Common and Sum Rate Optimization for Multi-carrier Energy Harvesting Wireless Networks

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Communications

Department of Electrical and Computer Engineering

University of Alberta

Abstract

Energy harvesting techniques, which exploit ambient energy to power communications devices, have gained increased attention in recent years. Such techniques have emerged as a promising solution for energy-constrained wireless networks, with possible applications in the future Internet of things. The focus of this thesis is on multi-carrier wireless energy harvesting networks (WEHNs) where users adopt a harvest-then-transmit protocol to communicate with an access point. For such networks, we study the subchannel assignment and power allocation at the users to maximize the common rate and sum rate considering the effect of channel fading and path loss on the signals. Both common rate and sum rate optimization problems result in a non-convex mixed binary optimization formulation without a known systematic solution to the best of our knowledge. That being said, we propose multiple heuristic suboptimal solutions for the rate optimization problems providing different trade-offs between computational complexity and performance. The performance of the proposed solutions are evaluated under several WEHN setups through computer simulations.

"Information is the resolution of uncertainty."

Claude E. Shannon

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R_{s}	Sum rate of the system	7
R_{c}	Common rate of the system	8

Chapter 1

Introduction

Future wireless networks hold the promise of providing a host of useful services ranging from traffic control [1] and structural health monitoring [2] to smart cities [3], farming [4], and patient tracking [5]. Such a broad range of applications will be made possible via a ubiquitous set of wireless devices equipped with different sensing, computation, and communication abilities. To assure the omnipresence of the network, these devices are often mobile or well-spread over a large area forcing them to rely on batteries as their source of power. However, the power constraint at the devices could potentially limit the applicability scope of the network as batteries' need for frequent charging or replacement is costly or infeasible, compromising the network functionality.

To address the devices' power constraint, in addition to developing more energy-efficient transmission techniques [6], an increasing attention has been paid to developing energy harvesting technologies in recent years. Such technologies harvest the ambient energy of the environment to charge the devices' batteries. There are a variety of energy harvesting technologies that can be leveraged to charge battery-powered devices. Examples are miniature thermoelectric generators that convert the body heat to electricity [7], bimorph piezoelectric generators for exploiting vibrational energy [7], and circuits for harvesting radio frequency (RF) signals.

Among these technologies, harvesting RF signals, also known as wireless energy harvesting (WEH), is of special interest as RF signals can be purposefully and directionally sent to the devices to charge their batteries. Further, many RF sources, e.g. on the air TV or wireless cellular signals, are readily available in the environment making WEH even more appealing.

Owing to their potential, application of WEH technologies has been explored in the 5G [8], wireless sensor networks [9], and the future Internet of things (IoT) networks [10]. More specifically, improved energy efficiency with the help of WEH technologies, which could potentially prolong the devices lifetime by a factor of ten, has been foreseen for 5G networks. IoT networks are also a major beneficiary of WEH technologies as their long-term and self-sustainable operation, directly affected by the devices lifetime, are key to their success.

To effectively exploit the limited harvested power in a wireless energy harvesting network (WEHN), optimizing the network resource allocation is of great importance [11, 12, 13]. The optimization includes different aspects of the network, for instance the power harvesting schedule, transmit power allocation, and subchannel assignment in multi-carrier WEHNs. In the following, some of these studies are reviewed.

Authors in [14] introduce *harvest-then-transmit* protocol where the users (devices) first harvest the energy during a fraction, say T, of the total harvesting and communication time, and then transmit their data during the remaining fraction, i.e. $1 - T$, of the time. Then, assuming Rayleigh fading, the outage probability of the system is minimized via optimizing T. For the harvest-then-transmit protocol, [15] finds the optimal value of T that maximizes the sum throughput of the network when users apply time division multiple access (TDMA) in the uplink.

In addition to optimizing the energy harvesting and transmission scheduling, majority of studies have looked into the optimal power allocation for

WEHNs. For instance, [16] studies the optimal power allocation to maximize throughput considering the channel conditions and time-varying energy sources. Ding *et al.* [17] focus on an energy harvesting cooperative network where the relay harvests its transmit power from its received signals. Then, power allocation to transmit the messages of source-destination pairs is performed at the relay to minimize the outage probability. The optimal power allocation analysis is extended to cooperative networks where both relay and source nodes harvest wireless energy in [18]. Optimal energy harvesting strategies for distributing cellular data via a wireless-powered collaborative mobile cloud are studied in [11]. More specifically, the authors investigate the optimal scheduling of the data offloading and radio resources, including power allocation, in order to maximize energy efficiency as well as fairness among mobile users.

Some studies have gone one step further and jointly optimize multiple network resources in a WEHN. For instance, a joint power and time allocation to maximize the throughput of a TDMA-based WEHN is performed in [19]. The optimization is done under an average transmit power and maximum transmit power constraint at the access point (AP). Another example is [20] where joint power and time resource allocation is performed to maximize the sum rate of a TDMA-based network.

Joint power and subchannel allocation for a multi-carrier WEHN is explored in [21]. For this, the authors consider a WEHN where a user harvests its energy from an energy AP and transmits its data to another AP, called data AP. Further, it is assumed that the links between the user and both APs are time varying and the user applies orthogonal frequency division multiplexing (OFDM) to combat with the fluctuations in the channel condition. Assuming full channel state information (CSI) knowledge at the user and APs, an algorithm for joint subchannel and power allocation is proposed. In another study [22], joint power and subchannel allocation is studied for a WEHN with full duplex hybrid AP, meaning that the AP can simultaneously transmit energy signal and receive data signals. For this, the authors consider two different scenarios to maximize the network sum rate: perfect self-interference cancellation (SIC), where the hybrid AP fully eliminates its self-interference, and imperfect SIC. It is shown that the sum rate maximization problem for both scenarios is non-convex making the problem very complicated. Nevertheless, the authors propose a Lagrange duality method and an iterative algorithm based on projected gradient to solve for perfect and imperfect SIC scenarios respectively.

In this thesis, we further extend the existing results on the joint subchannel and power allocation for multi-carrier WEHNs. More specifically, we consider a network setup where the users harvest the energy from the signals and communicate to a hybrid AP. The channel quality between the AP and the users on both uplink and downlink is affected by fading and path loss necessitating careful subchannel and power allocation to gain the best performance out of the network. For this setup, we focus on optimal power and subchannel allocation to achieve the maximum sum rate and common rate in the system. Both optimization problems are non-convex and have a mixed binary optimization form. There is no systematic known solution for either of these problems to the best of our knowledge, and thus, we focuses on developing heuristic sub-optimal solutions for them.

The reminder of this thesis is organized as follows: The system model and the formal definition of the studied sum rate and common rate maximization problems are presented in Chapter 2. We present several suboptimal solutions for the sum rate maximization and common rate maximization problems in Chapter 3 and Chapter 4, respectively. Chapter 5 concludes this thesis and discusses ideas for future research directions.

Chapter 2

System Model and Problem Statement

In this chapter, we first describe the system model in detail. Then, we formulate the sum rate and common rate maximization problems for a multi-carrier WEHN [23].

2.1 System Model

Here, we consider a WEHN consisting of K single-antenna energy-harvesting devices (users), namely $\mathrm{u}_1, \mathrm{u}_2, \ldots, \mathrm{u}_K$, that want to communicate their data to a single-antenna access point (AP). Users adopt a *harvest-then-transmit* protocol [15] where they first harvest power from the AP's energy signal in the downlink and then transmit their message to the AP through the uplink channel (Figure 2.1).

To transmit energy to the users via RF signals, the AP first sends an arbitrary complex random signal x_{AP} with power P_{AP} to the users. The power gain of the downlink channel from the AP to an arbitrary user u_k, $k \in \mathcal{K} = \{1, 2, \ldots, K\}$, is denoted by a_k. This gain incorporates both the wireless channel gain as well as the power harvesting efficiency at u_k. Now,

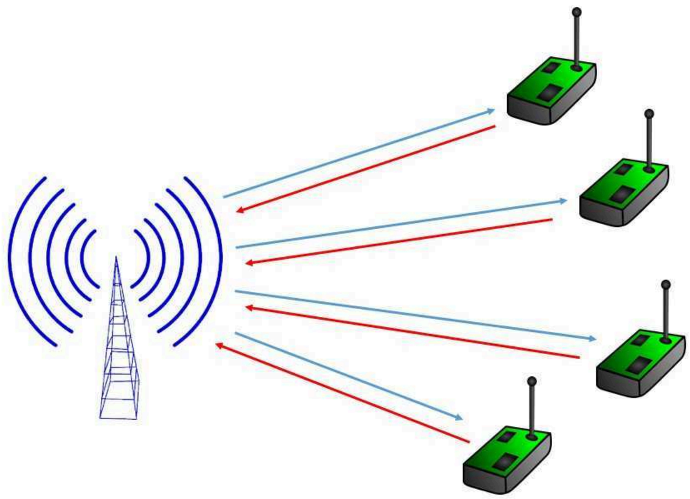

Figure 2.1: A WEHN with wireless energy transfer in the downlink and wireless information transmission in the uplink.

assuming that the receiver noise power at u_k is significantly smaller than P_{AP}, the harvested power at the user is

$$P_k = a_k P_{\mathrm{AP}}. \tag{2.1}$$

After harvesting the power from the AP signal, users enter the data transmission mode. To mitigate the wireless fading effect, users employ a multi-carrier transmission scheme, e.g. orthogonal frequency division multiplexing (OFDM) [23], in the uplink phase[1]. For this, the uplink transmission bandwidth is divided into N equal-size frequency subchannels. Then, a subchannel assignment strategy is used to assign the subchannels to the users where each subchannel is assigned to only one user to ensure the interference-free uplink transmissions. In the following, we denote the set of subchannels that are assigned to u_n by $\mathcal{A}_n$. If an arbitrary subchannel $n \in \mathcal{N} = \{1, 2, \ldots, N\}$ is

[1]Note that uplink and downlink frequency bands are different to prevent interference.

assigned to u_k, the received signal from u_k at the AP over this subchannel is

$$y_{\mathrm{AP},n} = \sqrt{h_{k,n}} x_{k,n} + n_{\mathrm{AP},n} \tag{2.2}$$

where $x_{k,n}$ is the transmit signal of u_k over subchannel n. Further, $h_{k,n}$ represents the power gain of the link and $n_{\mathrm{AP},n}$ is the receiver additive white Gaussian noise with zero mean and unit power.

2.1.1 Achievable Data Rates

Using the received signal model in (2.2), one can find the received data rate at the AP from u_k on subchannel n as[24]:

$$R_{k,n} = \frac{1}{N} \log_2 \left(1 + h_{k,n} P_{k,n}\right) \tag{2.3}$$

where $P_{k,n}$ is the transmit power of u_k on subchannel n, i.e. $P_{k,n} = E[x_{k,n}^2]$. Here we assume that the background noise has unit power, and the total bandwidth of all the subchannels is normalized to one. As a result, the overall received data rate from u_k at the AP is

$$R_k = \sum_{n=1}^{N} R_{k,n} = \frac{1}{N} \log_2 \left(\prod_{n=1}^{N} (1 + h_{k,n} P_{k,n}) \right). \tag{2.4}$$

Note that here, if a subchannel, say subchannel n', is not assigned to u_k, $P_{k,n'} = 0$ meaning that $R_{k,n'} = 0$.

Now that we have defined the individual user data rates, we introduce two important data rate measures of the network, namely *sum rate* and *common rate*. The sum rate of the network represents the cumulative data rate performance of the system and is defined as

$$R_{\mathrm{s}} = \sum_{k=1}^{K} R_k. \tag{2.5}$$

On the other hand, common rate reflects the bottleneck of the data rate performance which is

$$R_{\mathrm{c}} = \min_{k \in \mathcal{K}} R_k. \tag{2.6}$$

2.1.2 Achievable Data Rate Optimization

The aforementioned data rates are important measures of the network's throughput performance. As a result, it is desired to maximize R_{s} or R_{c} so that the best performance is achieved given the limited network resources. Note that by maximizing R_{c}, we attempt at simultaneously improving the quality of service (QoS) for all users. On the other hand, R_{s} maximization aims to improve the performance of the network as a whole even at the price of sacrificing the QoS of some of the users.

To maximize the data rates, the subchannel assignment as well as the users power allocation on each subchannel are the optimization parameters. That said, one can formulate a joint optimization problem to maximize the sum rate as follows:

$$\max_{\substack{x_{k,n}, P_{k,n} \\ k \in \mathcal{K}, n \in \mathcal{N}}} \frac{1}{N} \sum_{k=1}^{K} \sum_{n=1}^{N} \log_2 \left(1 + x_{k,n} h_{k,n} P_{k,n}\right), \tag{2.7a}$$

$$\sum_{n=1}^{N} P_{k,n} = a_k P_{\mathrm{AP}} \quad \forall k \in \mathcal{K}, \tag{2.7b}$$

$$\sum_{k=1}^{K} x_{k,n} = 1 \quad \forall n \in \mathcal{N}, \tag{2.7c}$$

$$x_{k,n} \in \{0, 1\} \quad \forall k \in \mathcal{K}, n \in \mathcal{N}. \tag{2.7d}$$

In (2.7), $x_{k,n}$s are binary variables specifying how the subchannels are assigned. More specifically, $x_{k,n} = 1$ means that subchannel n is assigned to user k and $x_{k,n} = 0$ otherwise. Further, the constraint in (2.7b) makes sure that the transmit power of the users is not more than their harvested power while (2.7c) guarantees that each subchannel is assigned to only one user.

Similarly, the common rate maximization problem for the aforementioned WEHN is formally defined as:

$$\max_{\substack{x_{k,n},P_{k,n}\\ k\in\mathcal{K},n\in\mathcal{N}}} \min_{k\in\mathcal{K}} \frac{1}{N}\sum_{n=1}^{N} \log_2\left(1 + x_{k,n}h_{k,n}P_{k,n}\right), \tag{2.8a}$$

$$\sum_{n=1}^{N} P_{k,n} = a_k P_{\text{AP}} \quad \forall k \in \mathcal{K}, \tag{2.8b}$$

$$\sum_{k=1}^{K} x_{k,n} = 1 \quad \forall n \in \mathcal{N}, \tag{2.8c}$$

$$x_{k,n} \in \{0,1\} \quad \forall k \in \mathcal{K}, n \in \mathcal{N}. \tag{2.8d}$$

Both of the above optimization problems are mixed binary continuous optimization problems where the subchannel assignment and user power allocation are jointly optimized. To the best of our knowledge, there is no systematic solution for the optimization problems in (2.7) and (2.8). In the rest of this thesis, we propose heuristic iterative sub-optimal solutions for (2.7) and (2.7). In the following chapters, we discuss these proposed solutions in more detail.

Chapter 3

Sum Rate Maximization

In this chapter, we propose several suboptimal solutions for sum rate the sum rate optimization problem in (2.7). The performance of these approaches are then compared through computer simulations.

Before presenting these approaches, we introduce a matrix $\boldsymbol{G} = [g_{k,n}]_{K \times N}$ whose elements are defined as

$$g_{k,n} = a_k h_{k,n}, \quad \forall k \in \mathcal{K}, n \in \mathcal{N}. \tag{3.1}$$

The physical interpretation of $g_{k,n}$ is the end-to-end power gain of subchannel n if user k allocates all of its power to this subchannel. In the rest of this chapter, $\boldsymbol{G}$ is used to explain the proposed solutions.

3.1 Maximum Gain Assignment

In this approach, the subchannel assignment and the user power allocation are done completely in a separate manner. This means that first subchannels are assigned to the users and then power allocation is performed. An arbitrary subchannel, say subchannel n, is assigned to the user who has the largest end-to-end power gain on the subchannel. To be more specific, subchannel n is assigned to u_i where

$$i = \arg\max_{k \in \mathcal{K}} \; g_{k,n}. \tag{3.2}$$

Such a subchannel assignment is based on the intuition that assigning subchannel n to the user with the largest channel gain on it will possibly result in the maximum contribution to the sum rate from this subchannel. When all channels are assigned according to (3.2), the transmit power of each user over its assigned subchannels is then determined according to water filling which can achieve the maximal rate of the user given the assigned subchannels. [25]. The pseudocode of the maximum gain assignment approach is presented in Algorithm 1.

Algorithm 1 Maximum gain assignment algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
for $n \in \mathcal{N}$ **do**
  $i = \arg\max_{k \in \mathcal{K}} g_{k,n}$
  $\mathcal{A}_i \leftarrow \mathcal{A}_i \cup \{n\}$
for $k \in \mathcal{K}$ **do**
  Do water filling for u_k given $\mathcal{A}_k$

3.2 Balanced Maximum Gain Assignment

One disadvantage of the previous solution is that it may assign all or a large majority of subchannels to a small group of users. In an extreme case, all subchannels may be assigned to a user, say u_k, whose end-to-end gain, e.g. $g_{k,n}$, is larger than other users over all subchannels. After performing the power allocation, u_k, however, may end up allocating only a very small or even no power to some of these subchannels. This means that some of the subchannels, which could be assigned to other users for increasing the sum rate, are wasted.

To compensate for this disadvantage of the maximum gain subchannel assignment, we suggest another approach that still has a low complexity, through decoupling the subchannel assignment and power allocation, yet tries to assign the subchannels between the users in a more balanced way. For this purpose, we start by assigning the subchannel who has the strongest end-to-end channel gain, i.e. the maximum of $\boldsymbol{G}$'s elements. To be more specific, the strongest subchannel, namely subchannel j, is assigned to user i where

$$(i, j) = \underset{(k,n):\, k \in \mathcal{K}, n \in \mathcal{N}}{\arg\max}\; g_{k,n}. \tag{3.3}$$

Now, we mark the ith row and jth column of $\boldsymbol{G}$ as *tabu*[1] row and column. In the next step, the non-tabu subchannel with the strongest end-to-end gain is assigned to the user that has the strongest gain over it. This procedure continues until each user is assigned a subchannel. If there are still subchannels left, i.e. $K < N$, we first reset the set of tabu rows and proceed with the subchannel assignment over non-tabu subchannels. After assigning all subchannels, users allocate their power according to water filling algorithm.

The balanced maximum gain assignment is presented in Algorithm 2. Here, $\mathcal{T}_\mathrm{u}$ and $\mathcal{T}_\mathrm{s}$ represent the set of tabu users (rows) and tabu subchannels (columns) respectively.

Algorithm 2 Balanced maximum gain assignment algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
$\mathcal{T}_\mathrm{u}, \mathcal{T}_\mathrm{s} \leftarrow \varnothing$
while $\mathcal{T}_\mathrm{s} \neq \mathcal{N}$ **do**
    $(i, j) = \underset{(k,n):\, k \in \mathcal{K} \setminus \mathcal{T}_\mathrm{r}, n \in \mathcal{N} \setminus \mathcal{T}_\mathrm{c}}{\arg\max}\; g_{k,n}$
    $\mathcal{A}_i \leftarrow \mathcal{A}_i \cup \{j\}$
    $\mathcal{T}_\mathrm{u} \leftarrow \mathcal{T}_\mathrm{u} \cup \{i\}, \mathcal{T}_\mathrm{s} \leftarrow \mathcal{T}_\mathrm{s} \cup \{j\}$
    if $\mathcal{T}_\mathrm{u} = \mathcal{K}$ **then**
        $\mathcal{T}_\mathrm{u} \leftarrow \varnothing$
for $k \in \mathcal{K}$ **do**
    Do water filling for u_k given $\mathcal{A}_k$

[1] Inspired by tabu search algorithm [26].

3.3 Partial Sum Rate Incremental Assignment

Both of the previous approaches fully decouple the subchannel assignment and power allocation. While it has been compensated for to some extent in Algorithm 2, such decoupling has the risk of wasting the subchannels after performing power allocation. To address this shortcoming of the previous approaches, we present another suboptimal solution for the sum rate optimization problem that incorporates the subchannel power allocation into the subchannel assignment. This is done through a greedy algorithm where for assigning each new subchannel, a power allocation for all previously assigned subchannels is needed. At each iteration of the greedy algorithm, the goal is to assign a new subchannel in a way that the maximum increase in the sum rate is achieved.

First, we start from an arbitrary subchannel, say subchannel n. Then, we find the user that gives the highest sum rate if only this subchannel was used. This is equivalent to picking the user that has the largest $g_{k,n}$ for $k \in \mathcal{K}$. To continue, we pick another subchannel and assign it to the user that gives the maximum increase in the sum rate considering the first subchannel assignment. The subchannel assignments continue in the same fashion so that each subchannel is assigned to the user that produces the largest increase in the sum rate considering all previous subchannel assignments. The pseudocode of this approach is presented in Algorithm 3. In this algorithm, $R_{\mathrm{s}}(k,n)$ represent the sum rate of the system assuming subchannel n is assigned to user k given all previous subchannel assignments. Here, the subchannel assignment and power allocation for all users and subchannels finish at the same time.

3.4 Full Rate Incremental Assignment

The order of picking the subchannels to be assigned affects the output sum rate of the partial sum rate incremental subchannel assignment. While picking subchannels could be done randomly, picking them smartly could result in a

Algorithm 3 Partial rate incremental assignment algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
$\mathcal{T}_\mathrm{c} \leftarrow \varnothing$
while $\mathcal{T}_\mathrm{c} \neq \mathcal{N}$ **do**
    Pick a subchannel $n \in \mathcal{N} - \mathcal{T}_\mathrm{c}$
    $i = \arg\max_{k \in \mathcal{K}} R_\mathrm{s}(k, n)$
    $\mathcal{T}_\mathrm{c} \leftarrow \mathcal{T}_\mathrm{c} \cup \{n\}$
    $\mathcal{A}_i \leftarrow \mathcal{A}_i \cup \{n\}$

higher sum rate. For this purpose, we present another subchannel and power allocation strategy called full sum rate incremental subchannel assignment.

In this approach, at each iteration of the algorithm, the subchannel that results in the maximum sum rate increase is selected. For this, all the unassigned subchannels are first scanned at each iteration. The scan of each subchannel consists of evaluating the sum rate increase for all users by doing the power allocation and sum rate calculation for each user considering all previous subchannel assignments. After scanning all unassigned subchannels, the subchannel and its associated user for the maximum sum rate increase are identified. The pseudocode of this approach is presented in Algorithm 4. Similar to partial sum rate incremental approach, both subchannel assignment and power allocation are finished at the same time.

Algorithm 4 Full rate incremental assignment algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
$\mathcal{T}_\mathrm{c} \leftarrow \varnothing$
while $\mathcal{T}_\mathrm{c} \neq \mathcal{N}$ **do**
    $(i, j) = \arg\max_{(k,n):\, k \in \mathcal{K}, n \in \mathcal{N} \setminus \mathcal{T}_\mathrm{c}} R_\mathrm{s}(k, n)$
    $\mathcal{T}_\mathrm{c} \leftarrow \mathcal{T}_\mathrm{c} \cup \{j\}$
    $\mathcal{A}_i \leftarrow \mathcal{A}_i \cup \{j\}$

3.5 Simulation Results

In this section, we compare the sum rate performance of the aforementioned subchannel assignment approaches. For this, we consider a WEHN where the users have different distance from the access point. More specifically, the distance of an arbitrary user i from the access point follows a uniform distribution with a support over $[1, 2)$. To account for the pass loss, we assume that the harvested power at the users is inversely proportional to their squared distance from the AP. Further, we consider a non-light-of-sight environment. and thus, the effect of the multipath fading on the channel gain the effect of the multipath fading on the channel gain follows a Rayleigh distribution. The following results are averaged over 100 channel realizations.

The achievable sum rate results for $N = 100$ sunchannels and different number of users, when the AP transmit power is $P_{\mathrm{AP}} = 10$ dBW, are presented in Figure 3.1. In this figure, the x-axis represents the normalized number of users, i.e. $\frac{K}{N}$. As expected, full rate incremental subchannel assignment shows the best performance followed by partial rate incremental subchannel assignment. Further, it can be seen that balanced maximum gain assignment outperforms the plain maximum gain assignment in terms of the sum rate. Overall, the achievable sum rate expresses an increasing trend over the normalized number of users.

The achievable sum rate results for $N = 100$ subchannels and $P_{\mathrm{AP}} = 30$ dBW is presented in Figure 3.2. Again, as expected, full rate incremental and maximum gain assignment respectively show the best and worst performance among the aforementioned channel assignments.

We also study the network resources usage efficiency by looking into the number of subchannels that are actually used in the uplink for data transmission. By this, we mean subchannels that are assigned a non-zero transmit power at the end of the subchannel assignment and power allocation. The

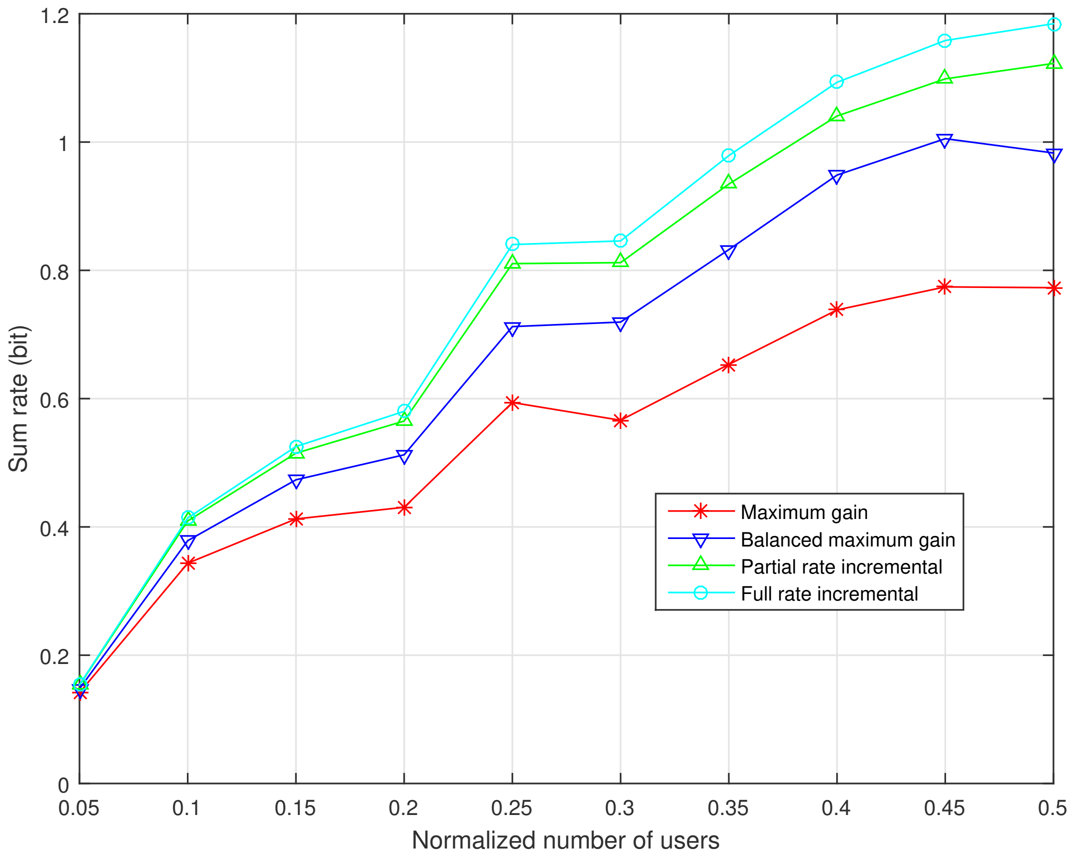

Figure 3.1: Achievable sum rate for different subchannel assignment approaches when $P_{\mathrm{AP}} = 10$ dBW.

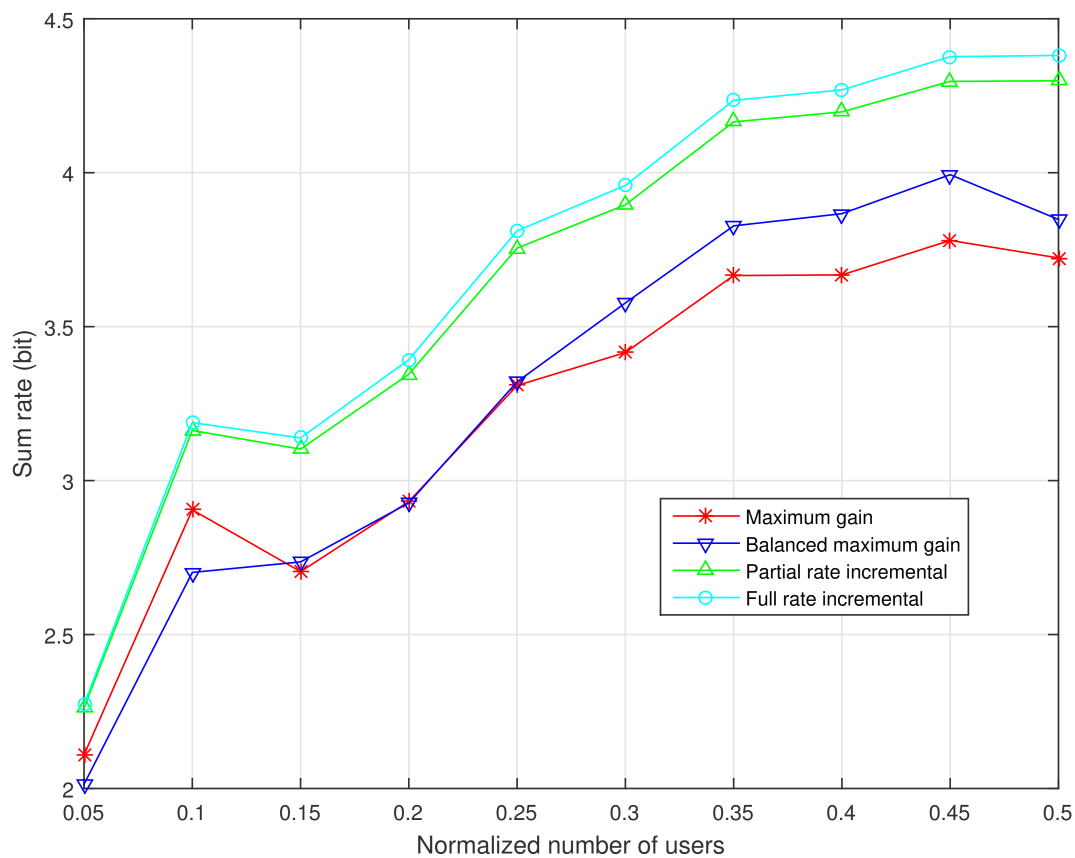

Figure 3.2: Achievable sum rate for different subchannel assignment approaches when $P_{\mathrm{AP}} = 30$ dBW.

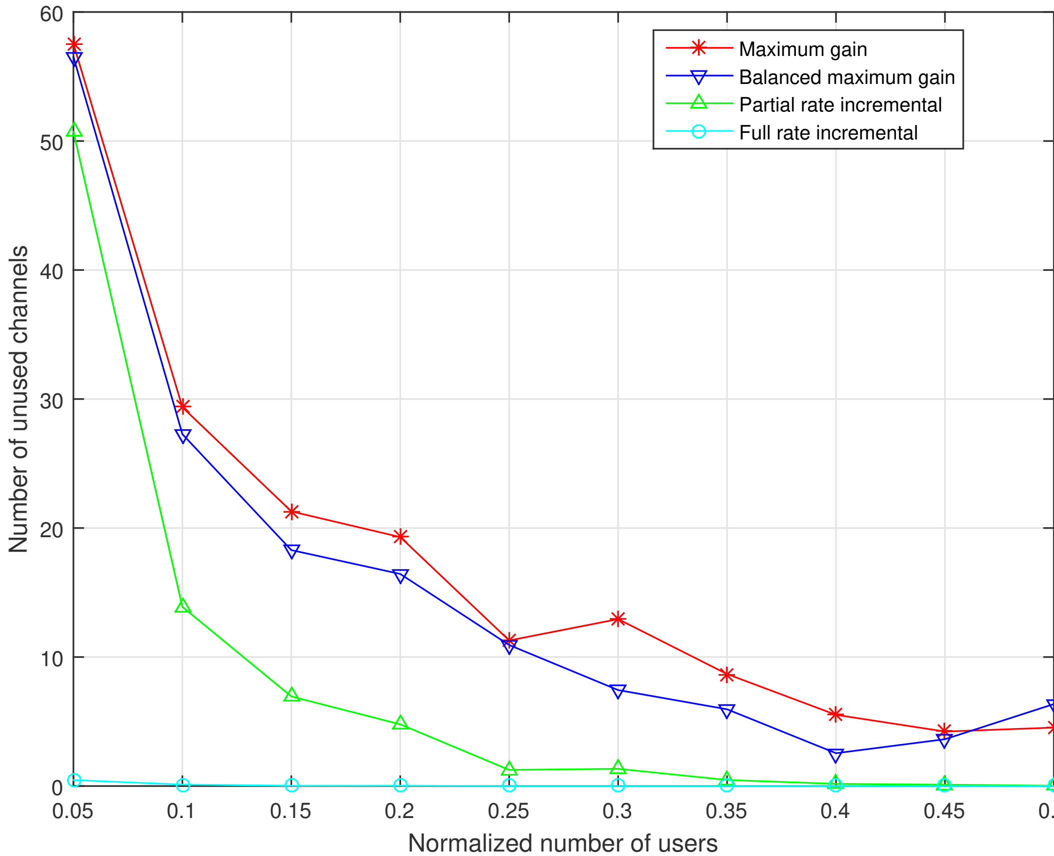

Figure 3.3: Number of unused subchannels when $P_{\mathrm{AP}} = 10$ dBW.

subchannel usage results for $P_{\mathrm{AP}} = 10$ dBW is presented in Figure 3.3. As seen, full rate incremental assignment utilizes almost all of the subchannels to achieve its superior sum rate performance over other approaches. On the other hand, at smaller number of users, a significant number of subchannels are left unused for the other three approaches.

The subchannel usage results for $P_{\mathrm{AP}} = 30$ dBW are shown in Figure 3.4. In this case, almost all of the subchannels are used by all subchannel assignment methods. This results from the fact that users harvest more power compared to $P_{\mathrm{AP}} = 10$ dBW (on average 100 times more), and hence, are able to allocate power to more subchannels.

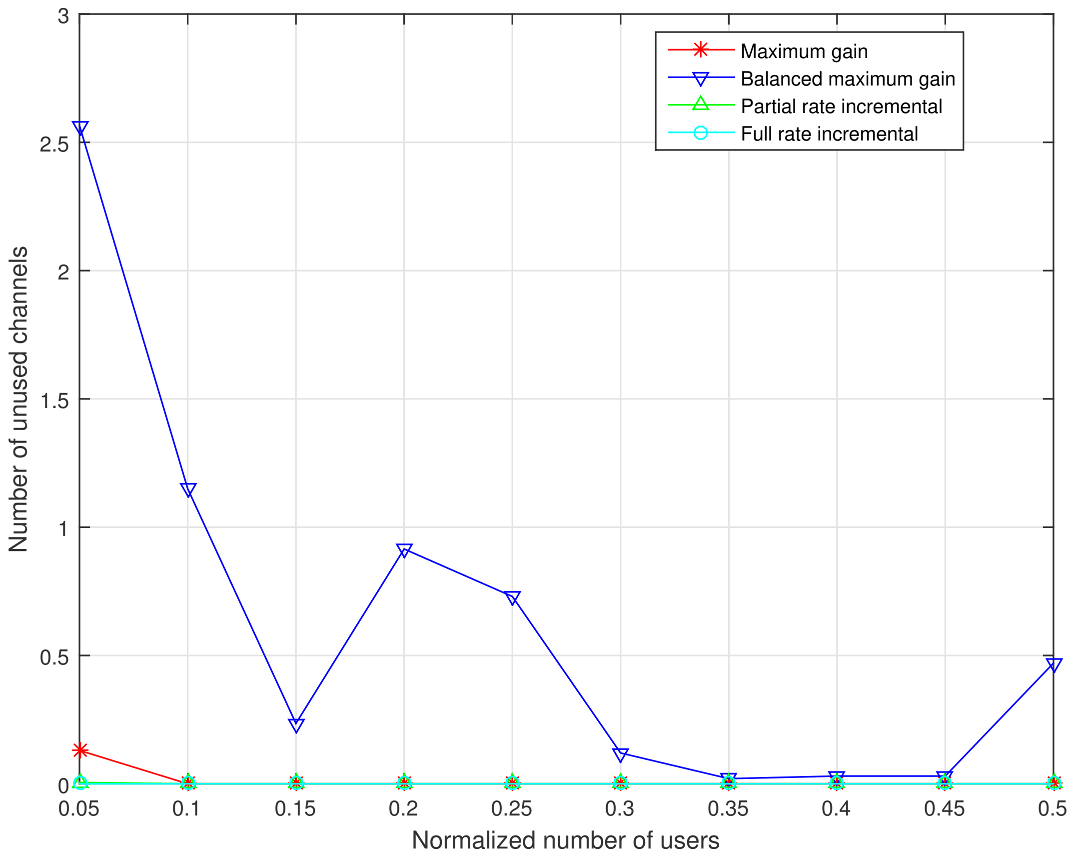

Figure 3.4: Number of unused subchannels when $P_{\mathrm{AP}} = 30$ dBW.

Chapter 4

Common Rate Maximization

While the goal of the sum rate maximization is to improve the data rate performance of the system as a whole, in common rate maximization, the individual data rate performance of the users are of more importance. For this to happen, one needs to ensure that all users get access to a fair share of the network resources. This mostly contradicts with the sum rate maximization approaches presented in the previous chapter where the users with the strongest channel are likely to receive most, if not all, the subchannels.

That being said, in the following, we present appropriate approaches for common rate maximization. The main idea behind all these approaches is to assign better subchannels to the users that have harvested less energy in the energy harvesting phase to boost their achievable data rates. Similar to sum rate, in the following we present approaches where the subchannel assignment and power allocation are decoupled as well as approaches where they are done simultaneously.

4.1 Individual Maximum Gain Assignment

In this approach, we first sort the users in terms of their harvested power. As for each user u_k, its harvested power P_k is proportional to a_k, which means that the users are basically sorted in terms of a_ks. Without loss of generality, let us assume that the users are labeled such that $a_1 \leq a_2 \leq \ldots \leq a_K$. Here, u_1 determines the bottleneck of the common rate and any improvement in its data rate directly translates into an increase in the common rate. To compensate for the lower harvested power by u_1 compared to the other users, we assign the stronger uplink subchannels to it. This is achieved by assigning the best M subchannels to the user and then we continue by assigning chunks of M subchannels to the rest of the users.

More specifically, the first best M subchannels are assigned to u_1. u_2 is the user with the second lowest harvested power and thus should receive strong subchannels. That being said, the best M subchannels of the remaining subchannels will be assigned to u_2. The next set of subchannels will be assigned to u_3 and so on. To ensure that no user remains without being assigned a subchannel, M is chosen such that $1 \leq M \leq \lfloor \frac{N}{K} \rfloor$. If after assigning M subchannels to all users, there are still unassigned subchannels left, the algorithm proceeds by assigning the subchannels to u_1 again and continues in the same fashion.

The pseudo code representation of the individual maximum gain assignment is outlined in Algorithms 5. Note that the choice of M affects the performance of this subchannel assignment approach and could be further optimized to reach the best performance by the system.

Algorithm 5 Individual maximum gain assignment algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
$k \leftarrow 1$
$\mathcal{T}_\mathrm{c} \leftarrow \varnothing$
while $\mathcal{T}_\mathrm{c} \neq \mathcal{N}$ **do**
  for $i \in \{1, 2, \ldots, M\}$ **do**
    $j = \underset{n \in \mathcal{N} \setminus \mathcal{T}_\mathrm{c}}{\arg\max}\ h_{k,n}$
    $\mathcal{T}_\mathrm{c} \leftarrow \mathcal{T}_\mathrm{c} \cup \{j\}$
    $\mathcal{A}_k \leftarrow \mathcal{A}_k \cup \{j\}$
  $k \leftarrow k + 1 \mod K$

4.2 Incremental Common Rate Improvement

In this approach, we assign M subchannels to a user at each iteration similar to the individual maximum gain assignment. However, it is different from individual maximum gain assignment in the sense that the subchannel assignment and power allocation are done simultaneously.

To explain the incremental common rate improvement in more detail, the approach allocates M subchannels to the user who has the lowest data rate among the users. To assign the first set of M subchannels when the data rates of all users are zero, the user who has the least harvested power, i.e. u_1, is selected. To decide on which M subchannels should be assigned to u_1, all possible M-subsets of the subchannels will be tested. The subset that results in the maximum data rate for u_1, considering water filling for the power allocation, is then selected and assigned to u_1. In the next iteration of the algorithm, the second user with the least harvested power, i.e. u_2, is selected who then receives an M-subset of unassigned subchannels. This continues until all users are assigned M subchannels.

From this point on, the user with the smallest data rate, i.e. the user imposing the bottleneck on the common rate, say u_k, is selected at each iteration of the approach. The next M subchannels are assigned to u_k so that it observes the maximum increase in its data rate considering water filling power allocation over the new and previously assigned subchannels. The approach continues assigning subchannels to the users in the same way until all subchannels are assigned. The pseudocode of the incremental common rate improvement approach is presented in Algorithm 6.

4.3 Simulation Results

In this section, we compare the sum rate performance of the aforementioned subchannel assignment approaches. For this, we consider a WEHN with a setup

Algorithm 6 Incremental improvement algorithm.

$\mathcal{A}_k \leftarrow \varnothing, \forall k \in \mathcal{K}$
$\mathcal{T}_\mathrm{c} \leftarrow \varnothing$
while $\mathcal{T}_\mathrm{c} \neq \mathcal{N}$ **do**
  if $\exists \mathcal{A}_k = \varnothing$ **then**
    $i = \underset{k \in \mathcal{K}, \mathcal{A}_k = \varnothing}{\arg\min}\ a_k$
  else
    $i = \underset{k \in \mathcal{K}}{\arg\min}\ R_k$
  for $m \in \{1, 2, \ldots, M\}$ **do**
    $j = \underset{n \in \mathcal{N} \setminus \mathcal{T}_\mathrm{c}}{\arg\max} R_i$
    $\mathcal{T}_\mathrm{c} \leftarrow \mathcal{T}_\mathrm{c} \cup \{j\}$
    $\mathcal{A}_k \leftarrow \mathcal{A}_k \cup \{j\}$

similar to what we considered for our sum rate study.

The achievable common rate results for $N = 100$ sunchannels and different number of users, when the AP transmit power is $P_\mathrm{AP} = 10$ dBW, are presented in Figure 4.1. In this case, maximum gain and rate incremental assignments result in similar common rate performance. This is possibly because of a bottleneck user, i.e. a user with low downlink and/or uplink channel gains, that limits the common rate regardless of the subchannel assignment strategy.

Similar results are presented for $P_\mathrm{AP} = 30$ dBW in Figure 4.2. In this case, the rate incremental approach provides a noticeable improvement over the subchannel assignment based on the maximum gain. This is because of the larger harvested power at the users making the subchannel and power allocation more relevant to the data rate performance of the network.

We also present the result for the number of unused network subchannels in Figure 4.3 and Figure 4.4. While the incremental improvement approach may not provide a significant rate enhancement over the maximum gain assignment, it achieves similar to even better common rate with using a significantly less number of subchannels. Hence, it is more efficient in terms of the subchannel usage.

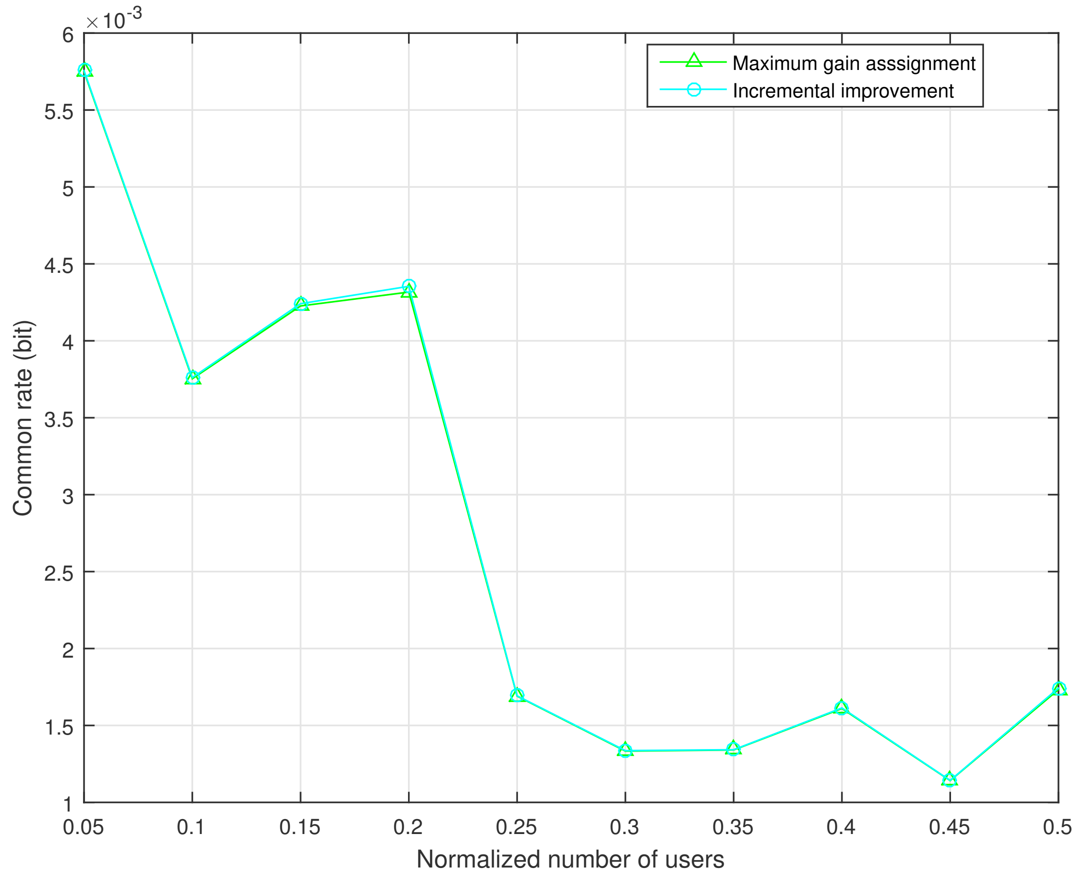

Figure 4.1: Achievable common rate for different subchannel assignment approaches when $P_{\text{AP}} = 10$ dBW.

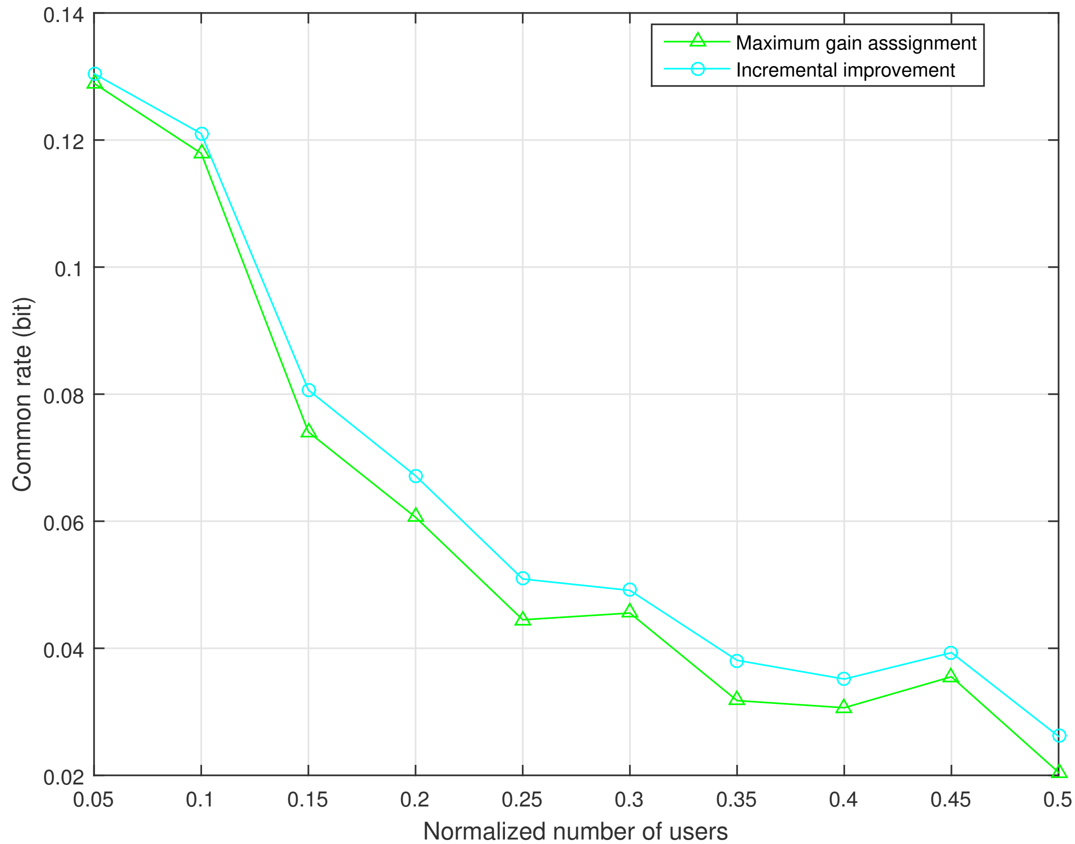

Figure 4.2: Achievable common rate for different subchannel assignment approaches when $P_{\text{AP}} = 30$ dBW.

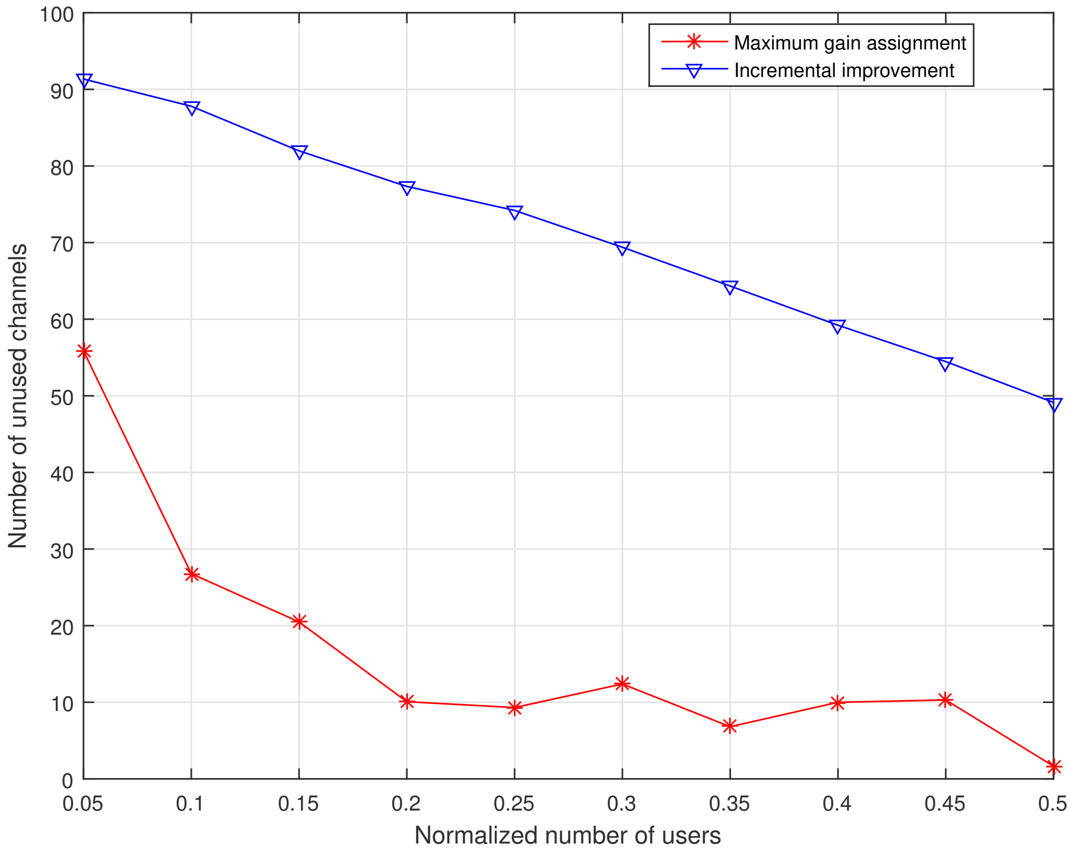

Figure 4.3: Number of unused subchannels when $P_{\mathrm{AP}} = 10$ dBW.

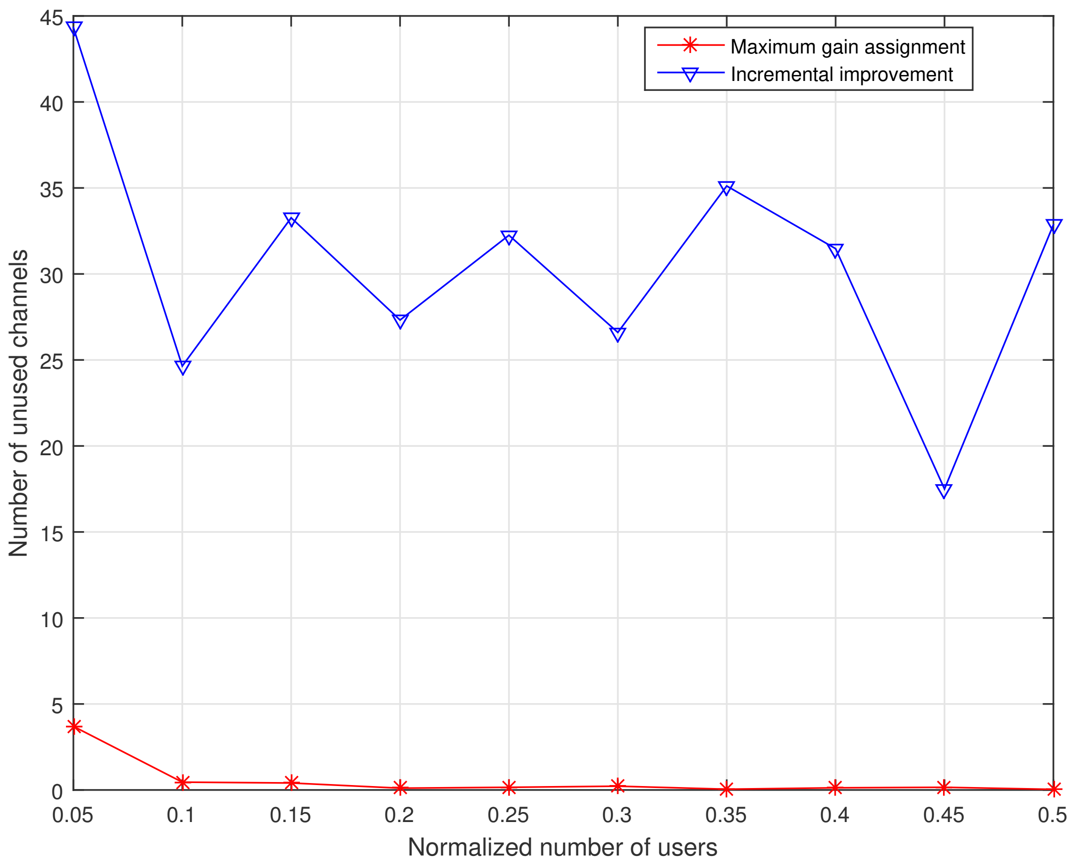

Figure 4.4: Number of unused subchannels when $P_{\mathrm{AP}} = 30$ dBW.

Chapter 5

Conclusion and Future Work

The achievable date rate of a multi-carrier WEHN is directly affected by the power allocation and subchannel assignment at the users. As a result, the power allocation and subchannel assignment at the users should be jointly optimized to reach the highest data rate performance in the network. For this purpose, we formulated two mixed binary optimization problems to maximize the sum rate and common rate of a WEHN, respectively. There is no systematic known solution for either of these problems to the best of our knowledge, and thus, we focused on developing heuristic suboptimal solutions for them.

To be more specific, we proposed two different sets of iterative suboptimal solutions. The first set of solutions were sequential meaning that instead of directly tackling the difficult joint optimization problems, we solved them sequentially by performing the subchannel assignment first and then power allocation later. The second set of solutions were incremental meaning that the subchannel assignment and power allocation were performed jointly. Simulation results were presented for different network setups to compare the performance of both sets of proposed solutions. It was observed that the incremental solutions result in higher rates for both common rate and sum rate, albeit at the price of higher computational complexity.

Another observation that we made from the simulation results was that some of the assigned subchannels were allocated no power for data transmissions. This is wasteful of network resources as these subchannels could be assigned to other users to further boost the data rate of the systems. An approach to tackle this issue is to check for the assigned subchannels whose assigned power is zero at each iteration and return them back to the pool of unassigned subchannels. Such study could be considered for future work.

In addition in this work, we assumed that equal time was dedicated for energy harvesting and data communication at the users. The performance of the network can be further improved through an adaptive scheduling where the energy harvesting and communication time slots are assigned according to the uplink and downlink channel gains. Intuitively, if the downlink channel gains is relatively smaller than the uplink channel gains, one can assign a longer time slot for energy harvesting and a shorter time slot for data communication to improve the achievable data rate. A joint scheduling, sub-channel assignment and power allocation could be considered as a future research direction to further enhance the sum rate and common rate of WEHNs.

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