (a) single RU pattern \((N_1, S_1)\); (b) multiple RU patterns.
We then solve (14) for each pattern under equal power allocation across RUs, and choose the one that yields the maximum objective value. We plot the results in Fig. 2 for a minimum throughput requirement $r_k^{\text{min}} = 20$ kb/sch. period, $\forall k \in K$. The control parameters of the DPP algorithm for the WMM and ESMR are $V_{\text{WMM}} = 900$ and $V_{\text{ESMR}} = 10$, respectively. As we observe, the WMM outperforms both the PF and ESRM policies. Note that, although the use of multiple RU patterns might increase the computational complexity of the scheduler, it yields substantial performance gains for the WMM policy. In particular, the minimum throughput requirement $r^{\text{min}}$ corresponds to the 95th percentile when a single RU pattern is employed, whilst it drops to the 3rd percentile for multiple RU patterns.

2) Number of Stations: We now examine how the performance of the schedulers under consideration scales as the number of stations increases. To this end, we calculate the average of the minimum throughput for the same number of network and small-scale fading realizations as previously. From Fig. 3, we see that the WMM delivers the highest minimum throughput even when the throughput constraint of 20 kb/sch. period cannot be fulfilled. Consequently, the performance of the proposed scheduler scales more efficiently compared to the PF and ESRM schedulers. Finally, we stress that the WMM policy benefits the most from the utilization of multiple RU patterns.

VI. CONCLUSIONS

In this letter, we provided a solution to the DL OFDMA scheduling problem in 11ax with minimum throughput requirements. First, we introduced a scheduling and rate allocation model which conforms with the 11ax implementation constraints. Then, we formulated the throughput-constrained scheduling problem as an unconstrained problem using weighted max-min fairness. Relying on Lyapunov optimization, we derived a dynamic scheduling policy which minimizes the maximum throughput constraint violation for infeasible instances, and maximizes the minimum throughput surplus otherwise. We finally provided numerical results showcasing that our approach outperforms the popular proportional fairness and constrained sum-rate maximization strategies in terms of the minimum throughput.

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