FAIR USER SCHEDULING FOR DOWNLINK POWER DOMAIN NOMA

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By
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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

FAIR USER SCHEDULING FOR DOWNLINK POWER DOMAIN NOMA

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Non-Orthogonal Multiple Access (NOMA) has been proposed as a new radio access technique in which multiple users (the case of user pairs or triples are covered in this thesis) are allowed to use the wireless channel simultaneously in a way to improve the overall system capacity. A bucket-based Temporal Fair Scheduling algorithm (TFS) has been proposed in the literature for Orthogonal Multiple Access (OMA) systems. In this thesis, we extend this existing work to downlink power domain NOMA by which user pairs or triples are to be scheduled with the goal of maximizing system capacity under temporal fairness constraints. The effectiveness of the proposed fair user scheduling algorithm for NOMA is validated with simulations in which the effects of transmit power and coverage radius of the base station, as well as the number of users are thoroughly studied.

Keywords: NOMA, fair user scheduling, temporal fair, 5G.

ÖZET

AŞAĞI YÖNLÜ GÜÇ ALANLI NOMA İÇİN ADİL KULLANICI SEÇİMİ

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Kablosuz iletişimde sistem kapasitesini iyileştirmek için yeni bir çoklu erişim sistemi olan Dikgen Olmayan Çoklu Erişim (NOMA) birden fazla kullanıcıya (bu çalışmada çiftler ve üçlüler ele alınmıştır) aynı anda hizmet vermek üzere önerilmiştir. Literatürde Dikgen Çoklu Erişim (OMA) sistemleri için kredi sepeti tabanlı zamanda adil kullanıcı seçimi algoritması yer almaktadır. Bu tezde, sistemin ortalama kapasitesini kullanıcılara adil davranarak iyileştirmek için literatürde yer alan bu çalışma aşağı yönlü güç alanlı NOMA sistemlerde kullanıcı çiftleri veya üçlüleri seçimi için genişletilmiştir. NOMA için önerilen adil kullanıcı seçme algoritmasının etkinliği baz istasyonunun kapsama alanı, gönderme gücü ve kullanıcı sayısındaki değişiklikler gibi değişkenler kullanılarak doğrulanmıştır.

Anahtar sözcükler: NOMA, adil kullanıcı seçimi, 5G.

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Chapter 1

Introduction

1.1 Fifth Generation: 5G

Wireless communication's needs for data rate, spectral efficiency, connectivity, and mobility are increasing as the wireless technologies are evolving [1]. First generation (1G) is just a simple phone call and has the data rate up to 2.4 kbps, second generation (2G) added some new features such as SMS and e-mail and has the data rate up to 64 kbps, and third generation (3G) brought video calls and fast communication and has the data rate up to 2 Mbps. Fourth generation (4G) has a data rate up to 1 Gbps for low mobility and 100 Mbps for high mobility [1–7].

Since the number of mobile devices are increased dramatically, a new generation, i.e. fifth generation (5G), is proposed to meet the requirements of very massive device connectivity, very high achievable data rate, very low latency, very high spectral efficiency, user fairness and energy and cost efficiency [8–11]. There are some proposed technologies such as massive MIMO, millimeter wave, and mobile femtocell to satisfy 5G requirements.

The main idea of the massive MIMO is to use arrays of hundreds of antennas to serve multiple UEs at the same frequency slot [1] which improves the achievable data rate and energy efficiency [12]. There are some issues need to be considered while implementing massive MIMO such as interference management, synchronization of antennas, modulation, and channel correlation [12].

Frequency range between 3 GHz and 30 GHz is called super high frequency (SHF) and 30 GHz and 300 GHz is called extremely high frequency (EHF). These frequency bands are known as mmWave since these frequencies have wavelengths between 1 to 100mm [13]. The main advantage of the mmWave is to have large amount of spectrum which helps to increase the spectral efficiency [14]. Due to the different signal attenuations such as atmospheric gaseous, rain and free space propagation [13], the distance coverage of mmWave is limited.

A Mobile Femtocell (MFemtocell) is a small cell that can move around and dynamically change its connection to an operator's core network [2]. It is shown in [2] that communicating with BS through MFemtocell has higher spectral efficiency than communicating with BS directly. Even small cell technology increases spectral efficiency and provides energy and cost efficient system [15], it is important to have synchronization between small cells in order to prevent the intra-cell interference.

Apart from these technologies, Non Orthogonal Multiple Access (NOMA), Sparse Code Multiple Access (SCMA), Multi-user Shared Access (MUSA), and Pattern Division Multiple Access (PDMA) [16] are introduced as promising multiple access schemes for 5G.

1.1.1 Multiple Access Schemes for 5G

In order to meet the various service requirements of different generations, some multiple access technologies were proposed through the wireless communication history. From 1G to 4G, resources were allocated to users by OMA techniques. FDMA divides frequencies orthogonally to users in 1G to provide service. For 2G, TDMA is used to allocate resources to users by dividing time orthogonally. To be able to solve the problem of the massive user connectivity, CDMA is proposed in 3G. Due to the rapid increase in the users and limited resource usage, in 4G, OFDMA is introduced to provide spectral efficiency to the system [17].

The main requirements of 5G, such as very massive device connectivity, very high achievable data rate, very low latency, and very high spectral efficiency [8–11], forced systems to use another multiple access technology. Even for low mobility, OFDM in 4G can provide up to 1 Gbps rate [2], this multiple access scheme has some weaknesses [16]. OFDM needs to have a cyclic prefix to solve the problem of the fading which can cause to reduce the effectiveness of the resource [16]. Also, it requires each sub-carrier to be orthogonal, use the same bandwidth, and synchronized which can prevent flexible usage of the resource [16].

SCMA is frequency domain non-orthogonal multiple access technique for both uplink and downlink to improve the spectral efficiency, uplink system capacity, and downlink cell throughput by using sparse code book. Even it improves the efficiency, it is hard to design and optimize the code and it increases the interference between users [16].

MUSA is another NOMA technique to improve the spectral efficiency, support massive users to access, and has lower BLER by using superposition symbol expansion technology. Spread symbol design is the challenging part of this multi access technology [16].

PDMA is increasing the uplink capacity and spectral efficiency by using non-orthogonal patterns in transmission side and resolve this patterns at the receiver side. Designing and optimizing these patterns are increasing the complexity of this method [16].

1.2 Non-Orthogonal Multiple Access (NOMA)

Since 5G requires very high spectral efficiency, very high achievable data rate, very massive device connectivity, very low latency, user fairness, and energy and cost efficiency, a new multiple access technique, i.e. NOMA, has been proposed to fulfill these requirements [8–11, 18]. NOMA improves the spectral efficiency and throughput of the system by using superposition coding (SC) at transmitter side and successive interference (SIC) detection at the receiver side which creates receiver to become more complex than other proposed schemes.

Assume that, there are two UEs in the system; one of them is a sensor device which needs low data rate and has low priority, and the other UE needs high data rate and has high priority for transmission. In the conventional orthogonal multiple access, i.e. OMA, the sensor device needs to wait for a long time to use the resource, since the other one has higher priority which introduces latency for the sensor to transmit data and results in low spectral efficiency. However, NOMA presents a suitable environment for UEs to be served simultaneously within the same resources such as time, frequency, etc., where a sensor device and the other UE is served at the same time which reduces the latency for the sensor device, increases spectral efficiency and the overall system will achieve high data rate [19].

One of the proposed NOMA methods is power domain multiplexing which adds a new domain, i.e. power, which assigns different power levels to UEs in the system, this assignment is a function of the channel conditions. At the transmitter side, SC is applied where each UE's information are superposed and transmitted at the same time. Transmitter side is applying point-to-point encoding for each UE's information [20]. At the receiver side, SIC is applied where UE gather its information by assuming the other UE's information as an interferer [21].

1.2.1 Downlink NOMA

For the downlink a base station (BS) with single antenna is serving N UEs where each UE has a single antenna. As it is expected in NOMA, the BS transmits data to UEs simultaneously by applying SC and each UE applies SIC to decode its data. Assume that each UE is represented as UE_i where $i = 1, 2, \ldots, N$. BS transmits data of all UEs by linearly superposing them. The total power, i.e. P, is fractioned for all UEs by weight factor β_i. So each UE has the power of

$P_i = P\beta_i$ [20]. BS broadcasts a packet for desired fractioned power allocation of each UE and UEs are gathering information about power and order of the decoding from that packet.

At each UE, the received signal is:

$$y_i = h_i x + w_i. \tag{1.1}$$

where y_i represents the received signal, h_i is the channel gain for UE, i.e. UE_i, x is the signal which is superposed by the BS, i.e. $x = \sum_{i=1}^{N} \sqrt{P_i} S_i$ where S_i is the data for UE_i. Finally, w_i represents zero mean and σ_n^2 variance AWGN. Then, achievable data rate of the user UE_i for 1 Hz BW system for $i = 1, 2, \ldots, N-1$, where channel gains are ordered as $0 < |h_1|^2 < |h_2|^2 < \ldots < |h_N|^2$, is:

$$R_i = \log_2 \left(1 + \frac{P_i |h_i|^2}{P|h_i|^2 \sum_{k=i+1}^{N} \beta_k + \sigma_n^2}\right) \quad \text{bits/s/Hz.} \tag{1.2}$$

The strongest UE, i.e. U_N, which has the channel gain h_N has the achievable data rate for 1 Hz BW system:

$$R_N = \log_2 \left(1 + \frac{P_N |h_N|^2}{\sigma_n^2}\right) \quad \text{bits/s/Hz.} \tag{1.3}$$

where the strongest UE removes all interferences from other UEs [20].

As seen in Equation 1.2, each UE decodes its signal and removes the interference of the weaker UEs by using SIC, but stronger UEs' signals are remained as the interference. Since the strongest UE can apply SIC to remove all weaker UEs' signals interferences, as observed in Equation 1.3, there is no interference left for strongest UE.

In order to apply SIC at the receiver side successfully, it is recommended to have higher power difference between UEs [22]. Since weaker UEs suffer from interference by stronger UEs, power assignment should be inversely proportional to channel gains [9]. In other words, assigning high power values to stronger UEs will cause more interference to weaker UEs, however, by decreasing the power of stronger UEs, all UEs can achieve fair data rate.

1.2.2 Uplink NOMA

Apart from downlink, in uplink, NOMA can be applied in order to increase the spectral efficiency. Similar to downlink, both BS and UEs have single antennas. UEs are transmitting their signals simultaneously to BS by applying SC and at BS SIC is conducted to distinguish received signals. Again, total power is fractioned to each UE by β_i and each UE transmits signal by using the power of $P_i = P\beta_i$ [20]. So the received signal at the BS is:

$$y_i = h_i x + w_i. \tag{1.4}$$

where y_i represents received signal at BS, h_i is channel gain for each UE, i.e. UE_i, x is the signal which superposed by UEs, i.e. $x = \sum_{i=1}^{N} \sqrt{P_i} S_i$ where S_i is data for UE_i. Finally, w_i represents zero mean and σ_n^2 variance AWGN. Then, achievable data rate of the user U_i for a 1 Hz BW system for $i = 1, 2, \ldots, N-1$ is written in [23]:

$$R_i = \log_2 \left(1 + \frac{P_i |h_i|^2}{P \sum_{k=i+1}^{N} \beta_k |h_k|^2 + \sigma_n^2} \right) \quad \text{bits/s/Hz.} \tag{1.5}$$

The strongest UE, i.e. U_N, which has the channel gain h_N has the achievable data rate for 1 Hz BW system [23]:

$$R_N = \log_2 \left(1 + \frac{P_N |h_N|^2}{\sigma_n^2} \right) \quad \text{bits/s/Hz.} \tag{1.6}$$

1.3 Contributions

A bucket-based Temporal Fair Scheduling (TFS) algorithm has been proposed for OMA in literature [24]. In this thesis, we extend this idea to downlink power domain NOMA where user pairs or triples will be selected and scheduled to use the desired wireless channel according to the value of the linear combination of instantaneous spectral efficiencies and buckets in order to maximize the average system capacity under the temporal fairness constraints. Proportional fairness and temporal fairness are popular criteria however, they are equivalent under certain assumptions [25], we selected temporal fairness as the fairness criteria in this thesis since we believe it is easier to be implemented. Also, for NOMA, a temporal fair scheduler has been proposed in [26]. However, main differences from [26] and contributions of this thesis as follows:

- The study in [26] uses off-line channel models to find the optimal thresholds for the algorithm, whereas, our proposed method uses bucket-based algorithm which contains learning-based iterations.
- Most of the works about the user scheduling in NOMA covers only pair sets. However, in this work, ordered triple set is created and TFS algorithm for triple selection is proposed in order to schedule user triples at any time slot.
- Moreover, instead of covering all user pairs and triples in N users scenarios, a proposed pre-pair and pre-triple construction algorithms are used to decrease the complexity of the algorithm from $\mathcal{O}(N^2)$ to $\mathcal{O}(N)$ and from $\mathcal{O}(N^3)$ to $\mathcal{O}(N)$ for pairs and triples, respectively.

1.4 Organization of the Thesis

The structure of this thesis as follows, in Chapter 2, details of the bucket-based TFS algorithms will be explained for single user (Section 2.2), pair (Section 2.3), and triple (Section 2.4) selections. Since, a fractioned power is required for each

UE in power domain dowlink NOMA, the proposed fair power allocation methods for pair [27] and triple [28] will be explained and used in TFS algorithms for pair and triple, respectively.

In order to observe the performance of the proposed TFS algorithms for pair and triple selections, different simulation setups will be formed in Chapter 3. The used wireless channel model parameters will be summarized in this chapter. The effect of the algorithm parameter in the linear combination of the instantaneous capacity and bucket, i.e. α, will be explained and suitable value for different UEs will be figured out in Section 3.1. Firstly, the effectiveness of the TFS algorithm for pair selection for all pairs, i.e. NOMA, will be studied in Section 3.2. After that, in order to decrease the computational complexity while construction of pairs, details of the proposed pre-pair construction algorithm [29], i.e. NOMA*, will be explained and the performance will be studied in Section 3.3. Moreover the effect of the coverage radius and the transmit power of the BS will be investigated in Section 3.4 and Section 3.5, respectively. Finally, in Chapter 3, the performance of the TFS algorithm for triple selection will be examined in Section 3.6 by using the proposed pre-triple construction method in [29].

In the last chapter, results will be discussed and future works will be summarized.

Chapter 2

Bucket-Based Temporal Fair Schedulers

A bucket-based Temporal Fair Scheduler (TFS) was proposed and the performance of this algorithm was investigated for OMA in [24]. In this thesis, the extended version of this algorithm is applied for downlink power domain NOMA to improve the average system capacity under the fairness constraints. The network is a time slotted single cell Cellular Network (CN) with bandwidth, BW, where time slots are indexed by $1 \leq \tau < \infty$. The Base Station (BS) is located at the center of the circular cell with radius of R and user equipments (UEs) are uniformly distributed around the BS. There are N UEs in the cell and each is denoted by UE_i, $i = 1, 2, \ldots, N$. In addition to single UEs, ordered pairs in the cell, i.e. $UE_{(i,j)}$, $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, N$ and $i \neq j$, and ordered triples in the cell are, i.e. $UE_{(i,j,k)}$, $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, N$, $k = 1, 2, \ldots, N$ and $i \neq j \neq k$, possible candidates for scheduler. It is assumed that all UEs always have data to receive from BS.

The proposed TFS algorithm guarantees that if the system and UEs are active for long enough period of time, all UEs may receive the same amount of resources in terms of time. The fairness constraint is measured by Jain's Fairness Index

(See Equation 2.1).

$$JFI = \frac{\left(\sum_{i=1}^{N} s_i\right)^2}{N \sum_{s=1}^{N} s_i^2}. \tag{2.1}$$

where s_i denotes the total number of slots used by UE_i and N is the total number of UEs in the system.

Given time slot τ, the TFS algorithm decides which single user, i.e. UE_i, or which pair, i.e. $UE_{(i,j)}$, or which triple, i.e. $UE_{(i,j,k)}$, will be served by BS. The value of the bucket for each UE, i.e. b_i, $i = 1, 2, \ldots, N$, is introduced for fairness purpose which helps to assign credits to each UE according to the slot usage and this bucket can be maintained at the BS by the TFS algorithm. The initial value of the bucket is set to zero at the beginning of the network operation. Instantaneous spectral efficiencies (SE) at time slot τ, which are $r_i(\tau)$, $r_{(i,j)}(\tau)$, and $r_{(i,j,k)}(\tau)$ in units of bits/s/Hz are introduced for UE_i, $UE_{(i,j)}$, and $UE_{(i,j,k)}$, respectively. For numerical examples, information theory-based SE formulas are used.

$$r_i^O = \log_2\left(1 + \xi |h_i|^2\right) \quad \text{bits/s/Hz.} \tag{2.2}$$

The Equation 2.2 shows the achievable rate for the UE_i when OMA is used where ξ represents the total transmit signal to noise ratio (SNR), h_i represents the channel gain of the UE_i.

The total power in the power domain downlink NOMA is fractioned to UEs which are served by the BS at the same time slot. Assume that a pair is selected to be served and UEs in that pair are UE_i and UE_j and the channel gains of these UEs are denoted as h_i and h_j. Also, assume that UE_j has greater channel gain than UE_i which means $|h_j|^2 > |h_i|^2$. UE_j applies SIC and removes interference from UE_i. Therefore, the SE of UEs in pair for power domain downlink NOMA can be found by:

$$r_i^N = \log_2\left(1 + \frac{\beta_i \xi |h_i|^2}{\beta_j \xi |h_i|^2 + 1}\right) \quad \text{bits/s/Hz.} \tag{2.3}$$

$$r_j^N = \log_2\left(1 + \beta_j \xi |h_j|^2\right) \quad \text{bits/s/Hz.} \tag{2.4}$$

$$r_{(i,j)} = r_i^N + r_j^N \quad \text{bits/s/Hz.} \tag{2.5}$$

where r_i^N and r_j^N are achievable data rates of UE_i and UE_j, respectively in power domain downlink NOMA. Here, ξ denotes the total transmit SNR, i.e. $\frac{P}{\sigma_n^2}$. The sum of the power coefficients gives 1, i.e. $\beta_i + \beta_j = 1$. Finally $r_{(i,j)}$ represents the achievable data rate of the ordered pair (i, j) which is selected by the TFS algorithm.

Now, it is assumed that an ordered triple is selected by the scheduler and UEs in this triple will be served by the BS, i.e. UE_i, UE_j, and UE_k. The channel gains are h_i, h_j, and h_k, respectively. Also assume that $|h_k|^2 > |h_j|^2 > |h_i|^2$. Consequently, the SE of UEs for an ordered triple for downlink power domain NOMA system can be found by:

$$r_i^N = \log_2\left(1 + \frac{\beta_i \xi |h_i|^2}{(\beta_j + \beta_k)\xi |h_i|^2 + 1}\right) \quad \text{bits/s/Hz.} \tag{2.6}$$

$$r_j^N = \log_2\left(1 + \frac{\beta_j \xi |h_j|^2}{\beta_k \xi |h_j|^2 + 1}\right) \quad \text{bits/s/Hz.} \tag{2.7}$$

$$r_k^N = \log_2\left(1 + \beta_k \xi |h_k|^2\right) \quad \text{bits/s/Hz.} \tag{2.8}$$

$$r_{(i,j,k)} = r_i^N + r_j^N + r_k^N \quad \text{bits/s/Hz.} \tag{2.9}$$

where r_i^N, r_j^N, and r_k^N are achievable data rates of UE_i, UE_j, and UE_k, respectively in power domain downlink NOMA. ξ denotes the total transmit SNR, i.e. $\frac{P}{\sigma_n^2}$. The sum of the power coefficients gives 1, i.e. $\beta_i + \beta_j + \beta_k = 1$. Finally $r_{(i,j,k)}$ represents the achievable data rate of the ordered triple (i, j, k) which is selected by the TFS algorithm.

In order to study the performance of the TFS algorithm for NOMA, bucket-based TFS algorithm for single user is proposed as the conventional OMA in which at τ only a single UE can be served by BS [24]. Since power allocation is not the main purpose of this study, the allocated power coefficients for UEs in NOMA is calculated by using the power allocation mechanism in [27] for TFS algorithm for pair selection and in [28] for TFS algorithm for an ordered triple selection. The details of the fair power allocation for downlink NOMA will be explained in the following section.

2.1 Fair Power Allocation for Downlink NOMA

Each UE in the power domain downlink NOMA requires a fractioned power as it was explained in Chapter 2. The proposed fair power allocation method [27] provides an interval for power coefficients of each UE which assures that each UE in the selected pair has a capacity at least the capacity that it can achieve when OMA is used. For each slot in TFS algorithm, interval of power coefficients for UEs in all possible pair sets are calculated.

The power region is calculated by using the following steps. Assume that there are two UEs in the system, i.e. UE_1 and UE_2 and the channel gains are represented by h_1 and h_2. Also assume that UE_2 has larger channel gain than UE_1 which means $|h_2|^2 > |h_1|^2$. UE_2 applies SIC and removes interference from UE_1 and UE_1 experiences interference from UE_1. Then as it was shown in Equation 1.3 and Equation 1.2,

$$C^{O}_{UE_n} = \frac{1}{2}\log_2\left(1 + \xi|h_n|^2\right) \quad \text{bits/s/Hz.} \tag{2.10}$$

$$C^{N}_{UE_1} = \log_2\left(1 + \frac{\beta_1\xi|h_1|^2}{\beta_2\xi|h_1|^2 + 1}\right) \quad \text{bits/s/Hz.} \tag{2.11}$$

$$C^{N}_{UE_2} = \log_2\left(1 + \beta_2\xi|h_2|^2\right) \quad \text{bits/s/Hz.} \tag{2.12}$$

where ξ represents the SNR, h_n denotes the channel gain for the UE_n where $n = 1, 2$ and $\beta_1 + \beta_2 = 1$. $C^{N}_{UE_1}$ and $C^{N}_{UE_2}$ represents the achievable rate for downlink NOMA of UE_1 and UE_2, respectively. Finally $C^{O}_{UE_n}$ shows the achivable capacity of UE_n when OMA is used, for this case each UE can access the channel only half of the time [27].

The main idea of the proposed fair power allocation algorithm is to satisfy the following inequalities, $C^{N}_{UE_1} \geq C^{O}_{UE_1}$ and $C^{N}_{UE_2} \geq C^{O}_{UE_2}$ where each UE in NOMA will have capacity at least they can achieve when conventional OMA is applied. Following inequalities give upper and lower boundaries for β_2 where β_1 can be calculated directly by $1-\beta_2$.

For $C^N_{UE_1} \geq C^O_{UE_1}$,

$$\log_2\left(1+\frac{\beta_1\xi|h_1|^2}{\beta_2\xi|h_1|^2+1}\right) \geq \frac{1}{2}\log_2\left(1+\xi|h_1|^2\right). \tag{2.13}$$

As the solution steps of the inequality (Equation 2.13) are shown in Appendix A, following upper bound is found for power coefficient.

$$\frac{\sqrt{\left(1+\xi|h_1|^2\right)}-1}{\xi|h_1|^2} \geq \beta_2. \tag{2.14}$$

For $C^N_{UE_2} \geq C^O_{UE_2}$,

$$\log_2\left(1+\beta_2\xi|h_2|^2\right) \geq \frac{1}{2}\log_2\left(1+\xi|h_2|^2\right). \tag{2.15}$$

As the solution steps of the inequality (Equation 2.15) are shown in Appendix A, following lower bound is found for power coefficient.

$$\beta_2 \geq \frac{\sqrt{\left(1+\xi|h_2|^2\right)}-1}{\xi|h_2|^2}. \tag{2.16}$$

In addition to this interval, it is suggested that the upper bound also maximizes the summation of the capacities, so the power value for β_2 is selected as it is equal to the value of the upper bound as stated in Equation 2.14.

For an ordered triple similar power allocation approach is proposed in [28], but the closed-form expression cannot be found. Assume that there are K UEs in the system and the channel gains are ordered as $|h_1|^2 < \ldots < |h_K|^2$.

$$C^O_{UE_k} = \frac{1}{K}\log_2\left(1+\xi|h_k|^2\right) \quad \text{bits/s/Hz}. \tag{2.17}$$

$$C^N_{UE_k} = \log_2\left(1 + \frac{\beta_k \xi |h_k|^2}{1 + \xi |h_k|^2 \sum_{l=k+1}^{K} b_l}\right) \quad \text{bits/s/Hz}. \tag{2.18}$$

where in both equations, K represents the total UEs where in the case of triple $K = 3$, ξ denotes the total transmit SNR, h_k is the channel gain for the UE_k where $k = 1, 2, 3$. β_k shows the power coefficient of the UE_k.

It is stated in [28] that, the power allocation coefficient of the UE with weaker channel gains depends on power allocation coefficient of the stronger UE. Thus, the power allocation process starts with the strongest UE where it does not experience any interference and power value is assigned to this UE to satisfy the condition of having capacity at least it is equal to the OMA capacity and the same process will continue till weakest UE in the ordered triple. First and second strongest UEs' power coefficients will be found by this method and $1 - \beta_1 - \beta_2$ will give the power coefficient of the weakest UE in selected triple.

2.2 TFS Algorithm for Single User Selection

Assume that the BS is located at the center of the circular cell and there are N numbers of UEs in the system and uniformly distributed around the BS. Each UE denoted as UE_i where $i = 1, 2, 3, ..., N$. Let w_i be the positive scheduling weight for each UE_i and its value is set to $1/N$. For fairness purpose, introduce a bucket value, i.e. b_i [24], for each UE and set it to initial value, i.e. 0, at the beginning of the scheduling operation. Also define the SE for each UE, i.e. $r_i(\tau)$, which has the unit of bits/s/Hz for user UE_i at the time slot of τ.

$$r_i(\tau) = \log_2\left(1 + \xi_i(\tau)|h_i(\tau)|^2\right) \quad \text{bits/s/Hz}. \tag{2.19}$$

The Equation 2.19 shows the achievable rate for the UE_i at slot τ when OMA is used where $\xi_i(\tau)$ represents SNR and h_i denotes the channel gain of UE_i. For each time slot τ, TFS algorithm is applied and at the cell level, the BS will serve a

UE, i.e. j_i, based on the linear combination of the instantaneous SEs and current bucket values (See Equation 2.20).

$$j_i = \underset{i \in 1,2,3,\ldots,N}{argmax} \, (r_i(\tau) + \alpha b_i). \tag{2.20}$$

where $\alpha > 0$ is the TFS algorithm parameter which has an effect on the convergence time of the TFS algorithm. After determining which UE will be served at τ, following update rule is applied for bucket b.

$$b = b + w - I\{j = j_i\}. \tag{2.21}$$

As it can be seen in the Equation 2.21, a vector which has the value of 1 only at the selected UE's row is subtracted from the bucket vector of UEs and scheduling weight vector, i.e. w, is added to the all UEs' buckets. In other words, the value of 1 is subtracted from the served UE's bucket and $1/N$ is added to all buckets. So, if any UE is not served for a long period of time, the value of it's bucket will increase which increases the chance for this UE (since the linear combination of bucket and SE is increasing, (see Equation 2.20)) to be served in following slots.

Data: UEs' SEs and buckets

Result: select a single UE and update buckets

initialization;

$w = 1/N$;

for *each UE* **do**

  $b_i = 0$;

end

for τ *= 0;* τ *<simulation time;* τ *=* τ*+1* **do**

  for *each UE* **do**

    calculate indiviual SE, i.e. r_i;

  end

  find which UE will use the slot;

  $j_m = \underset{i=1,\ldots,N}{argmax}(r_i(\tau) + \alpha b_i)$;

  update rule is applied for buckets;

  $b = b + w - I(m)$;

end

Algorithm 1: TFS Algorithm for Single UE Selection

2.3 TFS Algorithm for Pair Selection

Apart from the single UE selection, a pair selection TFS algorithm is proposed for power domain downlink NOMA in which an ordered pair will be served at the slot τ. Following steps summarize the working principle of the TFS algorithm for pair selection.

- At the beginning of the scheduling operation, weight vector is introduced, i.e. $w = 1/N$, and buckets of UEs set to 0.
- For every τ, individual SEs (See Equation 2.2), i.e. r_i, and pair-wise SEs (See Equation 2.3 and Equation 2.4), i.e. $r_{(i,j)}$, are calculated.
- In order to decide which pair will use the slot at τ, find the maximum value of the linear combination of pair-based SEs and buckets, i.e. $r_{(m,n)}$.

- By comparing the maximum value of the linear combination of single UE, i.e. r_m, and maximum value of the linear combination of the pair, i.e. $r_{(m,n)}$, decide an individual or a pair will be served.

- If $r_{(m,n)}$ has the maximum value, update the bucket of each UE by subtracting 1 from each UE in the pair and add $2w$ to all UEs' buckets, otherwise apply the update rule of the TFS algorithm for single user selection.

Data: UEs' SEs and buckets
Result: select a UE or a pair and update buckets
initialization;
$w = 1/N$;
for *each UE* **do**
    $b_i = 0$;
end
for $\tau = 0$; $\tau <$ *simulationtime*; $\tau = \tau + 1$ **do**
    for *each UE* **do**
        calculate indiviual SE, i.e. r_i;
    end
    find which UE will use the slot;
    $j_m = \underset{i=1,\ldots,N}{argmax}(r_i(\tau) + \alpha b_i)$;
    for *each pair* **do**
        calculate pair-based SEs, i.e. $r_{(i,j)}$;
    end
    find which UE pair will use the slot;
    $j_{(m,n)} = \underset{(i,j)pairs \in P}{argmax}\,(r_{(i,j)}(\tau) + \alpha(b_i + bj))$;
    if $j_{(m,n)} \geq j_{(m)}$ **then**
        pair will be served update rule is applied;
        $b = b + 2w - I((m,n))$;
    end
    else
        single user will be served update rule is applied;
        $b = b + w - I(m)$;
    end
end

Algorithm 2: TFS Algorithm for Pair Selection in NOMA

2.4 TFS Algorithm for Triple Selection

Most of the works on power domain downlink NOMA covers pair selection. However, in this work, apart from single UE and pair selection, TFS algorithm is proposed for triple selection which can select an ordered triple at any τ. Following steps summarize the working principle of the TFS algorithm for triple selection.

- At the beginning of the scheduling operation, weight vector is introduced, i.e. $w = 1/N$, and buckets of UEs set to 0.
- For every τ, individual SEs (See Equation 2.2), i.e. r_i, pair-wised SEs (See Equation 2.3 and Equation 2.4), i.e. $r_{(i,j)}$, and ordered triple SEs (See Equation 2.6, Equation 2.7, and Equation 2.8), i.e. $r_{(i,j,k)}$, are calculated.
- In order to decide which triple will use the slot at τ, find the maximum value of the linear combination of triple-based SEs and buckets, i.e. $r_{(m,n,l)}$.
- By comparing the maximum value of the linear combination of single UE, i.e. r_m, pair, i.e. $r_{(m,n)}$, and triple, i.e. $r_{(m,n,l)}$ decide an individual or a pair or a triple will be served.
- If $r_{(m,n,l)}$ has the maximum value, update the bucket of each UE by subtracting 1 from each UE in the triple and add $3w$ to all UEs' buckets, otherwise apply the update rule of the TFS algorithm for single user selection or pair selection by looking at which one is served.

Data: UEs' SEs and buckets

Result: select a UE or a pair or triple and update buckets

initialization;

$w = 1/N$;

for *each UE* **do**

  $b_i = 0$;

end

for $\tau = 0$*;* $\tau <$ *simulationtime;* $\tau = \tau + 1$ **do**

  for *each UE, each pair, each triple* **do**

    calculate indiviual SE, i.e. r_i;

    calculate pair-based SEs, i.e. $r_{(i,j)}$;

    calculate triple-based SEs, i.e. $r_{(i,j,k)}$;

  end

  $j_m = \underset{i=1,\ldots,N}{argmax}(r_i(\tau) + \alpha b_i)$;

  $j_{(m,n)} = \underset{(i,j) pairs \in P}{argmax} (r_{(i,j)}(\tau) + \alpha(b_i + bj))$;

  $j_{(m,n,l)} = \underset{(i,j,k) triples \in T}{argmax} (r_{(i,j,k)}(\tau) + \alpha(b_i + b_j + b_k))$;

  if $j_{(m,n,l)} == \max(j_{(m,n,l)}, j_{(m,n)}, j_m)$ **then**

    triple will be served update rule is applied;

    $b = b + 3w - I((m,n,l))$;

  end

  else if $j_{(m,n)} == \max(j_{(m,n,l)}, j_{(m,n)}, j_m)$ **then**

    pair will be served update rule is applied;

    $b = b + 2w - I((m,n))$;

  end

  else

    single user will be served update rule is applied;

    $b = b + w - I(m)$;

  end

end

Algorithm 3: TFS Algorithm for Triple Selection

As stated before, Algorithm 1 helps to select a single UE which can be seen as the conventional OMA. However, for power domain downlink NOMA, at any slot, Algorithm 2, and Algorithm 3 are applied for pair selection and triple selection, respectively. Subsequently, the effectiveness of the TFS algorithm for power domain downlink NOMA will be studied by comparing the average system capacities of the proposed algorithms for OMA and NOMA.

In these algorithms, updated buckets are not growing up to plus or minus infinity, they are bounded which indicates that temporal fairness constraint can be reached. The value of the parameter α in these algorithms has an effect on the convergence time. When the parameter α is increased, algorithms will give more emphasize to the buckets of UEs which helps to have shorter convergence time but the average system capacity will decrease. On the opposite side, when the value of the parameter α is decreased, it will take more time to converge, but the average system capacity will increase. So there is a trade-off between convergence time and average system capacity which will be investigated in the following chapter.

Chapter 3

Simulation Study of OMA and NOMA System Capacities

In order to assess the performance of the proposed TFS algorithms, a simulation setup with a single cell is constructed and average system capacities are obtained to validate the effectiveness of the TFS algorithm for NOMA (Algorithm 2 and Algorithm 3) by comparing with OMA (Algorithm 1). A BS is located at the center of the single cell and UEs are distributed uniformly at random around the BS. A broad range of UEs are used to observe the effect of UE based performance. The channels of UEs are assumed to have a Rayleigh distribution. The system frequency is assumed to be 2.5 GHz and BW is set to 10 MHz. Noise power spectral density is assumed to be -174 dBm/Hz. The used path-loss model is $128.1 + 37.6\log_{10}(d)$ where d is in km which of these parameters were obtained from macro cell parameters.

As explained before (in Section 2.1), for downlink power domain NOMA, fair power allocation method is applied. In addition to that, for NOMA, it is assumed that strong UEs in pair and triple performs SIC without any error. Moreover, NOMA in this thesis assumes that the user selection set consists of N individual UEs and all pair possibilities, i.e. $\binom{N}{2}$ pairs. In order to decrease the complexity more (from $\mathcal{O}(N^2)$ to $\mathcal{O}(N)$) in pair construction, NOMA* is proposed in [29] that, UEs are ordered according to their SNR values and the highest SNR valued UE will be paired with the lowest UE and second highest with second lowest and etc. Also, for TFS algorithm for triple selection, NOMA-T* is proposed by using the ordering principle in [29] where UEs are ordered according to their SNR values and split into three main clusters. First member in the first cluster, i.e. UE_1, first member in the second cluster, i.e. $UE_{(N/3)+1}$, and the last member of the third cluster, i.e. UE_N, are constructing an ordered triple and so on (See Section 3.6).

For Section 3.1, Section 3.2, and Section 3.3 the radius of the cell, i.e. R, is set to 300 meters. Also in these sections, the transmit power of the BS, i.e. P, is calculated as the UE at boundary, i.e. at 300 meters away from BS, experiences 10 dB SNR. So, these variables kept constant and different UEs (4, 16, 32, and 64) are used to determine the algorithm parameter α for different UE based scenarios (Section 3.1) and the performance of the TFS algorithm for pairs (Section 3.2 covers all pairs case (NOMA), Section 3.3 examines the effect of pre-pair construction (NOMA*)) are analyzed.

In Section 3.4, the effect of the coverage radius of the BS is studied by assigning different radius values from 100 to 500 meters. For this section, in order to keep the transmit power of the BS constant for all radii by setting the SNR value of UE at 100 meters to 10 dB. For Section 3.5, the effect of the transmit power of BS is observed by altering the SNR value of UEs from 5 to 15 dB.

Moreover, in the last section, performance of the TFS algorithm for triple selection is compared with TFS algorithm for pair selection and TFS algorithm for single UE selection. In order to construct both pair and triple sets from UEs, number of UEs are set to 18, 36, and 72 where these values are multiple of both 2 and 3. Thus, the average system capacities of NOMA*, NOMA-T*, and OMA will be used to observe whether applied TFS algorithm for ordered triple in NOMA is improved the average system capacity or not.

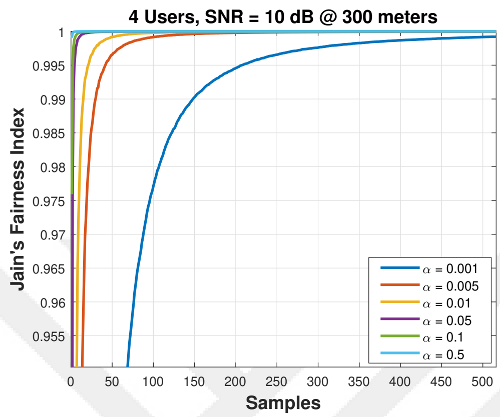
Wireless Model		
Cell Radius	R	100-500 m
Bandwidth	BW	10 MHz
System Frequency	Fs	2.5 GHz
UEs for Pair	N	4, 16, 32, 64
UEs for Triple	N	18, 36, 72
Noise Spectral Density	NSD	-174 dBm/Hz
Path Loss Model	PL	128.1+37.6log(d in km)

Table 3.1: Summary of the Used Wireless Model

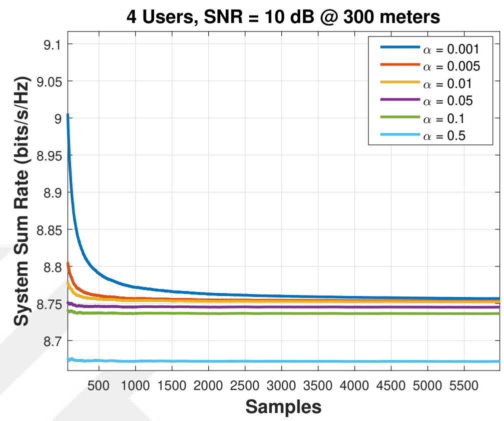
3.1 Finding the Algorithm Parameter α for TFS Algorithms

The algorithm parameter α is a combining factor for the TFS algorithms, which is used in the linear combination of the instantaneous SEs and current bucket values, to determine how fast the system will reach the fairness index 1. As it can be observed from the formulas about the bucket-based TFS algorithms in Section 2, as the value of the parameter α gets larger values, algorithms give more importance to the buckets. In other words, if a UE could not be served for a long time, as its bucket value increases due to the bucket update rules in TFS algorithms, the chance of using the following source of that UE also increases. Giving more importance to bucket will degrades the effect of the instantaneous SE which may cause to reduce the overall system capacity. So, there is a trade-off between the fairness convergence time and average system capacity of the system. In order to decide which algorithm parameter α should be used for these algorithms, firstly, 10^{-4} is used as a reference value for the parameter α and overall system capacity for all UE sets are obtained by using this reference value. Since proposed TFS algorithms guarantee that for a long time system provides temporal fairness for all UEs, the parameter α is selected as maximum 1% of the system capacity is degraded by comparing with the reference parameter value of the α. For that reason, behavior of TFS algorithm for pair selection with different algorithm parameter α values are examined for 4, 8, 16, 32, and 64 UEs. The algorithm parameter α is constructed as 0.001, 0.005, 0.01, 0.05, 0.1, and 0.5

in order to observe the effect of these values on the system capacity and decide which algorithm parameter meets the condition.



(a)



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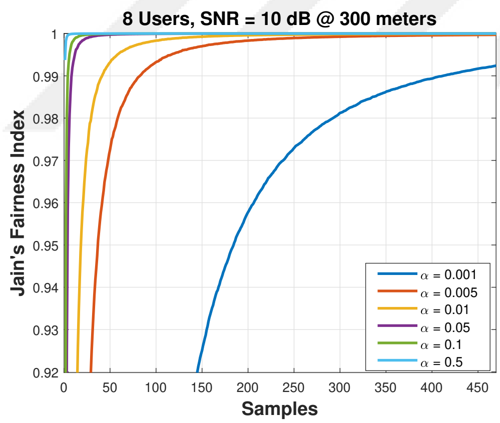
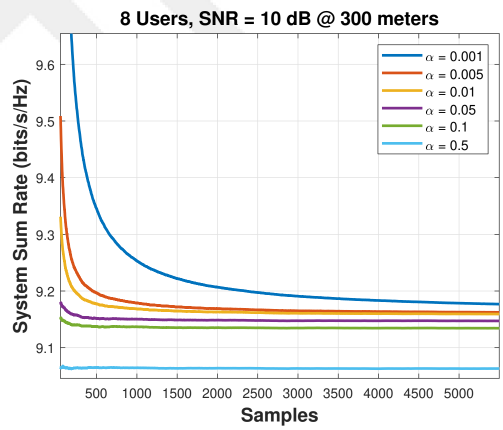


(c)



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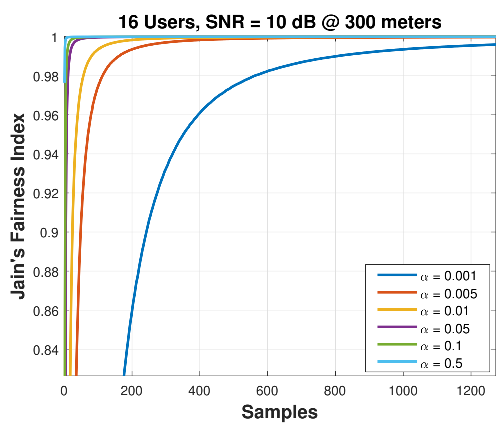
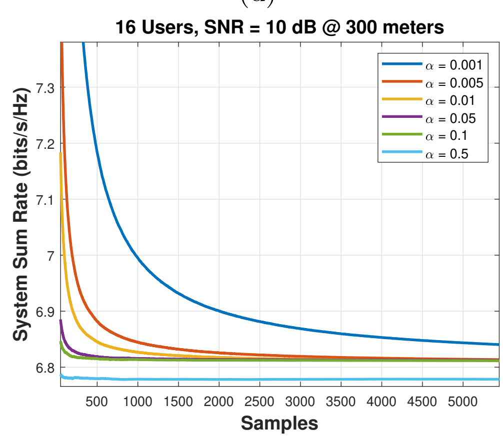
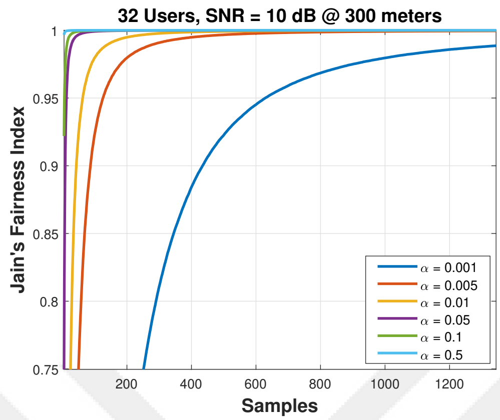


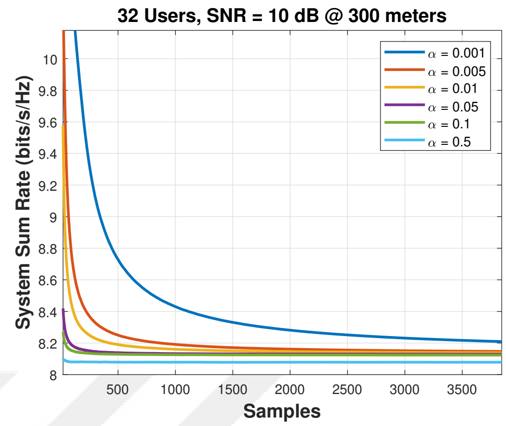
(e)



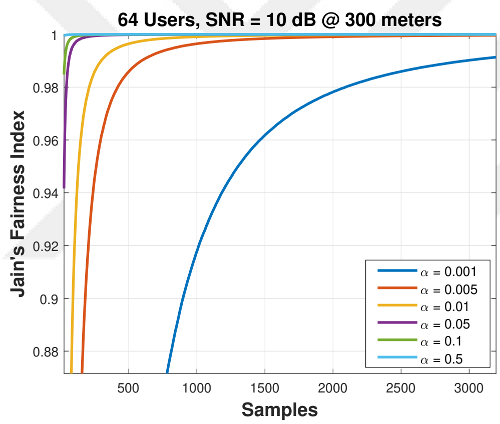
(f)



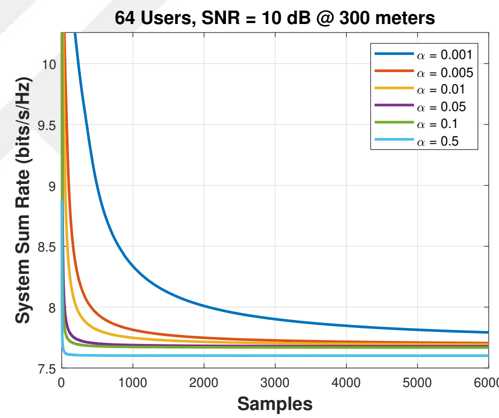
(g)



(h)



(i)



(j)

Figure 3.1: The effect of different algorithm parameters α observed in (a), (c), (e), (g), and (i) the Jain's fairness index and (b), (d), (f), (h), (j) the system sum rate for the TFS algorithm for pair selection, for the case of 4, 8, 16, 32, and 64 UEs cases, respectively.

Fig. 3.1 shows the effect of the algorithm parameter α on the fairness and the system sum rate for different UEs, where UEs are uniformly distributed around the BS with coverage radius of 300 meters and UE at 300 meters experiences 10 dB of SNR. From all sub-figures it can be concluded that for the fairness, as the parameter α gets larger values, it takes shorter time to reach Jain's Fairness Index of 1. However, as the parameter α increases, the system sum rate gets smaller value. As explained before, in order to decide the suitable value for the algorithm parameter α, 1% lost in the system sum rate is assumed as a reference value and system sum rate with different algorithm parameters are found to create the Table 3.2.

UEs	**System Sum Rate with the Parameter α**							**Reference Value**
	1e-4	**0.001**	**0.005**	**0.01**	**0.05**	**0.1**	**0.5**	**1% Loss**
4	**8.792**	**8.757**	**8.754**	**8.752**	**8.745**	**8.736**	8.672	8.704
8	**9.221**	**9.177**	**9.162**	**9.159**	**9.147**	**9.134**	9.063	9.129
16	**6.879**	**6.852**	**6.824**	**6.813**	**6.812**	6.804	6.779	6.810
32	**8.217**	**8.182**	**8.142**	**8.136**	8.129	8.124	8.078	8.135
64	**7.776**	**7.745**	**7.705**	7.693	7.678	7.668	7.601	7.698

Table 3.2: The system sum rate is obtained by using the TFS algorithm for pair (NOMA) with different algorithm parameters α for all UE cases.

The bold values in the Table 3.2 show that these values meet the condition of having at least 99% of the reference sum rate value. In addition to that, choosing the biggest parameter α in the subset helps to reach the Jain's Fair Index of 1 quicker. So, Table 3.3 is constructed to show the value of parameter α for each UE where these values are going to be used for the rest of the work.

UEs	**4**	**8**	**16**	**32**	**64**
α	0.1	0.1	0.05	0.01	0.005

Table 3.3: UE based selected the algorithm parameter α.

3.2 The Performance of the TFS Algorithm for NOMA

As the TFS algorithms were explained in the Chapter 2, the bucket-based TFS algorithm for single user selection is assumed as OMA and the bucket-based TFS algorithm for pair selection is assumed as NOMA. These algorithms are applied in this section for 4, 16, 32, and 64 UEs scenarios. For the simulation setup, all UEs are distributed uniformly at random around the BS between 20-300 meters and UE at 300 meters, i.e. UE at boundary, experiences 10 dB SNR so the power of BS is calculated accordingly. The other parameters for the simulation are used as they were summarized in Table 3.1. The analysis metric is the normalized ratio between the average system capacities of NOMA and OMA which shows the percentage improvement of the average system capacity.

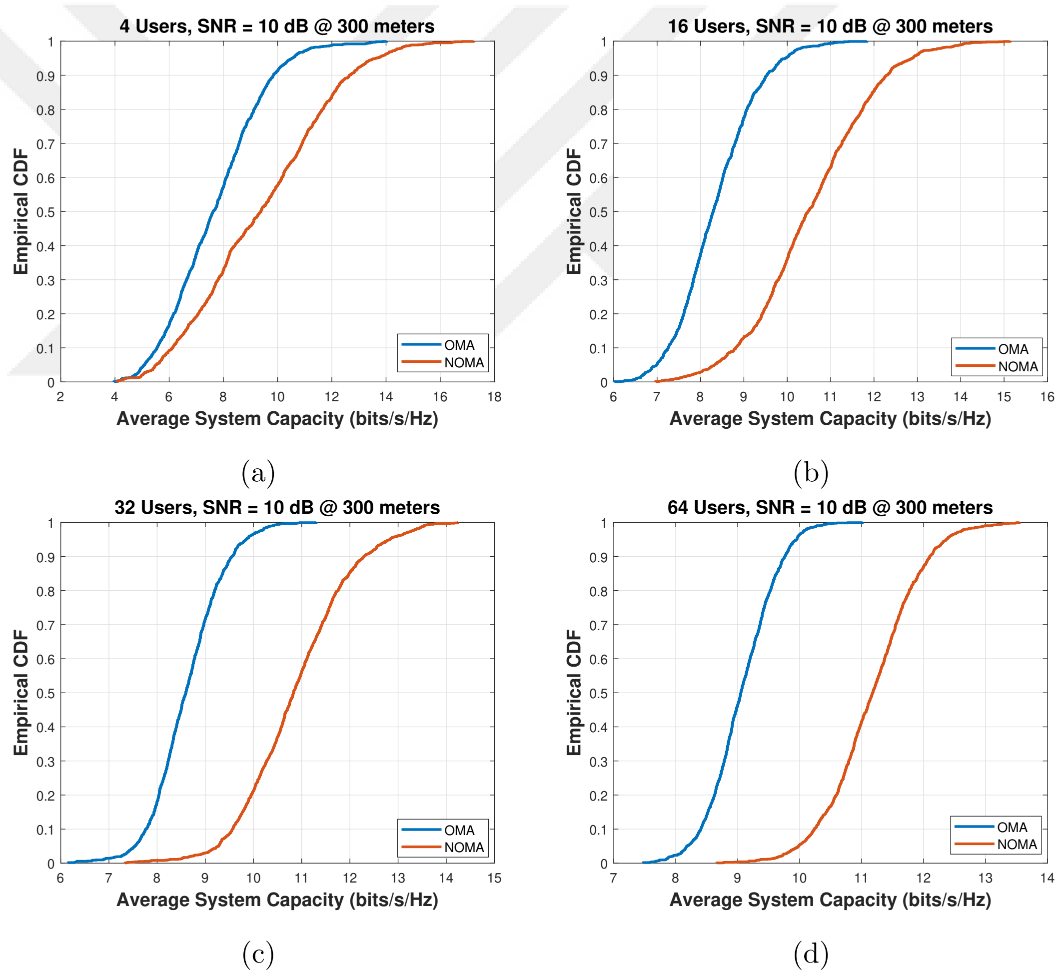


Figure 3.2: ECDF of the average system capacity of OMA and NOMA obtained by the TFS algorithm for the case of 4, 16, 32, and 64 UEs where SNR of the UE at 300 meters is set to 10 dB.

Fig 3.2 shows the empirical cdf of the average system capacities of OMA and

NOMA cases for different UEs cases. It is clearly observed that, as the number of UEs increase, the space between the ecdf of NOMA and OMA curves increases. It can be concluded that for large number of UEs, applying NOMA is more beneficial where the set of the possible choices (individuals and pairs) becomes larger.

From Fig. 3.2a, the mean of the average system capacities were found as 7.68 bits/s/Hz and 9.48 bits/s/Hz for OMA and NOMA, respectively where the improvement of the average system capacity of NOMA can be calculated as 23.44% for the case of 4 UEs. From Fig. 3.2b the percentage improvement of the average system capacity of NOMA can be calculated as 26.45% where the mean of the average system capacities of OMA and NOMA are 8.33 bits/s/Hz and 10.52 bits/s/Hz, respectively. Moreover, by the help of Fig. 3.2c and Fig. 3.2d the percentage improvement of the average system capacity of NOMA for 32 and 64 UEs scenarios can be found as 26.95% and 26.83%, respectively.

Apart from the average system capacity improvement, emprical cdfs of the UE-based improvement for different UE cases are shown in Fig. 3.3. As the number of UEs increases, UE-based capacity improvement also increases. Moreover, for small number of UEs, even applying NOMA improves the average system capacity, the UE-based capacity of the some UEs decreases. However, average UE-based capacity improvement for 4, 16, 32, and 64 UEs cases are calculated as 17.26%, 22.30%, 23.20%, and 24.53%, respectively.

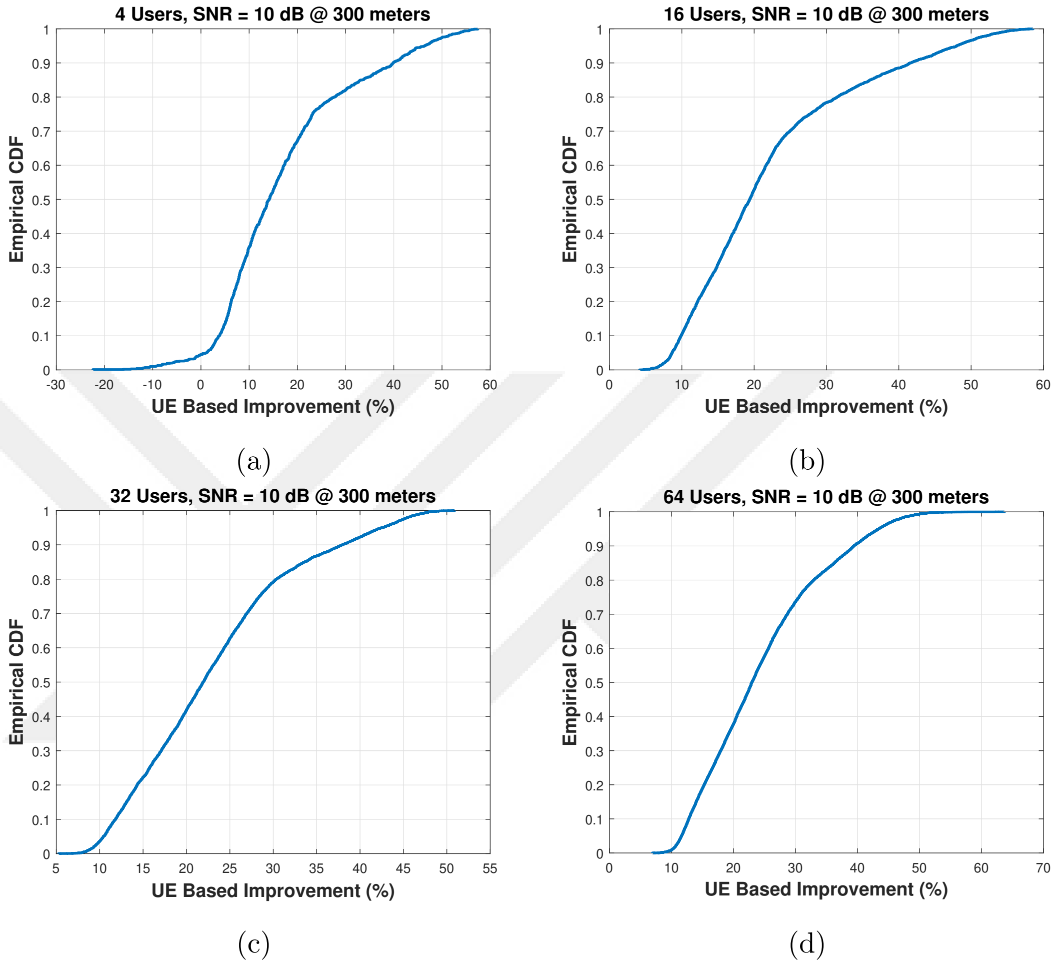


Figure 3.3: ECDF of the UE-based improvement of NOMA with respect to OMA for the case of 4, 16, 32, and 64 UEs where SNR of the UE at 300 meters is set to 10 dB.

3.3 The Performance of the TFS Algorithm for NOMA*

In previous sections, for NOMA, a pair was selected from $\binom{N}{2}$ pairs which can increase the computational complexity as the number of users increases. Instead of having $\binom{N}{2}$ pairs, $N/2$ pairs may help to decrease the computational complexity of the scheduler from $\mathcal{O}(N^2)$ to $\mathcal{O}(N)$. For this reason, a new pair construction method is proposed in [29] where UEs are ordered according the their SNR values and split into two clusters. First member in the first cluster, i.e. UE_1, will be paired with the last member of the second cluster, i.e. UE_N, and UE_2 will be paired with UE_{N-1} and so on as seen in the Fig. 3.4.

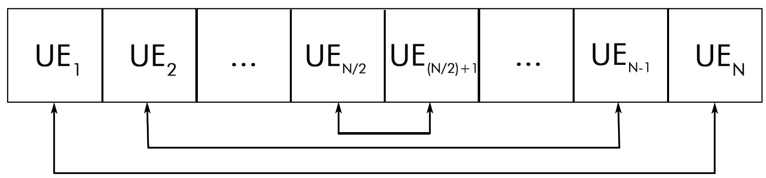


Figure 3.4: The proposed pre-pair construction method for downlink NOMA for N UEs.

In addition to this clustering, UEs can be clustered as the first member in the first cluster, i.e. UE_1 will be paired with the first member in the second cluster, i.e. $UE_{(N/2)+1}$ and the second member of the first cluster, i.e. UE_2 will be paired with the second member of the second cluster, i.e. $UE_{(N/2)+2}$ and so on as seen in the Fig. 3.5.

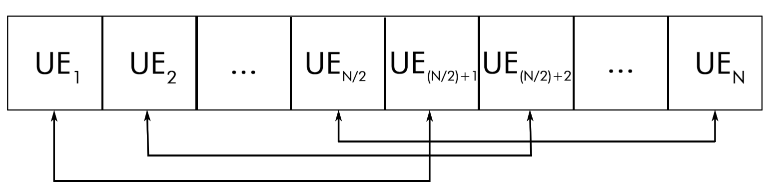
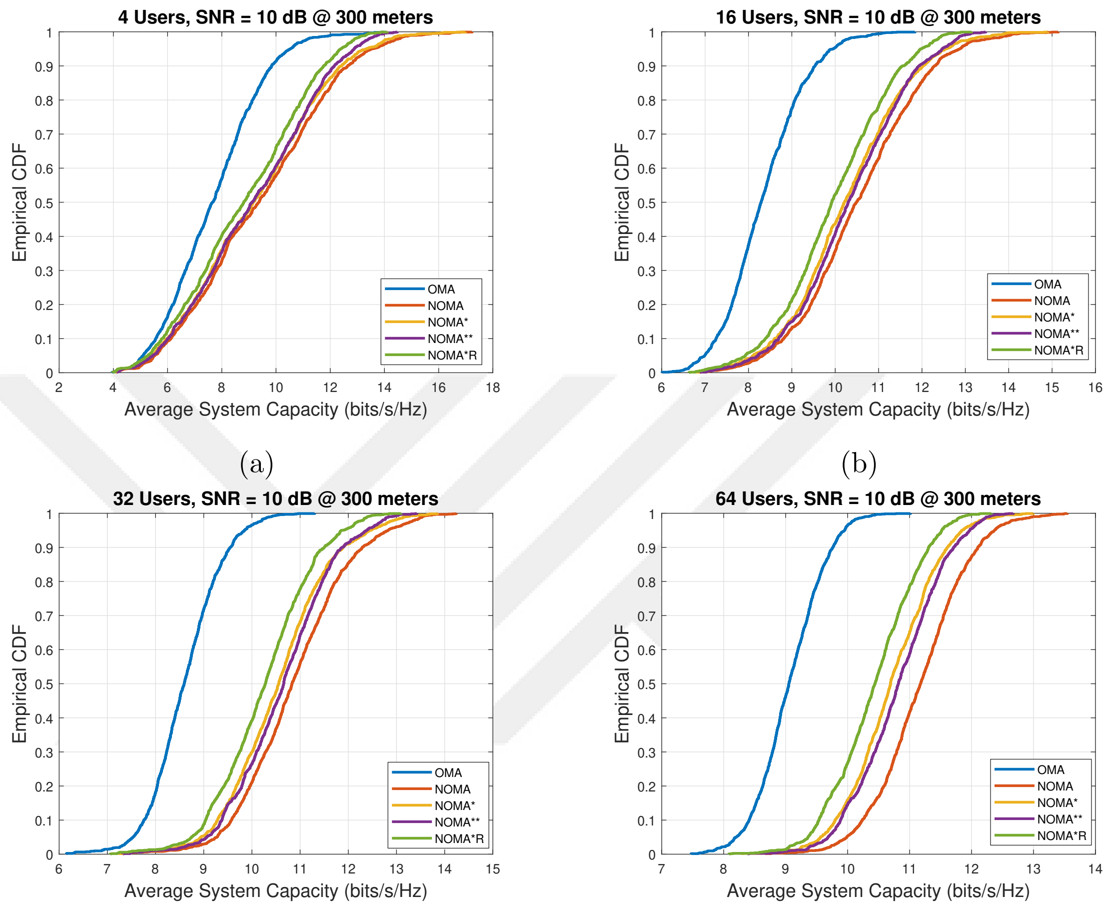


Figure 3.5: Another proposed pre-pair construction method for downlink NOMA for N UEs.



(a) (b) (c) (d)

Figure 3.6: ECDF of the average system capacities of TFS algorithms for OMA, NOMA, NOMA*, NOMA**, and NOMA*R with 4 UEs (a), 16 UEs (b), 32 UEs (c), and 64 UEs (d) cases where for all cases UE at 300 meters experiences 10 dB SNR.

The proposed pairing in downlink NOMA in Fig. 3.4 is assumed as NOMA* and in Fig. 3.5 is assumed as NOMA**. In addition to that, a random pre-pair construction method is used as a benchmark and this pairing is assumed as NOMA*R. As seen in the Fig. 3.6, when NOMA*, NOMA** and NOMA*R are applied in TFS algorithm for pair selection, the average system capacity decreasing by comparing the NOMA with all pairs. Since these pairings create less number of pair sets while reducing the complexity, it can be acceptable to observe decrease in the average system capacity. The increase in number of UEs in the system increases the spacing between all pairs and pre-pair constructions, due to the significant reduction of the number of pairs. For instance, NOMA in 4 UE creates 6 pairs whereas pre-pair construction methods create 2 pairs, however, as the number of UE is increased to 64, instead of having 2016 pairs, NOMA* provides 32 pairs for each run.

For 4 UEs case, i.e. Fig. 3.6a, the mean value of the average system capacity for OMA is 7.68 bits/s/Hz, for NOMA is 9.48 bits/s/Hz, and for NOMA*, NOMA**, NOMA*R are 9.13 bits/s/Hz, 9.11 bits/s/Hz, and 8.90 bits/s/Hz, respectively. So, the average system capacity improvement of NOMA, NOMA*, NOMA**, and NOMA*R by comparing with OMA can be calculated as 23.44%, 18.89%, 18.62%, and 15.90%, respectively. Similarly, Fig. 3.6b represents 16 UEs case where the average system capacity improvement can be found as 26.29%, 22.69%, 23.77%, and 19.45% for NOMA, NOMA*, NOMA**, and NOMA*R, respectively.

In addition to these results, 32 UEs case and 64 UEs case can be seen in Fig. 3.6c and Fig. 3.6d, respectively. For 32 UEs the capacity improvement can be calculated as 26.95%, 21.35%, 23.80%, and 19.95% for NOMA, NOMA*, NOMA**, and NOMA*R, respectively. Finally, for 64 UEs case the capacity improvements are calculated as 26.83%, 20.51%, 21.40% and 16.52% for NOMA, NOMA*, NOMA**, and NOMA*R, respectively by comparing with OMA.

Table 3.4 is summarizes the results of average system capacity improvements of NOMA, NOMA*, NOMA** and NOMA*R by comparing with OMA for different UEs scenarios. In all scenarios, UEs are uniformly distributed around the BS where BS has coverage radius of 300 meters. Also, UE at 300 meters experiences 10 dB SNR is another assumption in these simulations.

UEs	Scheme	Percentage Gain
4	**NOMA**	23.44
	NOMA*	18.89
	NOMA**	18.62
	NOMA*R	15.90
16	**NOMA**	26.29
	NOMA*	22.69
	NOMA**	23.77
	NOMA*R	19.45
32	**NOMA**	26.95
	NOMA*	21.35
	NOMA**	23.80
	NOMA*R	19.95
64	**NOMA**	26.83
	NOMA*	20.51
	NOMA**	21.40
	NOMA*R	16.52

Table 3.4: Percentage gain of the average system capacities of applied TFS algorithm for pair selection of NOMA, NOMA*, NOMA**, and NOMA*R by comparing with TFS algorithm for single user selection (OMA) where SNR value of the UE at 300 meters is 10 dB.

As it can be seen from the Table 3.4 NOMA* and NOMA** have larger percentage gain by comparing with NOMA*R. The percentage gain of the NOMA** is slightly larger than NOMA*, but for 4 UEs case, NOMA* has the largest percentage gain. For the remainder of this work, NOMA* will be used as the pre-pair construction method to decrease the computational complexity.

3.4 The Effect of the BS Coverage Radius on the TFS Algorithms

To be able to observe the effect of the coverage radius of the BS on the TFS algorithms, the power of the BS is fixed by setting the SNR of the UE at 100 meters to 10 dB in simulation. As an example, the Fig. 3.7 is created to show the ecdf of the average system capacities of OMA and NOMA with different coverage radii of BS for 32 UEs case. For the 100 meters coverage radius, from Fig. 3.7, the ratio between the mean of the average system capacities of NOMA and OMA is calculated as 19.35%. As the coverage radius increases, for instance set coverage radius to 500 meters, this ratio becomes 42.01% which shows that increase in the coverage radius of the BS helps NOMA to have higher percentage improvement.

For smaller coverage radius of the BS, most of the UEs experience better channel conditions where applying NOMA to these UE sets will not cause so much improvement in the average system capacity. However, by the effect of increase in the coverage radius of the BS, variety of channels and SNR values among UE sets increase which help NOMA to perform better.

Apart from 32 UEs scenario with 100 and 500 meters radii, the TFS algorithm for pair selection is applied for 4, 16, 32, and 64 UEs cases where the radius of the BS gets value from 100 to 500 meters with 50 meters steps. Also, the proposed pre-pair construction method, i.e. NOMA*, is implemented for different coverage radii of the BS and the following table (Table 3.5) is presented to summarize the percentage improvement of the NOMA and NOMA* by comparing with OMA for different UEs and coverage radii scenarios.

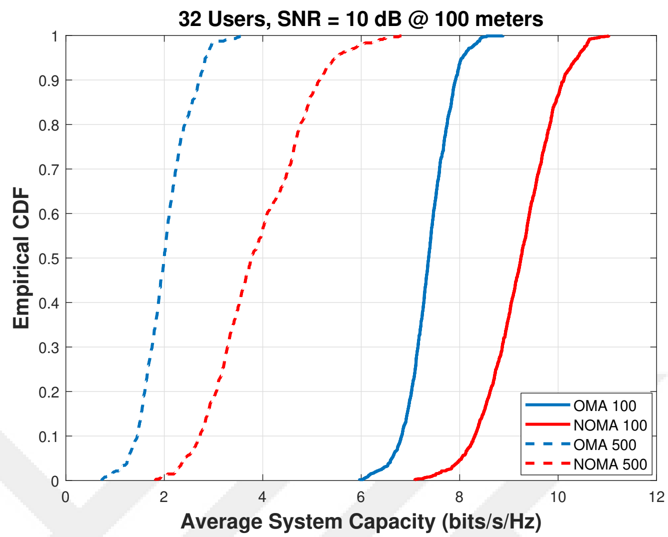


Figure 3.7: ECDF of the average system capacities of NOMA and OMA with different coverage radii for 32 UEs case where SNR of the UE at 100 meters is set to 10 dB.

Percentage Gain						
UE	**Scheme**	**Coverage Radius (meters)**				
		100	**200**	**300**	**400**	**500**
4	**NOMA**	16.49	23.75	28.15	31.69	35.59
	NOMA*	12.33	21.18	24.69	27.38	30.35
16	**NOMA**	18.92	28.97	33.34	36.20	40.29
	NOMA*	16.19	26.04	29.91	31.57	34.53
32	**NOMA**	19.35	29.93	34.21	37.62	42.01
	NOMA*	14.82	23.10	26.17	29.49	33.27
64	**NOMA**	19.01	29.04	34.21	36.37	40.85
	NOMA*	14.18	21.95	25.79	27.60	31.05

Table 3.5: Effect of the coverage radii of the BS on the percentage improvement of the average system capacities where TFS algorithm for pair selection is applied in both NOMA and NOMA* by comparing with TFS algorithm for single user selection (OMA) where the SNR of UE at 100 meters is set to 10 dB.

One of the most important observation from the table is that, as the value of the radius of the BS increases, the difference between the improvement of NOMA* and NOMA also increases. Because, NOMA covers all pair scenarios, it is most likely to schedule suitable UEs, however NOMA* loses the precision in pairing which may cause to decrease in the improvement.

In addition to the previous scenario, for different radii, the power of the BS is selected as the UE at the boundary experiences 10 dB SNR. By using this setup, effect of the coverage radius is observed and as an example, ecdf of average system capacity of 32 UEs case is shown in the Fig. 3.8 and the ratio between the average system capacities of NOMA and OMA are calculated as 19.32% and 29.32% for 100 and 500 meters, respectively. For different UEs and different coverage radii, obtained results for this setup are presented at Table 3.6.

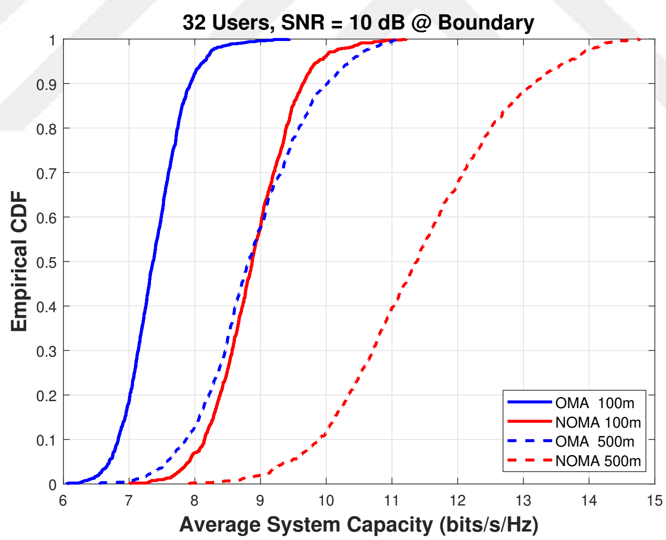


Figure 3.8: ECDF of the average system capacities of NOMA and OMA with different coverage radii for 32 UEs case where SNR of the UE at boundary is set to 10 dB.

Percentage Gain						
UE	**Scheme**	**Coverage Radius (meters)**				
		100	**200**	**300**	**400**	**500**
4	**NOMA**	16.01	22.08	23.44	23.87	25.49
	NOMA*	13.87	17.44	18.93	19.27	20.79
16	**NOMA**	18.73	24.43	26.24	27.51	28.08
	NOMA*	15.96	21.30	22.75	23.79	24.21
32	**NOMA**	19.31	25.16	26.90	28.10	29.32
	NOMA*	14.69	19.64	21.39	22.61	23.45
64	**NOMA**	19.28	25.09	26.79	27.56	28.38
	NOMA*	15.38	19.09	20.46	21.63	22.08

Table 3.6: Effect of the coverage radii of the BS on the percentage improvement of the average system capacities where TFS algorithm for pair selection is applied in both NOMA and NOMA* by comparing with TFS algorithm for single user selection (OMA) where the SNR of UE at boundary is set to 10 dB.

Table 3.6 shows that, increase in the radius of the BS increases the percentage gain for all UEs. Since the SNR value of the boundary UE is set to 10 dB, UEs experience better channel conditions comparing with the previous setup which may cause to have less percentage gain for both NOMA and NOMA*. Also, in this scenario, the difference between the percentage gain of NOMA and NOMA* is also increasing but this time the amount of the difference is smaller.

3.5 The Effect of the BS Transmit Power on the TFS Algorithms

In this section, the effect of the transmit power of the BS is observed by altering the SNR value of UEs at 100 meters and at boundary to create different scenarios. Since the noise figure in the system is kept constant, altering SNR value, i.e.

5, 10, and 15 dB, has impact on transmit power of the BS. Moreover, miscellaneous results are obtained by changing both SNR and coverage radii of the BS to summarize the overall performance of the TFS algorithm for pair selection.

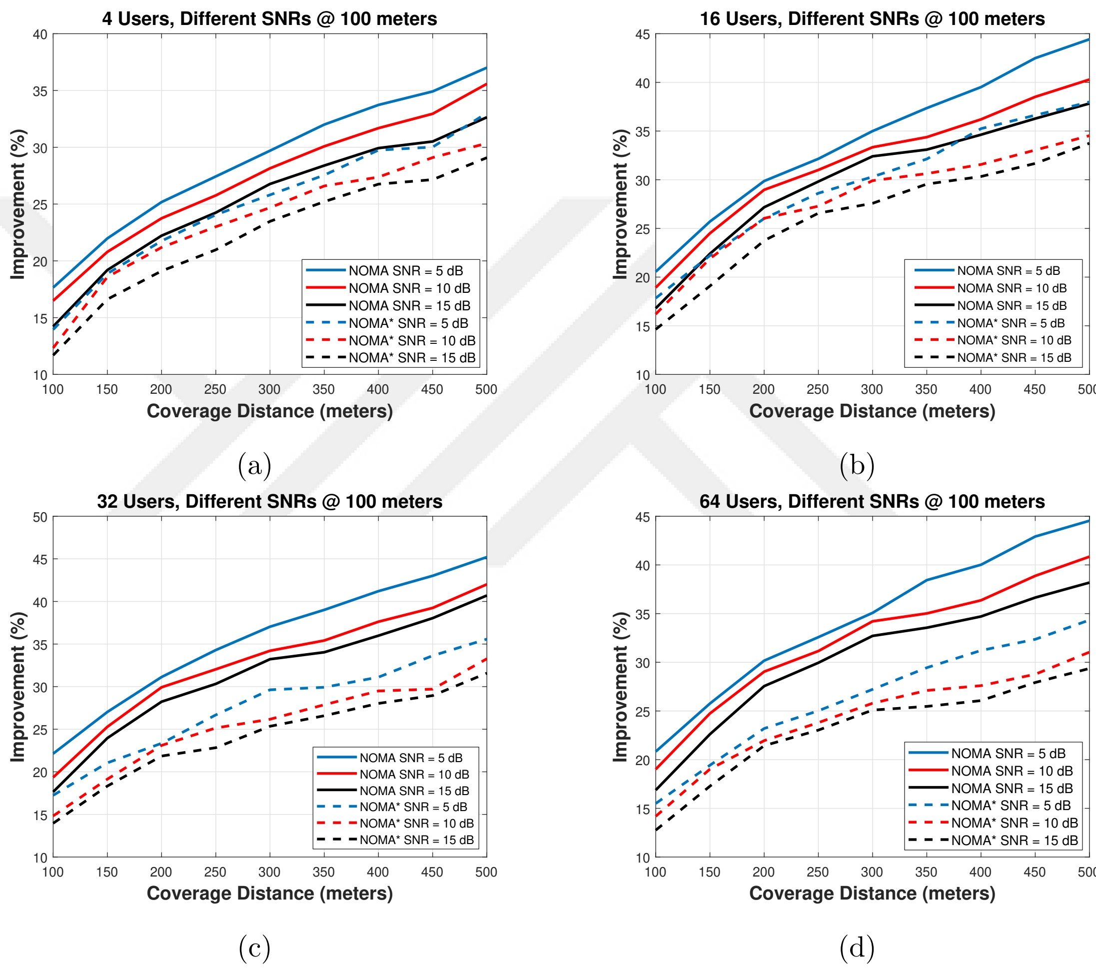


Figure 3.9: Percentage improvement of the average system capacities of the applied TFS algorithm for pair selection for both NOMA and NOMA* by comparing with the TFS algorithm for single user selection, i.e. OMA, for 4, 16, 32, and 64 UEs cases where the SNR of the UEs at 100 meters is set to 5, 10, and 15 dBs.

From the Fig. 3.9, it can be concluded that the increase in the SNR value of the UEs at 100 meters decrease the percentage improvement of both NOMA and NOMA* since UEs experience better channel conditions as the SNR value increases. Also, as it was observed in previous section, for all SNR values, increase in the coverage radius help NOMA and NOMA* to achieve more percentage improvement. Following table (Table 3.7) shows the percentage gain results obtained for different UEs, schemes, SNRs, and coverage radii.

Percentage Gain							
UEs	**Scheme**	**SNR (dB)**	**Coverage Radius (meters)**				
			100	**200**	**300**	**400**	**500**
4	**NOMA**	5	17.65	25.18	29.70	33.73	37.01
		10	16.49	23.75	28.15	31.69	35.59
		15	14.22	22.22	26.77	29.93	32.64
	NOMA*	5	13.95	21.75	25.81	29.75	33.01
		10	12.33	21.18	24.69	27.38	30.35
		15	11.69	19.11	23.48	26.75	29.09
16	**NOMA**	5	20.55	29.87	35.00	39.52	44.43
		10	18.92	28.97	33.34	36.20	40.29
		15	16.80	27.17	32.41	34.63	37.83
	NOMA*	5	17.84	26.01	30.31	35.25	37.99
		10	16.19	26.04	29.91	31.57	34.53
		15	14.63	23.75	27.58	30.33	33.74
32	**NOMA**	5	22.13	31.13	37.04	41.21	45.21
		10	19.35	29.93	34.21	37.62	42.01
		15	17.65	28.23	33.22	35.98	40.70
	NOMA*	5	17.24	23.35	29.63	31.11	35.58
		10	14.82	23.10	26.17	29.49	33.27
		15	13.96	21.85	25.35	28.03	31.58
64	**NOMA**	5	20.83	30.17	35.08	40.02	44.54
		10	19.01	29.04	34.21	36.37	40.85
		15	16.87	27.55	32.71	34.71	38.19
	NOMA*	5	15.50	23.20	27.22	31.22	34.34
		10	14.18	21.95	25.79	27.60	31.05
		15	12.76	21.44	25.09	26.06	29.36

Table 3.7: Overall percentage gain of the average system capacities of the applied TFS algorithm for pair selection for both NOMA and NOMA* cases by comparing with the TFS algorithm for single user selection, i.e. OMA, for 4, 16, 32, and 64 UEs cases where the SNR of the UE at 100 meters is set to 5, 10, and 15 dBs.

Instead of fixing the SNR value of the UE at 100 meters away from the BS for all UE cases, following simulation results are obtained for each coverage radius, where the SNR value of the UEs at boundary is fixed. As the value of the SNR increases, the average system capacity improvement decreases and as the coverage radius of the BS increases the average system capacity increases, which are the similar results obtained in previous simulation setups.

By comparing Fig. 3.9 and Fig. 3.10, it can be seen that slope of the graphs are smaller for all UEs and SNR values, which shows that the average system capacity obtained by fixing the SNR value of the boundary UE is smaller than fixing the SNR value of the UE at 100 meters. Moreover, Table 3.8 summarizes the percentage improvement results of all SNR values at the boundary and different coverage radii of the BS for all UE cases for both NOMA and NOMA* schemes.

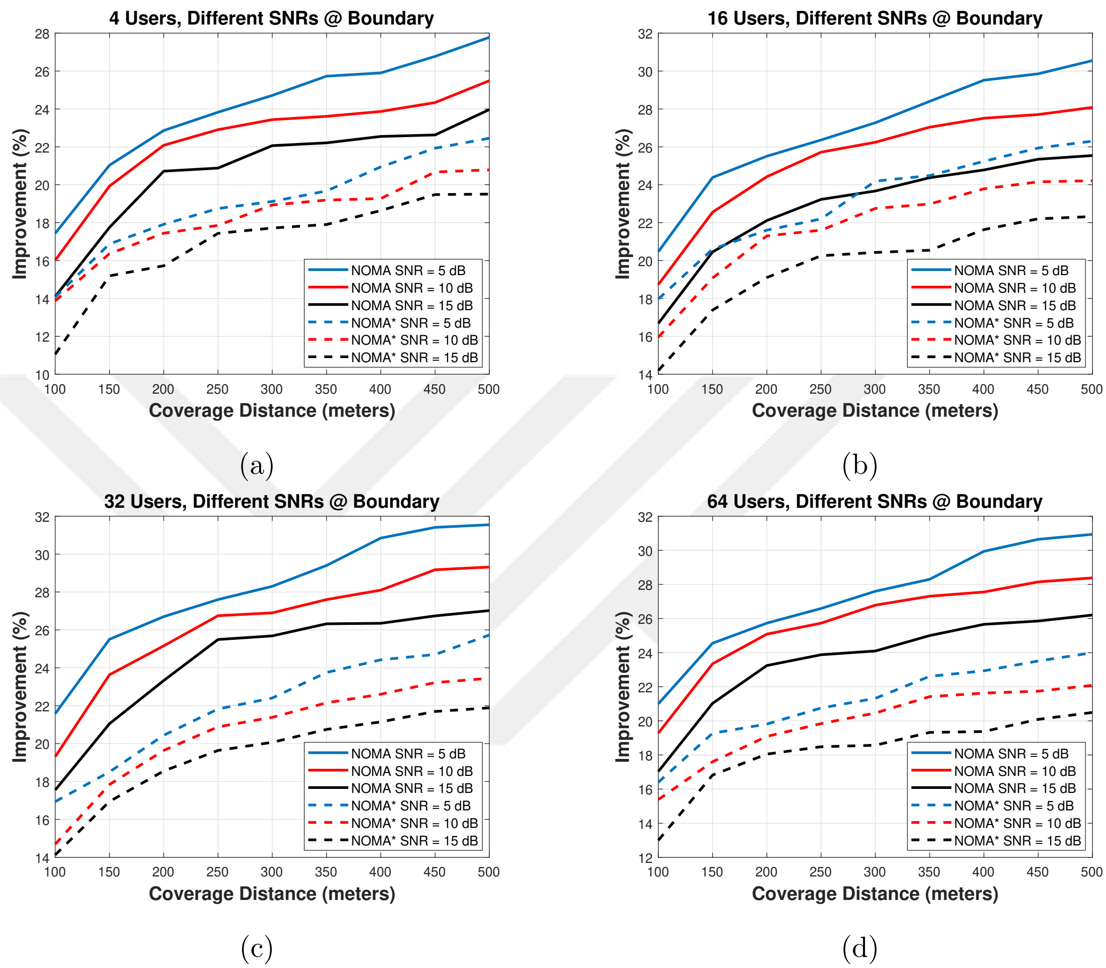


Figure 3.10: Percentage improvement of the average system capacities of the applied TFS algorithm for pair selection for both NOMA and NOMA* by comparing with the TFS algorithm for single user selection, i.e. OMA, for 4, 16, 32, and 64 UEs cases where the SNR of the UEs at boundary is set to 5, 10, and 15 dBs.

Percentage Gain							
UEs	Scheme	SNR(dB)	Coverage Radius (meters)				
			100	200	300	400	500
4	NOMA	5	17.44	22.86	24.71	25.90	27.78
		10	16.01	22.08	23.44	23.87	25.49
		15	14.10	20.72	22.06	22.55	23.97
	NOMA*	5	14.07	17.91	19.12	20.94	22.46
		10	13.87	17.44	18.93	19.27	20.79
		15	11.06	15.72	17.72	18.64	19.51
16	NOMA	5	20.46	25.51	27.27	29.52	30.55
		10	18.73	24.43	26.24	27.51	28.08
		15	16.68	22.11	23.67	24.78	25.54
	NOMA*	5	17.97	21.60	24.19	25.24	26.30
		10	15.96	21.30	22.75	23.79	24.21
		15	14.20	19.10	20.43	21.63	22.32
32	NOMA	5	21.58	26.70	28.30	30.85	31.55
		10	19.31	25.16	26.90	28.10	29.32
		15	17.55	23.33	25.68	26.35	27.02
	NOMA*	5	16.94	20.44	22.41	24.42	25.73
		10	14.69	19.64	21.39	22.61	23.45
		15	14.13	18.55	20.07	21.15	21.88
64	NOMA	5	21.00	25.73	27.60	29.94	30.94
		10	19.28	25.09	26.79	27.56	28.38
		15	17.03	23.24	24.10	25.66	26.21
	NOMA*	5	16.40	19.81	21.32	22.93	23.99
		10	15.38	19.09	20.46	21.63	22.08
		15	12.99	18.05	18.57	19.38	20.49

Table 3.8: Overall percentage gain of the average system capacities of the applied TFS algorithm for pair selection for both NOMA and NOMA* cases by comparing with the TFS algorithm for single user selection, i.e. OMA, for 4, 16, 32, and 64 UEs cases where the SNR of the UE at boundary is set to 5, 10, and 15 dBs.

3.6 The Performance of the TFS Algorithm for NOMA-T*

In order to observe the performance of the TFS algorithm for triple selection as it was explained in Chapter 2.4, the average system capacity obtained by this algorithm is compared with the average system capacities of NOMA and OMA. The main purpose of this approach is to increase the average system capacity more by serving 3 UEs at the same time. Since the main purpose of this study is not to assign suitable powers for UEs, the power allocation algorithm for multiuser systems is used as it was proposed in [28] where each UE satisfies the condition of having NOMA capacity at least it is equal to the OMA capacity as it was explained in Chapter 2.1. In addition to the fair power allocation for each UE, following triple selection algorithm (See Fig. 3.11) [29] is used in this section to construct ordered triples which helps to decrease the computational complexity of the system in each trial. The proposed ordered triple construction approach is quite similar to the pair construction in Section 3.3, where all UEs are ordered according the experienced SNR values and split into three clusters. First member in the first cluster, i.e. UE_1, first member in the second cluster, i.e. $UE_{(N/3)+1}$, and the last member of the third cluster, i.e. UE_N, are set an ordered triple and other triples are constructed by the help of the same approach.

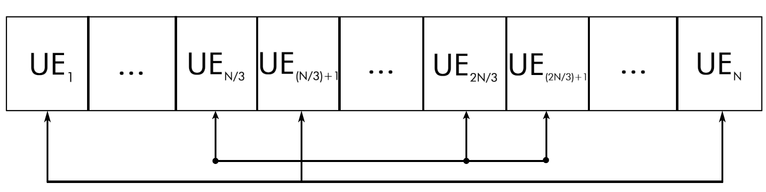
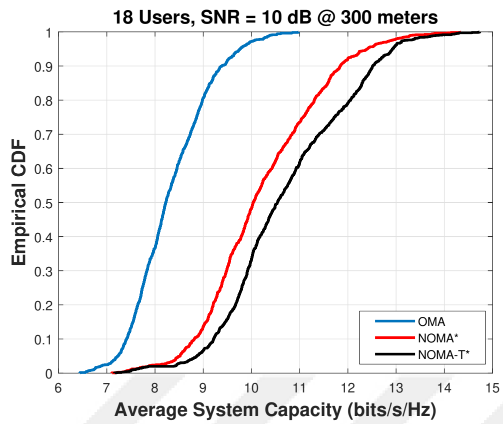


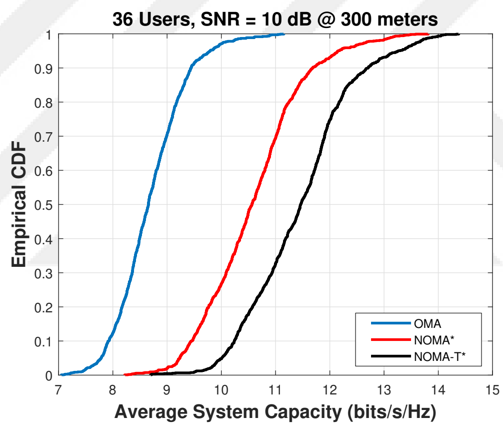
Figure 3.11: The proposed pre-triple construction method for downlink NOMA for N UEs.

In order to investigate the performance of the TFS algorithm for triples, i.e.

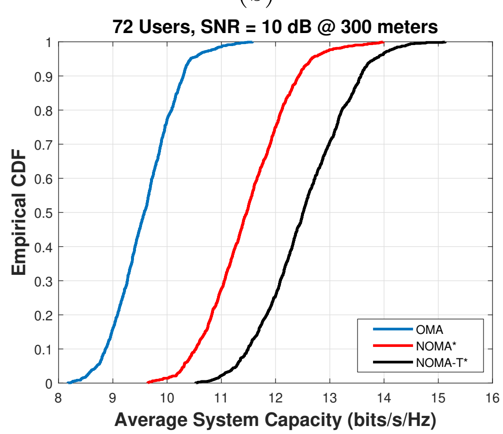
NOMA-T*, by comparing with NOMA* and OMA, the number of UEs are selected as that can be divided by 6, where UEs can construct both pairs and triples. So, for this section the number of UEs are selected as 18, 36, and 72 and other parameters for simulation were used as they were stated in the Chapter 3.



(a)



(b)



(c)

Figure 3.12: ECDF of the average system capacities of TFS algorithms for OMA, NOMA*, NOMA-T* with 18 UEs (a), 36 UEs (b), and 72 UEs (c) cases where for all cases UE at 300 meters experiences 10 dB SNR.

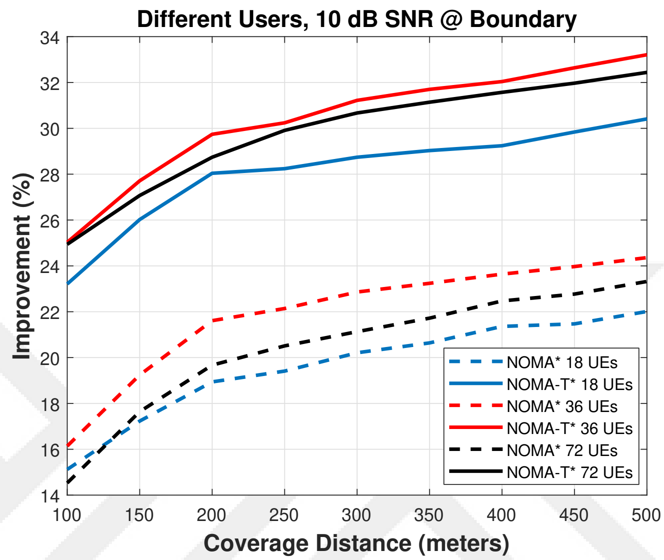


Figure 3.13: Percentage improvement of the average system capacities of applied TFS algorithm for triple selection (NOMA-T*) and TFS algorithm for pair selection (NOMA*) by comparing with TFS algorithm for single user selection (OMA) for 18, 36, and 72 UEs by setting the SNR of the UE at boundary as 10 dB.

Fig. 3.13 shows the average system capacity improvement of the NOMA capacities by altering the coverage distance of the BS. As the number of UE increases, the improvement in the average system capacity in NOMA-T* increases too by comparing with the NOMA*. In addition to that, increase in the coverage radius of the BS increases the percentage improvement of the TFS algorithm for both NOMA* and NOMA-T* cases. Table 3.9 summarizes the results of this section.

Percentage Gain						
UEs	**Scheme**	**Coverage Radius (meters)**				
		100	**200**	**300**	**400**	**500**
18	**NOMA***	15.12	18.94	20.21	21.36	22.01
	NOMA-T*	23.21	28.04	28.74	29.24	30.41
36	**NOMA***	16.14	21.61	22.86	23.64	24.36
	NOMA-T*	25.03	29.74	31.22	32.04	33.21
72	**NOMA***	14.53	19.67	21.13	22.47	23.32
	NOMA-T*	24.94	28.74	30.67	31.57	32.44

Table 3.9: Overall percentage gain of the average system capacities of applied TFS algorithm for triple selection (NOMA-T*) and TFS algorithm for pair selection (NOMA*) by comparing with TFS algorithm for single user selection (OMA), for 18, 36, and 72 UEs cases where SNR value of the UE at boundary is set to 10 dBs.

Chapter 4

Conclusion and Future Works

In this thesis, we have proposed a bucket-based temporal fair scheduler (TFS) for power domain downlink NOMA systems. There are three versions of the proposed scheduler. NOMA in this thesis shows that all pairs were covered. The proposed pair construction method, i.e. NOMA*, decreases the computational complexity of the TFS algorithm where $N/2$ pairs are possible candidates to be scheduled for desired slots. Moreover, for TFS algorithm for triple selection, NOMA-T* was proposed where $N/3$ ordered triples were constructed to be scheduled and served by the BS.

We have observed that:

- As the number of UEs increase in the system, the percentage improvement of the average system capacity of NOMA increases, which was compared with OMA. Because, the channel gains of the distributed UEs become more diverse which helps to have plenty of pairs with strong and weak UEs. Moreover, it can be concluded that, the diversity among the channel gains in the system favors the NOMA systems.
- The proposed pair construction algorithm, i.e. NOMA*, helps to reduce the computational complexity of the TFS algorithm since it provides smaller set of pairs to be scheduled. However, the improvement NOMA* is slightly

lower than NOMA since NOMA* gives rise to $N/2$ pairs to be scheduled as oppose to $N(N-1)/2$ pairs in the case of NOMA. In addition to that, as the number of UEs increase, the spacing between the emprical cdf of the average system capacities of NOMA and NOMA* becomes larger.

- As the coverage radius of the BS increases, the average system capacity of NOMA and NOMA* increase. Since, the channel gains of the UEs vary and the difference between the channel gains of strong and weak user increase.
- As the transmit power of the BS increases, the percentage improvement of the NOMA systems decreases where the difference between the channel gains of the strong and weak UEs decreases.
- The TFS algorithm for triples, i.e. NOMA-T*, shows that the triple selection improves the average system capacity. As the number of UEs in the system increases, the difference between the average system capacities of NOMA* and NOMA-T* significantly increased.

The proposed TFS algorithms were analyzed by using a single cell where BS and UEs have a single antenna. The TFS algorithm can be implemented for single cell with multi-antenna systems.

For future work, the extended version of TFS algorithm can be proposed for multi-cell systems where every UE can broadcast its bucket information and BSs can decide which user set will be scheduled by which BS, especially for the UE within the coverage range of more than one BS, in accordance with the output of the TFS algorithm. This system requires an additional control overhead between UEs and BSs. Coordinated Multi-Point (CoMP) [30] technique, which helps cooperation between different BSs, can be used to increase the overall capacity of the edge UE.

As it was stated in [31], most of the works about the scheduling algorithms first developed for single-carrier systems and adapted to multi-carrier environments. So, for multi-channel systems, for instance OFDM, TFS algorithm can be applied by allocating the same resource blocks (RBs) to multiple users. However, RB allocation constraints of the applied system should be taken into consideration such as how many RBs can be allocated to each UE, adjacency constraint of RB allocation for different UEs and etc.

Moreover, it is assumed in this work as all UEs have the identical priority and data constraints. However, TFS algorithm can be implemented for wireless systems with variety of constraints during which a weighted bucket-based TFS algorithm can be proposed to assign weight to the buckets, thus UEs with higher priority and data requirements can be served more often.

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Appendix A

Solution Steps for Inequalities for Fair Power Allocation in Downlink NOMA

For $C^{N}_{UE_1} \geq C^{O}_{UE_1}$,

$$\log_2\left(1+\frac{\beta_1\xi|h_1|^2}{\beta_2\xi|h_1|^2+1}\right) \geq \frac{1}{2}\log_2\left(1+\xi|h_1|^2\right), \tag{A.1}$$

$$\log_2\left(1+\frac{\beta_1\xi|h_1|^2}{\beta_2\xi|h_1|^2+1}\right) \geq \log_2\left(1+\xi|h_1|^2\right)^{1/2}, \tag{A.2}$$

Since $\beta_1 = 1-\beta_2$,

$$1+\frac{(1-\beta_2)\xi|h_1|^2}{\beta_2\xi|h_1|^2+1} \geq \left(1+\xi|h_1|^2\right)^{1/2}, \tag{A.3}$$

$$\frac{(1-\beta_2)\xi|h_1|^2}{\beta_2\xi|h_1|^2+1} \geq \left(1+\xi|h_1|^2\right)^{1/2}-1, \tag{A.4}$$

$$\frac{\xi|h_1|^2-\beta_2\xi|h_1|^2}{\beta_2\xi|h_1|^2+1} \geq \left(1+\xi|h_1|^2\right)^{1/2}-1, \tag{A.5}$$

$$\xi|h_1|^2 - \beta_2\xi|h_1|^2 \geq \big((1+\xi|h_1|^2)^{1/2} - 1\big)\big(\beta_2\xi|h_1|^2 + 1\big), \tag{A.6}$$

Let $\beta_2\xi|h_1|^2$ is equal to X then Equation A.6 becomes:

$$\xi|h_1|^2 - X \geq \big((1+\xi|h_1|^2)^{1/2} - 1\big)\big(X + 1\big), \tag{A.7}$$

$$\xi|h_1|^2 - X \geq X\big(1+\xi|h_1|^2\big)^{1/2} - X + \big(1+\xi|h_1|^2\big)^{1/2} - 1, \tag{A.8}$$

$$\xi|h_1|^2 + 1 \geq \big(X+1\big)\big(1+\xi|h_1|^2\big)^{1/2}, \tag{A.9}$$

$$\big(1+\xi|h_1|^2\big)^{1/2} - 1 \geq X, \tag{A.10}$$

Replace X with $\beta_2\xi|h_1|^2$ and Equation A.10 becomes:

$$\big(1+\xi|h_1|^2\big)^{1/2} - 1 \geq \beta_2\xi|h_1|^2, \tag{A.11}$$

The upper bound is found as:

$$\frac{\sqrt{\big(1+\xi|h_1|^2\big)} - 1}{\xi|h_1|^2} \geq \beta_2. \tag{A.12}$$

For $C^N_{UE_2} \geq C^O_{UE_2}$,

$$\log_2\left(1+\beta_2\xi|h_2|^2\right) \geq \frac{1}{2}\log_2\big(1+\xi|h_2|^2\big), \tag{A.13}$$

$$\log_2\left(1+\beta_2\xi|h_2|^2\right) \geq \log_2\big(1+\xi|h_2|^2\big)^{1/2}, \tag{A.14}$$

$$1 + \beta_2 \xi |h_2|^2 \geq \left(1 + \xi |h_2|^2\right)^{1/2}, \tag{A.15}$$

$$\beta_2 \xi |h_2|^2 \geq \left(1 + \xi |h_2|^2\right)^{1/2} - 1, \tag{A.16}$$

Then the lower bound for β_2 can be found as:

$$\beta_2 \geq \frac{\sqrt{\left(1 + \xi |h_2|^2\right)} - 1}{\xi |h_2|^2}. \tag{A.17}$$