Rethinking Power Allocation in OFDMA: A Throughput-Optimized Multi-User Strategy

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***Abstract*—Modern networks rely on orthogonal frequency division multiple access (OFDMA) to efficiently allocate bandwidth among multiple users. While resource allocation mechanisms primarily focus on bandwidth distribution, transmit power is typically flat along the spectrum, potentially limiting achievable data rates due to heterogeneous channel conditions. In this paper, we investigate the impact of power allocation on modulation and coding scheme (MCS) selection. Specifically, we formulate an optimization problem aimed at maximizing the aggregate data rate in a wireless local area network (WLAN), subject to constraints on minimum packet delivery ratio (PDR). The key insight is that reallocating transmit power across users can alter the signal-to-noise ratio (SNR), enabling higher MCS levels and improving throughput without modifying bandwidth assignments. Due to the discrete nature of MCS levels, the problem is inherently combinatorial and difficult to solve optimally. To address this, we propose a practical heuristic inspired by water-filling principles, combined with a Knapsack-based selection strategy to prioritize users that yield the highest rate gains per unit of power. The approach redistributes power from users with excess margin to those who can benefit from an MCS upgrade. Simulation results based on IEEE 802.11ax settings show that the proposed method improves the aggregate throughput while preserving reliability constraints.**

I. Introduction

The increasing demand for high-throughput and low-latency wireless connectivity has driven the evolution of modern communication systems toward more efficient resource allocation mechanisms. In particular, orthogonal frequency division multiple access (OFDMA) has emerged as a key multiple access technique in a wide range of wireless technologies, including cellular networks—e.g., long term evolution (LTE) and fifth generation (5G)—and wireless local area networks (WLANs). By dividing the available spectrum into orthogonal subcarriers or groups of subcarriers, OFDMA enables simultaneous transmissions to multiple users, significantly improving spectral efficiency and system capacity compared to single-user or contention-based approaches.

In OFDMA-based systems, resource allocation typically involves assigning frequency resources (e.g., subcarriers or resource units (RUs)), transmit power, and transmission rates to users based on channel conditions and traffic demands. While extensive research has focused on bandwidth and subcarrier allocation, transmit power is often distributed uniformly across users or frequency resources for simplicity and, sometimes, standard compliance. This design choice reduces implementation complexity but may lead to suboptimal performance, especially in heterogeneous channel conditions where users experience widely different signal qualities.

A fundamental aspect of OFDMA systems is that the achievable data rate depends jointly on the allocated bandwidth and the signal-to-noise ratio (SNR). In practical systems, however, the mapping between SNR and throughput is not continuous but determined by discrete modulation and coding scheme (MCS) levels, each associated with a specific reliability constraint such as the packet delivery ratio (PDR). As a consequence, small variations in SNR may have no impact on throughput until a threshold is crossed, at which point a higher MCS—and thus a higher data rate—can be selected. This discrete behavior fundamentally differentiates practical systems from classical information-theoretic models.

Despite this, most existing power allocation strategies are derived from continuous-rate formulations, where the objective is to maximize channel capacity. Such approaches, including water-filling, implicitly assume a smooth relationship between SNR and rate, which only provides an upper bound on the achievable throughput. In practice, this mismatch limits their effectiveness, as they do not directly account for the discrete nature of MCS selection.

In this work, we investigate the role of power allocation in improving system throughput in OFDMA-based systems under realistic discrete-rate constraints. Specifically, we explore whether redistributing transmit power across users—while keeping the bandwidth allocation unaltered—can increase the SNR of selected users enough to trigger MCS upgrades, thereby improving the aggregate throughput. We formulate this as a constrained optimization problem that maximizes the total data rate while ensuring that reliability requirements are met and no user experiences performance degradation below a threshold. The discrete nature of MCS levels makes the problem inherently combinatorial and unsuitable for direct application of classical convex optimization techniques. To address this challenge, we propose both an optimal formulation and a practical heuristic algorithm inspired by water-filling [1] principles, combined with a Knapsack-based selection strategy [2], [3]. The proposed approach prioritizes users that

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provide the highest throughput gain per unit of additional power and redistributes power from users with excess margin.

Although the proposed framework is general and applicable to any OFDMA-based system, we evaluate its performance in the context of IEEE 802.11ax (Wi-Fi 6), which provides a concrete and practically relevant setting. Through MATLAB simulations compliant with the standard [4], we quantify the throughput gains achieved by adaptive power allocation for different numbers of users ($M = \{2, 4, 8, 16\}$) compared to a baseline with flat power distribution. The results demonstrate that significant performance improvements can be obtained by explicitly accounting for MCS discretization, highlighting an additional degree of freedom that is largely overlooked in current resource allocation strategies.

II. Related Work

Resource allocation in OFDMA systems has been extensively studied in both cellular and Wi-Fi networks, with most works focusing on bandwidth scheduling, power allocation, or their joint optimization. However, a key distinction across the literature lies in the modeling assumptions: many approaches rely on continuous-rate formulations based on Shannon capacity, whereas practical systems such as IEEE 802.11ax operate with discrete MCSs, leading to fundamentally different optimization structures.

A. Water-filling and continuous optimization approaches

A large body of work addresses power allocation through water-filling and related convex optimization techniques. Classical formulations aim at maximizing sum-rate or minimizing power under rate constraints by exploiting the continuous relationship between SNR and achievable rate [5], [6]. Extensions consider energy efficiency [7] or joint frequency and power allocation in cellular systems [8].

However, these approaches inherently assume that the achievable rate follows the Shannon capacity formula, which represents only an upper bound. In practical systems, throughput evolves in discrete steps dictated by the selected MCS. As a result, water-filling [1] cannot provide an exact solution for throughput maximization in real WLANs. This limitation has been explicitly highlighted in prior work, showing that water-filling policies may even fail to achieve long-term optimality when realistic system constraints are considered [9]. Moreover, rounding continuous-rate solutions to discrete constellations introduces performance gaps [7].

B. Scheduling and bandwidth-oriented resource allocation

In the context of IEEE 802.11ax [4], a significant portion of the literature focuses on scheduling and bandwidth (RU) allocation rather than power control. Works such as [10] and [11] formulate the problem as assigning resource units to users based on channel conditions, often maximizing sum-rate under practical constraints on RU structure and allocation. Similarly, coordinated RU allocation schemes and fairness-oriented designs are proposed in the recent works [12], [13].

These approaches typically assume flat power allocation across the spectrum or treat power as a secondary parameter. In many cases, equal power per RU is adopted due to its simplicity and limited marginal gains in certain scenarios [8]. Consequently, the potential impact of power allocation on MCS selection—and thus on throughput—is often overlooked.

C. Rate adaptation and discrete MCS optimization

Another line of work explicitly considers the discrete nature of MCS selection. Rate adaptation algorithms map SNR measurements to discrete transmission rates, aiming to maximize throughput under reliability constraints [14], [15]. These methods highlight that throughput depends on threshold-based transitions between MCS levels rather than smooth capacity variations.

To address the combinatorial nature of this problem, several works employ learning-based techniques. Reinforcement learning (RL) and multi-armed bandit approaches have been proposed to optimize rate selection or network parameters in the presence of discrete actions and uncertain environments [16]–[18]. Deep learning has also been applied to approximate solutions to mixed-integer resource allocation problems [19]. While these methods can handle discretization, they often introduce significant complexity and require training data or online exploration.

D. Discussion and positioning of this work

From the above, three main gaps emerge. First, classical water-filling-based methods provide optimal solutions only under continuous-rate assumptions and cannot directly capture the discrete MCS-driven throughput of real systems. Second, most Wi-Fi-oriented works prioritize bandwidth allocation and scheduling, frequently assuming flat power distribution. Third, approaches that explicitly handle discretization typically rely on learning-based techniques with higher complexity.

In contrast, our work focuses on the direct optimization of transmit power with the explicit goal of improving throughput through MCS transitions, while keeping the bandwidth allocation fixed. Different from capacity-based formulations, we model throughput as a discrete function of SNR, leading to a combinatorial problem. We propose both an optimal and a low-complexity approximated solution, and we quantify the achievable gain over the baseline flat power allocation for different numbers of users ($M = \{2, 4, 8, 16\}$). This provides a clear characterization of the benefits of power redistribution in practical IEEE 802.11ax systems, bridging the gap between theoretical power allocation and discrete-rate operation.

III. Problem Definition

A. System model

We consider a wireless local area network (LAN) with a single IEEE 802.11 access point (AP) and a set $\mathcal{N} = \{1, \ldots, n, \ldots, N\}$ of wireless stations (STAs), namely, the users, communicating in the downlink direction. The system is depicted in Fig. 1.

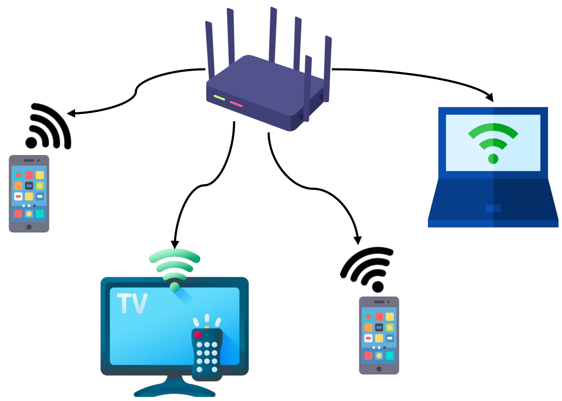


Fig. 1. Typical home wireless local area network (WLAN), with an AP and different devices (STAs), communicating in the downlink direction.

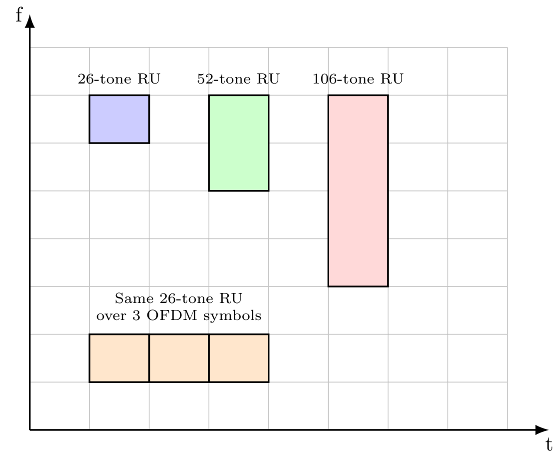


Fig. 2. Exemplification of OFDMA RUs allocation to different users (colors) in the time $\times$ frequency domain.

Each STA is connected with the AP via OFDMA, a physical layer (PHY)-medium access control (MAC) scheme that assigns orthogonal RUs in the time $\times$ frequency cartesian product to users. A schematic representation of the OFDMA allocation scheme is shown in Fig. 2. The fundamental RU is constituted by 26 frequency tones, and larger allocatable RUs amount to $\{52, 106, 242, 484, 996\}$ tones in a bandwidth of $B = 80$ MHz, which we consider in this work.

As per the standard [4], at each time slot (corresponding to an orthogonal frequency division multiplexing (OFDM) symbol), users are assigned a non-overlapping portion of the spectrum, possibly of different size depending on the data rate needed. The data rate is affected by (i) the bandwidth B_n allocated to user n and (ii) by the SNR experienced, defined as

$$\Gamma_n = \frac{|h_n|^2 P_n^{\mathrm{tx}}}{B_n N_0}, \tag{1}$$

where P_n^{tx} is the transmit power to STA n, h_n is the complex number associated with the channel gain between the AP and n, and N_0 is the noise power spectral density (PSD).

The specific data rate achieved is a direct consequence of the MCS used. The MCS is an index $m \in \{0, \ldots, M\}$ ($M = 11$ since Wi-Fi 6) defining the digital modulation and the coding rate adopted for forward error correction (FEC) at the receiver. As the SNR of the wireless channel decreases, to keep the PDR at a satisfactory level, the number of redundant bits used for coding must increase and/or the cardinality of the modulation constellation must decrease, changing sometimes even the type of digital modulation chosen. These effects make the MCS decrease with the SNR.

B. Problem formulation

Motivated by this, we study whether there are ways to have an impact on the MCS to improve the data rate by acting on the SNR rather than simply on the bandwidth allocation. Actually, while the bandwidth can be allocated unevenly, power is usually split among RUs equally. In this work, we aim to optimize the users' data rate by controlling power allocation.

Without loss of generality, we assume the bandwidth allocated to each STA B_n is fixed and a parameter of the system. Let us denote by $R_n^{m_n}$ the data rate of STA n achievable with MCS m_n in the hypothesis that the transmit power is allocated evenly among RUs. Our aim is that of maximizing the overall WLAN data rate by allocating the total transmit power $P_{\mathrm{tot}}^{\mathrm{tx}}$ available at the AP, subject to the constraints that (i) no STA experiences a lower data rate with respect to the standard flat power allocation, and (ii) the PDR η_n does not fall below a threshold ϑ for each STA. Changing the power allocation strategy results in a different SNR experienced at the STAs and hence a possibly different MCS m'_n at receiver n.

In mathematical terms, this amounts to

$$\begin{aligned}
\max_{P_n^{\mathrm{tx}}} \quad & \sum_{n \in \mathcal{N}} R_n^{m'_n} \\
\text{s.t.} \quad & R_n^{m'_n} \geq R_n^{m_n} \qquad \forall\, n, \\
& \eta_n \geq \vartheta \qquad \forall\, n, \\
& \sum_{n \in \mathcal{N}} P_n^{\mathrm{tx}} \leq P_{\mathrm{tot}}^{\mathrm{tx}}
\end{aligned} \tag{2}$$

where, if we restrict to the case where the bandwidth is fixed (or it has already been allocated), the first constraint on the non-degradation of the data rate is equivalent to $m'_n \geq m_n$.

IV. Algorithmic Solution

Due to the discrete nature of MCSs and achievable data rates, the problem cannot be solved easily at optimum in a reasonable amount of time. Hence, we propose a practical heuristic inspired by the water-filling algorithm for power control [1]. It is important, however, to notice that the water-filling cannot be directly applied, as we are not interested in maximizing the channel capacity but rather the actual discrete data rate experienced.

A. Preliminary steps

We assume that a procedure for the bandwidth allocation has already been performed, and STAs are assigned a bandwidth B_n that is considered a parameter in our context. This assumption does not limit the fact that bandwidth can be allocated and optimized unevenly before allocating the power. We further assume that we know the achievable data rates under the flat distributed power assumption $R_n^{m_n}$ so that the PDR $\eta_n \geq \vartheta$ (i.e., we know the best MCSs under the hypothesis of a flat split of power). The following steps constitute the preparation phase of our algorithmic proposal.

Step 1 Find the best MCSs m_n under the hypothesis of flat split power P^{tx}, so that $\eta_n \geq \vartheta$.
Step 2 Estimate the channel gain $|h_n|^2$ and the ratio $\frac{B_n N_0}{|h_n|^2}$ through channel state information (CSI) feedback with the STAs.
Step 3 Estimate how much power $(\Delta P_n^{\text{tx}})^+ = P_{n,\text{next}}^{\text{tx}} - P^{\text{tx}}$ each STA needs to increase its MCS to $m'_n = m_n + 1$ in such a way that $\eta_n \geq \vartheta$.
Step 4 Estimate how much power $(\Delta P_n^{\text{tx}})^- = P^{\text{tx}} - P_{n,\min}^{\text{tx}}$ each STA can save to keep the same $m'_n = m_n$ while guaranteeing $\eta_n \geq \vartheta$.
Step 5 Order the STAs in decreasing order per data rate gain $\Delta R_n = R_n^{m_n+1} - R_n^{m_n}$.

As for step 2, we note that a reliable and frequently updated measure of the SNR is required from the CSI. Typical channel sounding intervals are of the order of the tens of milliseconds [19], [20], which is sufficient to run the proposed preliminary steps with enough precision.

B. Optimal solution

If we were to obtain an optimal solution after this preprocessing, the problem could be written, thanks to the use of binary variables y_n and z_n, as

$$\begin{aligned} \max_{y_n, z_n} \quad & \sum_{n\in\mathcal{N}} \Delta R_n y_n \\ \text{s.t.} \quad & \sum_{n\in\mathcal{N}} \left(\Delta P_n^{\text{tx}}\right)^+ y_n \leq \sum_{n\in\mathcal{N}} \left(\Delta P_n^{\text{tx}}\right)^- z_n \\ & y_n + z_n \leq 1 \qquad\qquad \forall n \\ & y_n, z_n \in \{0,1\} \qquad\quad \forall n \end{aligned} \tag{3}$$

where $y_n = 1$ if n receives more allocated power and $z_n = 1$ if power is reallocated somewhere else from n. However, the solution to this combinatorial problem needs to check among all possible combinations and cardinalities of STAs that either yield or gain allocated power. Here, the first constraint ensures the maximum power conservation, while the second constraint enforces the fact that a STA either yields or gains power (or nothing happens). For a large number of STAs, it might be difficult to solve this problem at optimum in real-time on an AP processing unit. For this reason, we also propose an approximated greedy heuristic.

C. Approximated optimized solution

A useful practical observation is that, in general, ΔR_n is larger if a change in modulation scheme is triggered, and smaller if only the coding rate changes. We show an example of this in Fig. 3, where the proposed power flow with two nodes is depicted. Therefore, we can split the STAs into two sets, set $\mathcal{D}$ is composed of the first $\lfloor \frac{N}{2} \rfloor$ STAs according to the ordering given by the target ΔR_n, while the remaining $\lceil \frac{N}{2} \rceil$ compose set $\mathcal{S}$. $\mathcal{D}$ is the set of candidate destination nodes, while $\mathcal{S}$ is the set of the candidate source nodes for the power flow problem. Let

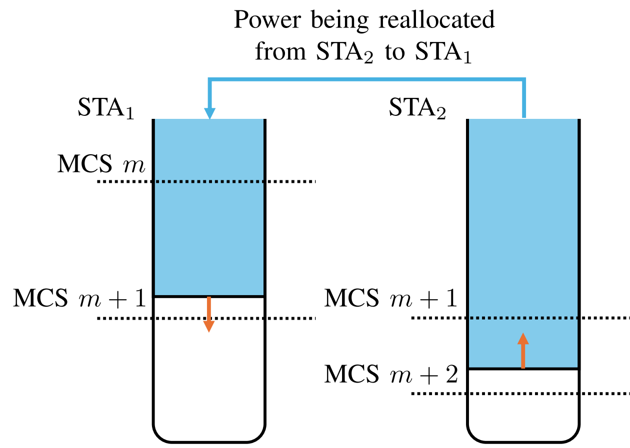


Fig. 3. Water-filling exemplification of the idea. The throughput increase is not continuous with the capacity increase but rather discrete. We should allocate power in such a way to enable MCS $m+1$ at STA$_1$ without lowering the MCS at STA$_2$. Here, the throughput increase yielded by $m \rightarrow m+1$ is higher than the one yielded by $m+1 \rightarrow m+2$. The dotted thresholds represent the target SNR that is to be reached to sustain the given MCS with the target PDR.

$$P_{\text{budget}}^{\text{tx}} = \sum_{n\in\mathcal{S}} \left(\Delta P_n^{\text{tx}}\right)^- \tag{4}$$

be the power budget that we can allocate to nodes in the set $\mathcal{D}$. We can now reformulate the following subproblem as a $0-1$ Knapsack with binary variables x_n, as

$$\begin{aligned} \max_{x_n} \quad & \sum_{n\in\mathcal{D}} \Delta R_n x_n \\ \text{s.t.} \quad & \sum_{n\in\mathcal{D}} \left(\Delta P_n^{\text{tx}}\right)^+ x_n \leq P_{\text{budget}}^{\text{tx}}, \\ & x_n \in \{0,1\} \qquad\qquad \forall n. \end{aligned} \tag{5}$$

Given the typical dimensions of a LAN network, this problem can be easily solved at optimum numerically or via the known dynamic programming (DP) solution [2], [3].

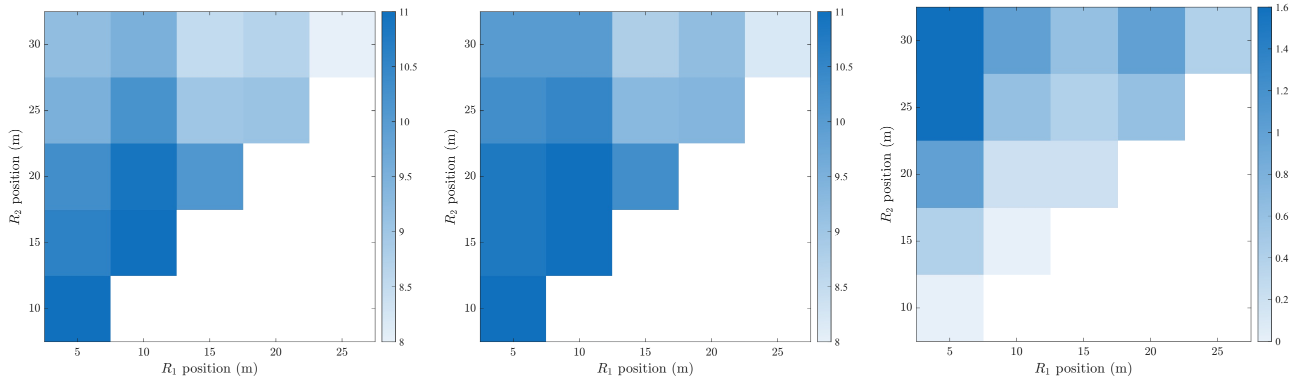
After solving the Knapsack problem with an optimal solution $x_n^\star$, we might be left with a remaining budget

$$P_{\text{left}}^{\text{tx}} = P_{\text{budget}}^{\text{tx}} - \sum_{n\in\mathcal{D}} \left(\Delta P_n^{\text{tx}}\right)^+ x_n^\star. \tag{6}$$

$P_{\text{left}}^{\text{tx}}$ can be split proportionally among nodes to improve the PDR η_n above the minimum required threshold.

Remark 1. While the split into two sets of cardinality $N/2$ can be suboptimal in situations where more STAs experience a good channel quality and can therefore easily be donors, we explore the optimality gap of the approach and showcase the effectiveness under uniformly distributed channel qualities (see Fig. 7 in Sect. V-C).

Remark 2. We also note that, to address a possibly imbalanced channel quality distribution, the cardinality of sets $\mathcal{S}$ and $\mathcal{D}$



(a) Average MCS for receivers R_1 and R_2 under the equal power allocation scheme.
(b) Average MCS for receivers R_1 and R_2 under the optimized power allocation scheme.
(c) Average MCS gain for receiver R_2 when optimizing the power allocation.

Fig. 4. MCS for receivers R_1 and R_2 testing different relative positions.

TABLE I
SUMMARY OF SIMULATION PARAMETERS

Parameter	**Value**	**Description**
N	$\{2,4,8,16\}$	number of STAs
d	$[5,30]$ m	distance of STAs from the AP
σ	4 dB	shadowing variance
κ	3.5	path loss exponent
P^{tx}	30 dBm	total AP transmit power
B	80 MHz	total WLAN bandwidth
N_0	-174 dBm/Hz	noise power spectral density
C	20	Monte Carlo runs
P	100	# of independent pkts per run
S	1400 B	Pkt size used for $N = \{2,4,8\}$
	900 B	Pkt size used for $N = 16$

can be selected via the use of a quality threshold using the rate increase ΔR_n or the power reallocatable elsewhere $(\Delta P_n^{\text{tx}})^-$.

V. NUMERICAL RESULTS

A. Simulation settings

For the OFDMA simulations, we considered the IEEE 802.11ax (Wi-Fi 6) use case, simulated with the MATLAB WLAN Toolbox.[1] We tested a circular scenario where the AP is in position $(d,\varphi) = (0,0)$ in polar coordinates, and the $N \in \{2,4,8,16\}$ STAs are sampled in random positions with $d \in [5,30]$ m, for any value of the angle φ (~ 2750 m^2). The communication channel is set to have path loss and shadow fading according to the WLAN Toolbox Model-B.[2] The Monte Carlo (MC) simulation settings are summarized in Tab. I.

B. Improving the MCS of the user with a poor channel

For the first experiment, we consider $M = 2$ STAs and label them R_1 and R_2, where R_1 is the closest STA to the AP, so that $\mathbb{E}[|h_1|] > \mathbb{E}[|h_2|]$. We tested all possible combinations of positions (x,y), where x and y are the positions of R_1 and R_2, respectively, in a discrete grid with step $\delta = 5$ m between 5 and 30 m: This gives 15 different combinations (we excluded the combinations where the STAs were co-located). Figures 4a and 4b show the heatmap of the average MCS of R_1 and R_2 under the flat power distribution and reallocated power policies, respectively. As it can be observed, a gain in MCS is present when the power is partially reallocated from R_1 to R_2, especially when R_1 is close to the AP and R_2 is far from the AP. This situation of particularly heterogeneous channel conditions yields the largest gains in MCS for the disadvantaged user R_2. This is also confirmed by Fig. 4c, which shows the MCS gain for R_2 as $m_2' - m_2$. We can observe that the first column of the heatmap, corresponding to $x = 5$ m, yields the largest possible gains for R_2, as power can safely be reallocated from R_1 elsewhere, since it has a sufficiently good channel. The reason why at a high distance of both STAs (top right corner) the heatmap is non-monotonic is due to the large effect of the shadowing variance and specific channel realizations.

[1]https://www.mathworks.com/products/wlan.html
[2]https://it.mathworks.com/help/wlan/ref/wlantgaxchannel-system-object.html

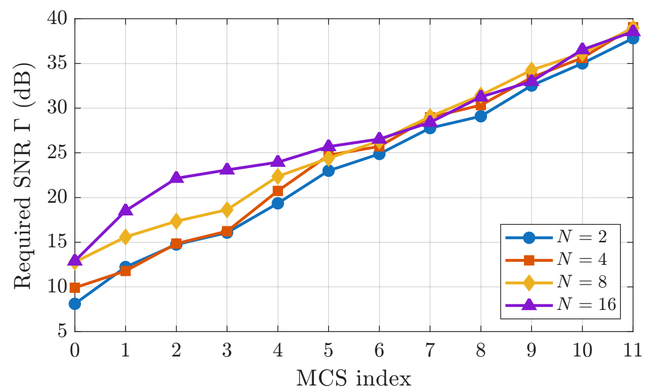
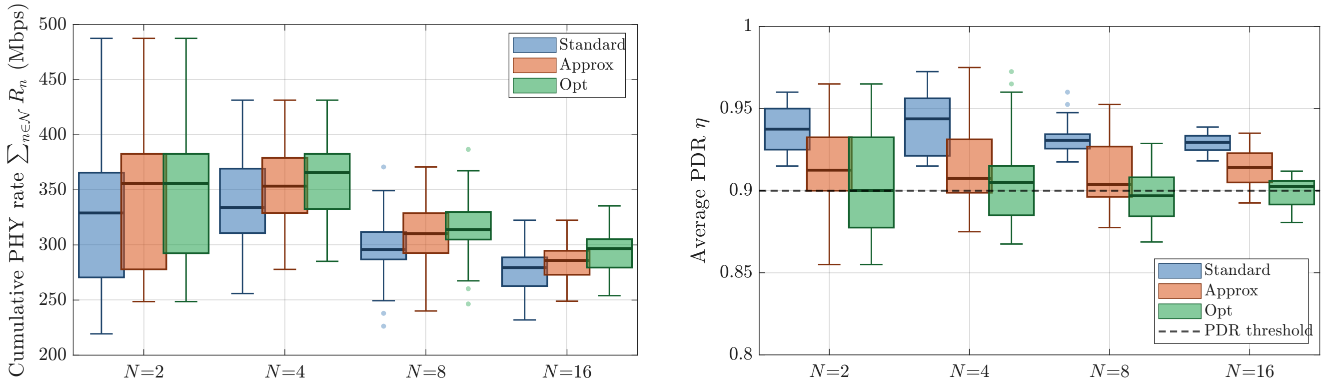


Fig. 5. Minimum required SNR Γ to sustain the given MCS m at the required PDR $\eta = 0.9$.

C. Performance metrics varying N

In this section, we evaluate our proposed approximated optimized solution (Eq. (5)), labeled "approx", by comparing it with the "standard" baseline allocating flat power over the spectrum, and the global optimal solution "opt" (Eq. (3)). Specifically, the performance metrics considered are the STAs



(a) (b)

Fig. 6. Optimization metrics. Cumulative PHY data rate of the N users (left) and average PDR (right).

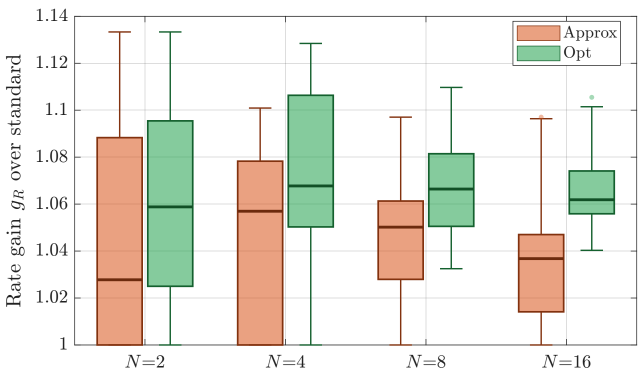


Fig. 7. Rate gain of the two proposed power allocation methods over the standard flat allocation.

(i) data rate and (ii) PDR, as they are the primary target of our optimization; further, to highlight the difference in allocation among methods, we show (iii) the STAs power distribution, and (iv) the data rate gain over the "standard" of the optimized methods.

In Fig. 5, we preliminarily show the minimum SNRs required to operate the WLAN downlink at a given MCS (on the abscissa) by targeting a PDR $\eta_n = \eta = 0.9$. Different curves correspond to different numbers of users. As can be seen, the SNR estimation monotonically increases with the MCS index, as expected. It is worth noting that, for high MCSs, the four curves almost coincide, and a different number of STAs does not impact the choice of the MCS. On the other hand, for low MCSs, when the users grow to $N = \{8, 16\}$, a significantly higher SNR is needed to ensure communication with the same PDR level. For instance, at MCS $m = 0$, we need about 6 dB more when $N = 16$ with respect to $N = 2$. This amounts to allocating a transmit power $\times 4$. The highest gap is observed at $m = 2$, where a 8 dB gap is present between $N = 2$ and $N = 16$. This result suggests that, at least for low MCS indices, the minimum required SNR is not independent of the number of STAs, but grows with it.

Figure 6 shows the two main optimization metrics of our framework: the data rate (the maximization objective, Fig. 6a), and the PDR (the main operative constraint, Fig. 6b). The cumulative PHY data rate $\sum_{n\in\mathcal{N}} R_n$ is a proxy to evaluate also the increase in MCS for some STAs in the WLAN. We observe that the optimal approach corresponding to solving the combinatorial problem yields the best increase in terms of rate, but also the highest decrease in average PDR $\eta = \frac{1}{N}\sum_{n\in\mathcal{N}} \eta_n$. This is because the optimization problem trades rate for PDR. Nonetheless, the requirement $\eta \geq 0.9$ is statistically satisfied for all values of N, demonstrating the validity of the approach of estimating the SNR thresholds and the re-allocatable power (preliminary steps 2 and 3, Sect. IV-A). We also observe that the low computational cost approximated solution yields rate increases close enough to the optimal solution, while delivering a slightly higher PDR. This translates into an almost equivalent throughput $\rho_n = \eta_n R_n$, about 5% higher than the standard flat allocation on average, which is the one having the highest PDR, but at the same time being suboptimal in rate. It is worth noting that, while the average gain in throughput is relative, the specific users who experience an increase in MCS can see up to a 50% higher throughput.

In Fig. 7, we show the average rate gain for the methods "approx" and "opt" over the "standard" computed as

$$g_R = \frac{\sum_{n\in\mathcal{N}} R_n^{m'}}{\sum_{n\in\mathcal{N}} R_n^{m}}. \tag{7}$$

While the results show a gain distribution over the MC simulations that is around 5%, this translates to up to 30 Mbps higher PHY data rate for selected users, while not affecting the MAC throughput significantly for other users. The gain over the standard is almost constant for different numbers of users, considering the interquartile ranges. Nonetheless, a peak of up to 13% gain can be observed for $N = 2$, and, in general, we can see that the approximated solution only loses $2-3\%$ when compared to the global optimum.

Finally, in Fig. 8, the power distribution of different users is presented for the two proposed solutions "approx" and "opt". While the "standard" has a flat distribution over RUs of the same size, we can observe how the reallocation alters this result.[3] For both algorithms, the majority of the distribution

[3]We only tested cases where users had allocated RUs of the same size, hence for the "standard" we would obtain degenerate distributions with the same power for all users.

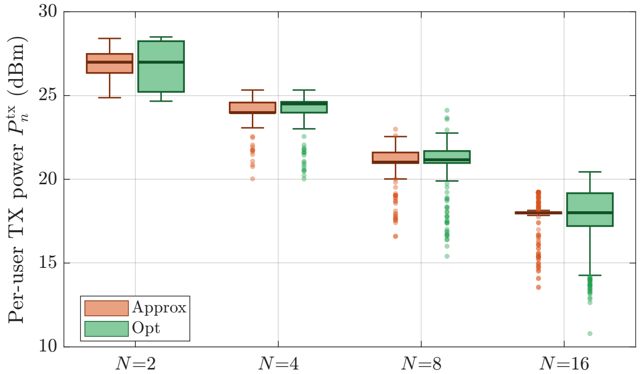


Fig. 8. Transmit power distribution (dBm) of the two proposed methods. The standard has a degenerate distribution allocating equal power for each RU.

mass is assigned in a zone around ± 2 dBm from the average value. However, especially for $N \geq 4$, there are outlier donors that can lose up to $5-6$ dBm of power, which is then reallocated elsewhere. These STAs are the ones experiencing a good channel, and that can easily yield power without degrading the MCS and the PDR.

VI. Conclusions

In this paper, we investigated the role of transmit power allocation in enhancing throughput in OFDMA-based WLAN systems, explicitly accounting for the discrete nature of modulation and coding schemes (MCS). Unlike traditional approaches based on continuous-rate assumptions, we formulated a constrained optimization problem that directly targets throughput improvements through SNR-driven MCS transitions, while preserving reliability requirements in terms of packet delivery ratio.

To address the combinatorial complexity of the problem, we proposed both an optimal formulation and a practical low-complexity heuristic inspired by water-filling and Knapsack optimization. The proposed approach redistributes power from users with excess SNR margin to those that can benefit from MCS upgrades, without modifying bandwidth allocation or degrading user performance.

Simulation results in IEEE 802.11ax scenarios demonstrated that adaptive power allocation yields consistent throughput gains over standard flat power distribution. In particular, the heuristic solution achieves performance close to the optimal one, while maintaining higher PDR and significantly lower computational complexity. Although the average throughput improvement is moderate (around 5%), individual users experiencing MCS upgrades can benefit from substantially higher gains, highlighting the practical relevance of the approach.

Overall, this work shows that power allocation represents an additional and largely underexplored degree of freedom in OFDMA systems. By explicitly considering discrete-rate behavior, it is possible to bridge the gap between theoretical resource allocation strategies and practical system performance. Future work will extend this framework to joint bandwidth and power optimization, multi-cell scenarios, and real-time implementations in commercial WLAN systems.

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