Decoupled Uplink-Downlink User Association in Full-Duplex Small Cell Networks

by

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Abstract

In multi-tier cellular networks, user performance is largely affected by the varying transmit powers, distances, and non-uniform traffic loads of different base stations (BSs) in both the downlink (DL) and uplink (UL) directions of transmission. In presence of such heterogeneity, decoupled UL-DL user association (DUDe), which allows users to associate with different BSs for UL and DL transmissions, can be used to optimize network performance. Again, in-band full-duplex (FD) communication is considered as a promising technique to improve the spectral efficiency of future multi-tier fifth generation (5G) cellular networks. Nonetheless, due to severe UL-to-DL and DL-to-UL interference issues arising due to FD communications, the performance gains of DUDe in FD multi-tier networks are inconspicuous. To this end, this thesis develops a comprehensive framework to analyze the usefulness of DUDe in a full-duplex multi-tier cellular network. We first formulate a joint UL and DL user association problem (with the provision of decoupled association) that maximizes the sum-rate for UL and DL transmission of all users. Since the formulated problem is a mixed-integer non-linear programming (MINLP) problem, we invoke approximations and binary constraint relaxations to convert the problem into a Geometric Programming (GP) problem that is solved using Karush-Kuhn-Tucker (KKT) optimality conditions. Given the centralized nature and complexity of the GP problem, the solution of which serves as the upper bound for any sub-optimal solution, we formulate a distributed two-sided iterative matching game and develop a solution to obtain the solution of the game. In this game, the users and BSs rank one another using preference metrics that are subject to the externalities (i.e., dynamic interference conditions). The solution of the game is guaranteed to converge and provides Pareto-efficient stable associations. Finally, we derive efficient light-weight versions of the iterative matching solution, i.e., non-iterative matching and sequential UL-DL matching algorithms. The performances of all the solutions are critically evaluated in terms of aggregate UL and DL rates of all users, the number of unassociated users, and the number of coupled/decoupled associations. Simulation results demonstrate the efficacy of the proposed algorithms over the centralized GP solution as well as traditional coupled and decoupled user association schemes.

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Chapter 1

Introduction

1.1 HetNets

The Heterogeneous Network (HetNet) technology (illustrated in Fig. 1.1 [?]) is a promising technology to cope with the ever-increasing demand of mobile users served by the cellular networks. It is basically densification of the traditional homogeneous macrocellular network with the integration of small cells. A HetNet comprises of a system with large-power macro base stations (BSs) underlaid with small-power cells (or nodes) such as relays, femtocells, picocells etc. The objective of the small cells is to improve the capacity by serving the users of highly dense areas. All the small cells may use the same frequency band but with a reduced transmit power to improve the network performance. Actually higher received signal strength can be achieved due to the reduction in the distance between the small cells and the users. Small cells are able to provide better quality of service (QoS) guarantee by offloading users from the macrocells to the small cells. The performance of the cell-edge users are also enhanced (i.e., coverage range of a macrocell is improved) via instalment of the small cells.

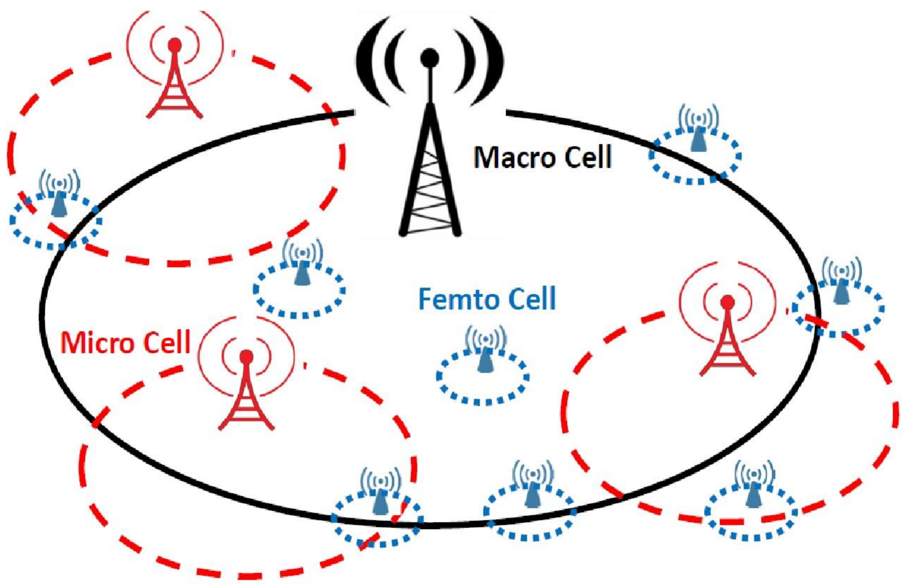

Figure 1.1: Heterogeneous network.

HetNets with small cells will be a key ingredient of the evolving fifth generation (5G) cellular wireless technology (Fig. 1.2). 5G networks will include different types of small cells such as femtocells, picocells, and microcells with different characteristics. A qualitative comparison among the different types of cells in a HetNet is shown in Table 1.1.

1.2 User Association

User association is a fundamental problem for a cellular wireless network. It refers to the method of assigning BSs to the users for uplink (UL) and down link (DL) transmissions. The heterogeneity of the 5G systems (Fig. 1.2 [?]) due to the deploy-

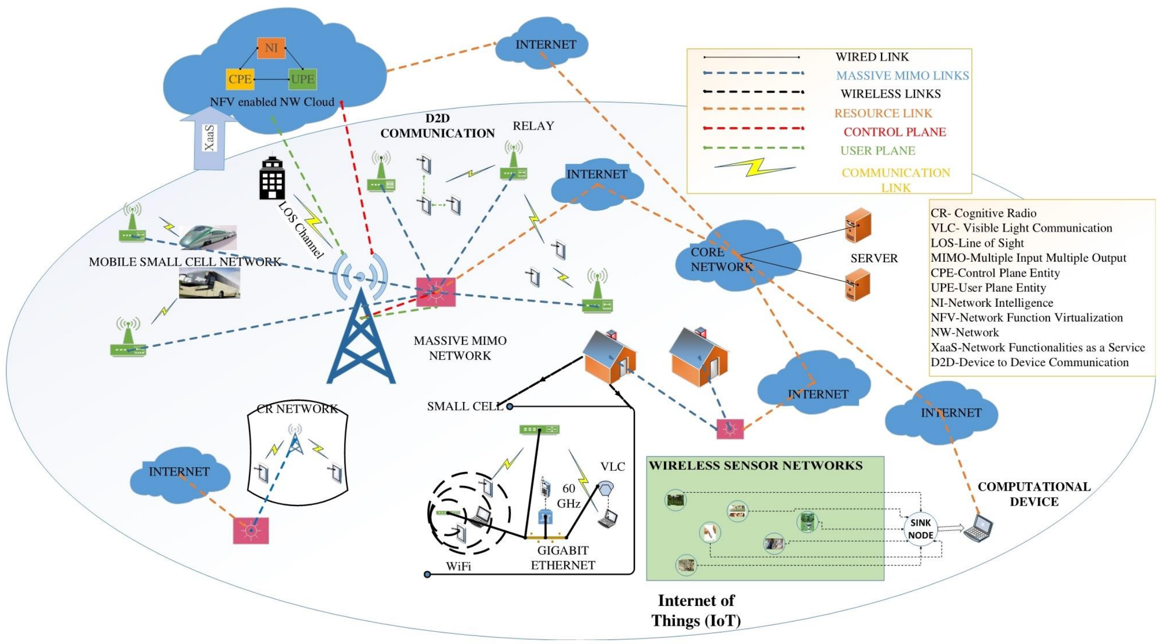

Figure 1.2: 5G cellular network architecture.

ment of different types of small cells significantly increases the density of the network compared to conventional single-tier networks. Disparities in the cell sizes introduce a major challenge in the association strategies. For such networks, user association schemes need to be developed to efficiently handle the challenges such as system capacity maximization (i.e., to maximize the number of users that can be served in the network), load balancing, quality of service (QoS) guarantees, reduce the outage probability for cell-edge users, simultaneous association to multiple BSs, etc. The traditional notion of associating users to the strongest BS may not be optimal in such networks. Also, the associations in the downlink and the uplink may not be to the same BS. For example, Fig. 1.3 shows the association of a user (i.e., mobile

Attribute	Macrocell	Picocell	Femtocell	Wi-Fi
Coverage	Wide area	Hot spot	Hot spot	Hot spot
Type of coverage	Outdoor	Outdoor, indoor	Indoor	Indoor
Density	Low	High	High	High
BS installation	Operator	Operator	Subscriber	Customer
Site acquisition	Operator	Operator	Subscriber	Customer
Tx. range	300-2000m	40-100m	10-30m	100-200m
Tx. power	40W (approx.)	200mW-2W	10-100mW	100-200mW
Band license	Licensed	Licensed	Licensed	Unlicensed
System bandwidth	5, 10, 15, 20MHz (upto 100MHz)	5, 10, 15, 20MHz (upto 100MHz)	5, 10, 15, 20MHz (upto 100MHz)	5, 10, 20MHz
Tx. rate	upto 1Gbps	upto 300Mbps	100Mbps-1Gbps	upto 600Mbps
Cost (approx.)	$60,000/yr	$10,000/yr	$200/yr	$100-200/yr
Power consump.	High	Moderate	Low	Low
Backhaul	S1 interface	X2 interface	IP	IP
Mobility	Seamless	Nomadic	Nomadic	Nomadic
QoS	High	High	High	Best-effort

device) to a macro BS in the downlink and to a small cell BS in the uplink.

1.3 Full-Duplex Communication

Full-duplex (FD) transmission has been recently considered as a viable technique to enable efficient spectral reuse in 5G multi-tier cellular networks [?]. Contrary to the popular half-duplex transmissions, FD transmissions imply simultaneous transmission and reception of information in the same frequency band; thus doubling the spectral efficiency ideally [?]. However, the performance gains of FD transmissions were initially dubious due to the overwhelming nature of the **self-interference** (SI), which is generated by the transmitter to its own collocated receiver. Recently, with the advent of antenna and digital baseband technologies, it has been shown that SI can be reduced close to the level of noise floor; thus making FD transmission a practical solution. The FD transmission can be realized in two modes, i.e., bi-directional full-duplex (BFD) and three-node full-duplex (TNFD) as illustrated in Fig. 1.4. In the BFD mode, a user associates to a single BS for simultaneous UL and DL trans-

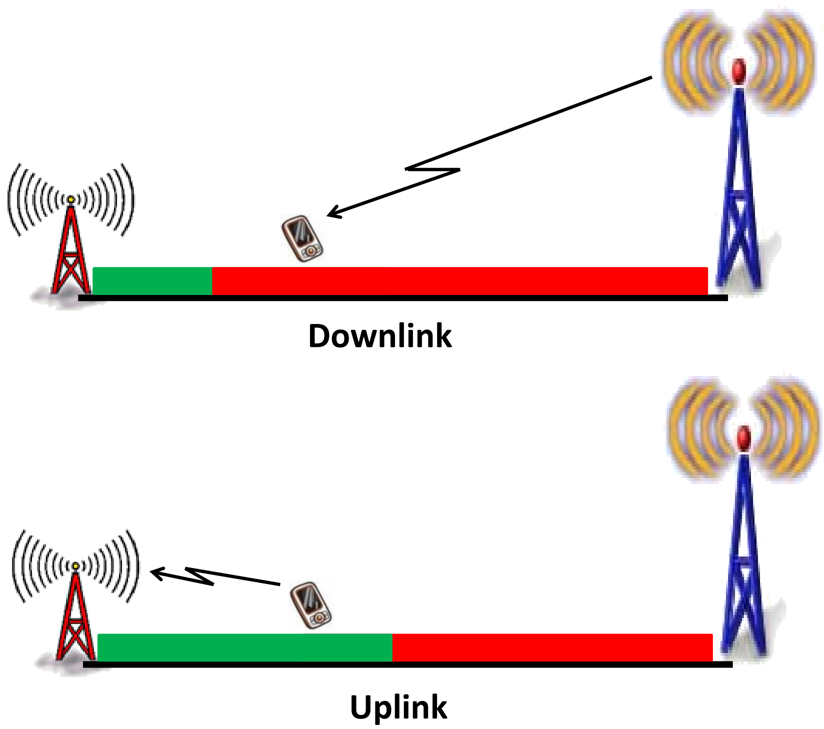

Figure 1.3: User association in downlink and uplink in a HetNet.

missions in the same frequency band, whereas in the TNFD mode a user (or BS) associates to different BSs (or users) for simultaneous UL and DL transmissions. As such, the BFD mode is analogous to *coupled association*; whereas, the TNFD mode is analogous to the *decoupled association* [**?**]. SI in both modes have been also depicted in the Fig. 1.4. In the BFD mode, the user and the BS both are capable of FD and thus receives SI due to the simultaneous transmission and reception. On the other hand, in TNFD mode, the user is doing UL and DL with separate BSs and the UL is creating SI to the receiver of the user.

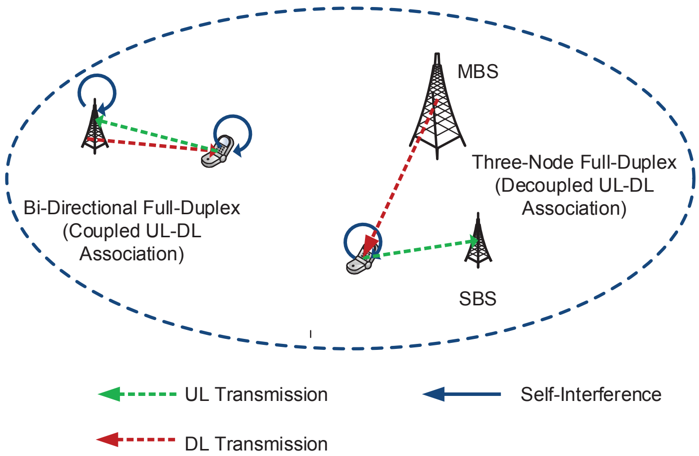

Figure 1.4: Graphical illustration of the BFD and TNFD modes of operation along with SI.

1.4 User Association Policies

Different user association policies have been adopted for cellular wireless networks. The major schemes are as follows :

- The most popular user association scheme is *max-RSS* scheme, where the users are associated to the BS from which they receive the highest signal power. But in HetNets, this policy may lead traffic load imbalance (and consequently reduced system performance) due to power disparity among BSs in different cells (e.g., macrocells, picocells).

- To overcome the problem of max-RSS based scheme, biased user association was proposed to offload the users from the macrocell by adding a biasing factor to the small cells. This scheme is also known as cell range expansion (CRE). However, the high interference realized at the offloaded users from the macro cells may affect the performances of the offloaded users significantly.

- Q-learning based scheme was proposed to offload users considering the interference so that the network throughput is maximized.

- Due to the high transmit power of the macrocells, network energy efficiency is directly affected by user association. Therefore, energy-efficient user association schemes were also considered in the literature.

- User association schemes were proposed to optimize the spectrum efficiency and coverage probability. Game theory has been widely studied in the context of cell association for optimizing spectrum efficiency.

Traditionally, in single-tier cellular networks, coupled association considers the same user association criterion (e.g., DL maximum received signal power) for both UL and DL transmissions. Due to the homogeneity of BSs in a single-tier network, this user association criterion guarantees optimal performance. Nonetheless, with the evolution of multi-tier cellular networks, the user performance is largely affected by the varying transmit powers, distances, and non-uniform traffic loads of different BSs in both the DL and UL transmissions [?]. In such a network, coupled association may no longer guarantee optimal performance. For instance, in a two-tier macrocell-small cell network, a user may achieve a higher UL rate by associating to a nearby small cell base station (SBS) instead of connecting to a far-away high power macro base station (MBS). Note that the UL transmission rate of a user is a function of its distance from the BS and its own transmit power (i.e., not the transmit power of the BS to which it is associated with). For this reason, the concept of associating a user with different BSs for UL and DL transmissions has been advocated recently for performance enhancement of 5G multi-tier cellular networks and is referred to as *Decoupled UL-DL User Association (DUDe)* [?, ?, ?].

1.5 Challenges in User Association in HetNets

In the presence of multiple network tiers, the network management and coordination become more challenging. One of the main objectives (or challenges) of user association in HetNets is to maximize the transmission rate in the network by mitigating co-tier and cross-tier interferences. Note that user association obviously affects these interferences which are defined as follows:

- **Co-tier interference** is the interference between neighboring small cells. It occurs in the same tier of the network. For example, in a two-tier macro and small cell network, a small cell user may cause UL co-tier interference to another small cell.

- **Cross-tier interference** is the interference between the macro cell and the small cell. For example, small cell users create cross-tier interference to the macro cell via UL and the macro users cause cross-tier interference to the small cell.

Compared to the single-tier networks, non-uniform coverage and load imbalance among different cells due to the disparity in the transmit powers make the problem more challenging. In addition, in presence of FD, the interference dynamics in the network changes due to the new types of interference introduced in the network, namely, self-interference, uplink-to-downlink interference, and downlink-to-uplink interference, in addition to the co-tier and cross-tier interferences in the downlink and in the uplink. Therefore, user association policies should be designed which can maximize the network capacity in presence of all of these type of interferences.

1.6 Motivation

The existing studies in the literature focus on investigating the performance of DUDe in half-duplex systems with distinct UL and DL frequencies. In particular, the new UL associations (after decoupling from DL associations) do not affect the performance of DL transmissions. As such, the performances of UL and DL transmissions can be optimized independently. However, this independent optimization of UL and DL transmissions is not valid for FD DUDe networks. The reason is, using the same frequency in both the UL and DL will result in the TNFD mode where UL-to-DL and DL-to-UL interferences can be significant [?]. Compared to the BFD mode, these additional interferences make the feasibility of TNFD networks uncertain. This necessitates dynamic user association methods that can exploit decoupled associations in an efficient manner (e.g., to maximize the overall UL and DL data rate) while considering severe interferences in FD DUDe networks. In this context, this thesis develops a comprehensive framework that analyzes the usefulness of DUDe in multi-tier FD cellular networks while providing efficient distributed solutions for user association.

1.7 Problem Definition

In this thesis, we deal with the problem of user association in a full-duplex small cell network. Each of the user in the network needs an association for both UL and DL transmission. Our target is to maximize the overall UL and DL sum-rate of all the users in the network. Users are allowed to choose either decoupled or coupled association to maximize the overall sum-rate. The utility of an individual user is calculated as the sum of the attained UL and DL rates. Each BS has a quota (Maximum number of users that can be associated to a BS) for both UL and DL. The

BSs can not associate to more than quota number of users. All the users as well as BSs are capable of doing FD transmission. As a result new kind of interference conditions i.e., self-interference, UL-to-DL and DL-to-UL interferences need to be considered while rate calculation. Maximization of the overall user rate in both the UL and DL demands for a careful choice of decoupled association in considered network. In this thesis, we will solve this aforementioned user association process to maximize the overall rates of the users.

1.8 Related Work

Recently, the performance of DUDe has been investigated in various half-duplex network scenarios using standard stochastic geometry tools [?, ?, ?, ?, ?, ?]. In [?], the authors investigate the performance of DUDe using system level simulations and demonstrate the significance of DUDe in UL with the increasing density of SBSs. Assuming decoupled UL and DL user association based on path-loss and maximum received signal power, respectively, the association probability of a user is derived for different BSs in [?].

It is shown that a large number of users prefer decoupled association. Another stochastic geometry framework is presented in [?] to derive the achievable capacity of a system with DUDe. The accuracy of the expressions is verified by using Vodafone's real-world simulation tool (Atoll). In [?], UL signal-to-interference-plus-noise ratio (SINR) and rate coverage analysis is presented for multi-tier cellular networks with the provisioning of DUDe. In [?], the authors propose a heuristic cell-load and backhaul-aware user association algorithm. Based on a Vodafone's trial network, the authors demonstrate the superiority of the proposed algorithm over the conventional approaches. In [?], the authors propose a decoupled user association strategy based on instantaneous received power in DL and UL. They derive the UL and DL user association probabilities for co-channel BSs in finite multi-tier networks.

The problem of optimizing UL and DL user association has been considered in various half-duplex system settings. For instance, [?] presents a gradient search-based UL and DL user association scheme that considers minimizing the user transmit power and network resource consumption. In [?], joint DL and UL cell association problem in a multi-tier network is formulated and solved while optimizing the sum of weighted UL and DL long-term average data rates. Considering the complexity of the exact solution, a two step sub-optimal solution is proposed.

In [?] and [?], UL and DL user association problem is formulated and solved to optimize the UL/DL energy efficiencies and ratio of the DL data rate and the UL power consumption, respectively. In [?], an algorithm for UL and DL user association is provided to minimize the sum of UL and DL average traffic delay, UL power consumption of the users, and on-grid power consumption in DL. A convex optimization problem is formulated to minimize the weighted sum of the cost of average traffic delay and power consumption.

Another set of relevant research works include [?] and [?] where stable matching is exploited separately for the DL and UL user association problem, respectively. In particular, [?] solves the DL user association problem for small cell networks where the utility function is in terms of rate and fairness to the users. Further, in [?], matching theory is exploited along with the coalition games to solve the UL user association problem. Interdependent user preferences are considered while formulating the matching game. In [?], the authors study context-aware user association for DL by formulating the problem as a matching game with externalities (i.e., the performance of each user and SBS is strongly affected by the dynamic formation of other associations in the system). In [**?**], the authors modelled the cooperative spectrum sharing of primary and secondary users as a matching market and a unique Pareto-optimal equilibrium is shown to be achieved for the primary users.

1.9 Contribution

The contributions of this thesis can be outlined as follows.

- For a multi-tier cellular network, we formulate a joint UL and DL user association problem (with provisioning for decoupled association) that maximizes the sum-rate for UL and DL transmission of all users. Due to complicated UL-to-DL and DL-to-UL interferences and integer optimization variables, the formulated problem is a non-convex NP hard problem. We thus perform binary relaxations and interference approximations to convert the problem into a convex Geometric Programming (GP) problem. The GP problem is then solved using KKT optimality conditions.

- Since the performance of the users is strongly affected by the dynamic formation of other associations in the system, we formulate and propose a distributed game based on iterative matching theory. In this matching game, users and BSs rank one another using preference metrics that are subject to the externalities (i.e., dynamic interference conditions). Since the formulated problem is in the form of many-to-many matching game, we solve the problem by transforming the many-to-many matching game into a many-to-one matching game. The proposed algorithm is guaranteed to converge and it provides Pareto-efficient and stable associations. The complexity and signaling overhead are discussed for the developed iterative matching algorithm.

- Finally, based on the proposed iterative matching, we derive non-iterative and light-weight matching algorithms (i.e., non-iterative matching and sequential UL-DL matching algorithms) and discuss their convergence, stability, and complexity. The performances of all the solutions are then critically evaluated in terms of aggregate UL and DL rates of all users, the number of unassociated users, and the number of coupled/decoupled associations. Simulation results demonstrate the efficacy of the proposed algorithms over the traditional decoupled user association scheme based on path-loss in the UL and received signal power in the DL. Our results clearly show the significance of decoupling not only in UL but also in DL. However, the results also reveal that the choice of the percentage of decoupling in high interference scenarios is also important to achieve overall rate maximization in the network.

1.10 Preliminaries

1.10.1 Rate Calculation

The propagation channel between BS and user is subject to path-loss, log-normal shadowing and Rayleigh fading. In particular, we denote the channel gain between two nodes a and b as $G_{a,b}$ which is modeled as follows:

$$G_{a,b} = |h_{a,b}|^2 d_{a,b}^{-\xi}$$

where $|h_{a,b}|^2$ denotes the fading channel power gain between nodes a and b, ξ is the path-loss exponent, and $d_{a,b}$ is the distance between a and b.

The signal-to-interference-plus-noise ratio (SINR) at the receiver determines the maximum transmission rate that can be achieved in a communication link. The SINR

γ at the receiver can be calculated by dividing the received signal power by the sum of interferences and noise power as follows:

$$\gamma = \frac{P}{I + \sigma^2}$$

where P is the received signal power, σ^2 is the noise power, and I denotes the interference power. Based on SINR, the data rate R in a transmission link can be calculated by using Shannon's formula as follows:

$$R = B \log_2(1 + \gamma)$$

where B is the bandwidth of the transmission channel.

1.10.2 Basics of Matching Game

In this thesis, we exploit "Matching Theory" to solve the considered decoupled UL-DL association problem in FD cellular networks. Matching theory is a framework that provides mathematically tractable solutions for the combinatorial problem of matching players in two distinct sets, depending on the individual information and the preferences of each player. Depending on the type of players, their partitioning, and the quota (maximum number of players that can be matched to a player of opposite group) of each player, there are different classes of matching problems as are mentioned herein [**?**, **?**, **?**]:

- *One-to-one matching*: In one-to-one matching, the quota of each player in a given set is one.

- *Many-to-one matching*: In this case, the quota of each player in one of the two sets is equal to one; whereas there exists at least one player in the second set whose quota exceeds one.

- *Many-to-many matching*: Many-to-many matching occurs when there exists at least one player in each of the two sets whose quota exceeds one.

Given the aforementioned classifications of the matching games, the considered user association problem falls in the category of many to many matching. The reason is that each user can possibly get associated to either 1 or 2 BSs for the UL and DL transmission; whereas, each BS can also associate to multiple (more than one) users at the same time. Thus the considered user association problem can be formulated as a many-to-many matching game.

1.11 Organization of the Thesis

The major contents of this thesis is organized in three chapters. The brief description of the chapters is given below.

- In Chapter 2, we present the system model, channel model, interference model, and other assumptions for the proposed user association scheme. Here we formulate the problem as a convex GP (geometric programming) problem and write the KKT conditions to solve the problem in a centralized fashion.

- Due to high computational complexity of the centralized solution, we propose a distributed solution based on well known matching theory in Chapter 3. We analyze the convergence, optimality and the computational complexity of the proposed scheme. The performance of the proposed iterative matching scheme is compared with that of centralized solution as well as conventional solutions.

- To reduce the complexity of the proposed iterative matching solution in Chapter 3, we propose some light-weight solutions in Chapter 4. We also present simulation results for the proposed schemes and compare the performance with iterative matching.
- We conclude the thesis in Chapter 5 highlighting several directions of future research.

1.12 Scholastic Outputs and Achievements

Table 1.1: Summary of scholastic outputs

1.	**S. Sekander**, H. Tabassum, and E. Hossain, "A matching game for decoupled uplink-downlink user association in full-duplex small cell networks," *IEEE Globecom Workshops (GC Wkshps)*, pp. 1–6, Dec. 2015.
2.	**S. Sekander**, H. Tabassum, and E. Hossain, "Matching with externalities for decoupled uplink-downlink user association in full-duplex small cell networks," *IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, pp. 411– 414, Dec. 2015.
3.	**S. Sekander**, H. Tabassum, and E. Hossain, "Decoupled uplink-downlink user association in multi-tier full-duplex cellular networks: A two-sided matching game," *IEEE Transactions on Mobile Computing*, to be submitted.

This thesis includes some previously published material in the conferences as summarized in Table 1.1. This work would not have been possible without the contribution of all the co-authors listed in the referenced publications. The copyright as well as all rights of the works (and therefore the parts of the thesis) are retained by the authors and/or by other copyright holders.

Chapter 2

Centralized Approach for User Association

2.1 System Model

2.1.1 Network Deployment Model

We consider a two-tier small cell network where MBSs are overlaid by open-access SBSs[1]. Let $\mathcal{L}$ and $\mathcal{K}$ denote the set of L BSs and the set of K users, respectively. Each BS l (which can either be a SBS or a MBS) can allow a maximum number of users (referred as quota) up to q_l^{u} and q_l^{d} for association in the UL and in the DL, respectively. We assume a shared spectrum access scenario, i.e., all tiers utilize the same channel for UL and DL transmissions. The considered network is illustrated in Fig. 2.1.

To enable efficient spectral reuse, we consider that users and BSs (both the MBS and SBSs) are capable of performing FD transmissions. FD transmission can be

[1]The framework is however valid for a general n-tier system where different BSs have distinct coverage regions and transmit power levels.

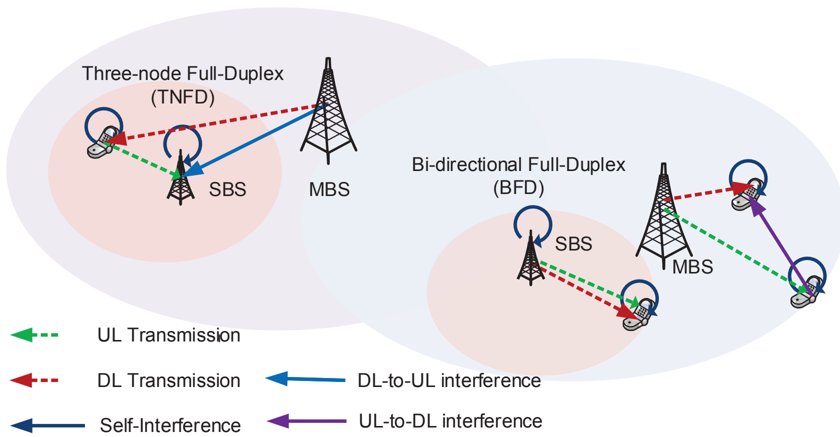

Figure 2.1: A two-tier cellular network with multiple full-duplex users, MBSs, and SBSs. Graphical illustration of UL-to-DL and DL-to-UL interference.

realized at all BSs and users with a single antenna for simultaneous transmission and reception via three-port circulator.

All BSs transmit using a maximum power of P_l, $l \in \mathcal{L}$; whereas, each user transmits with a maximum power of P_k, $k \in \mathcal{K}$.

Since multiple users (i.e., maximum of q_l^{u} and q_l^{d} in the UL and DL, respectively) can associate to a BS l, the probability of a user to transmit or receive on a given channel, referred to as *channel access probability*, can be defined as follows:

$$\beta_{k,l}^{(\cdot)} = \begin{cases} \frac{1}{\sum_{k'=1}^{K} \alpha_{k',l}^{(\cdot)}}, & \text{if } \sum_{k'=1}^{K} \alpha_{k',l}^{(\cdot)} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

where $(\cdot)$ = u for UL and $(\cdot)$ = d for DL, $\beta_{k,l}^{(\cdot)}$ denotes UL or DL channel access probability of a user k associated with BS l.

$$\alpha_{k,l}^{(\cdot)} = \begin{cases} 1, & \text{if a user } k \text{ is associated with BS } l \\ 0, & \text{otherwise} \end{cases}$$

That is, a BS schedules each associated user with equal probability, e.g., if four users are associated to a BS l, the channel access probability of a user k will be $\beta_{k,l}^{(\cdot)} = 0.25$.

2.1.2 Channel Propagation and Interference Model

The propagation channel between BS to BS (DL-to-UL), user to BS (UL), BS to user (DL), and user to user (UL-to-UL) is subject to path-loss, Log-Normal shadowing and Rayleigh fading. In particular, we denote the channel gain between two nodes a and b as $G_{a,b}$ which is modeled as follows :

$$G_{a,b} = |h_{a,b}|^2 d_{a,b}^{-\xi}$$

$G_{a,b}$ denotes the composite Rayleigh distributed channel fading power and Log-Normal shadowing power between nodes a and b, ξ is the path loss exponent, and $d_{a,b}$ is the distance between a and b. For the considered system, the interference incurred at the BSs and users can be elaborated as in the following.

Interference Incurred at Users

Interference received at a given user k associated to BS l in the DL is composed of the following two types of interferences, i.e.,

- *Traditional Downlink Interference ($I_{\mathrm{bs}\to\mathrm{ue}}$):* is received at user k from all other BSs transmitting in the DL except l and can be described as

$$I_{\mathrm{bs}\to\mathrm{ue}} = \sum_{l' \neq l} P_{l'} G_{k,l'} Z_{k',l'}$$

where $Z_{k',l'} = \sum_{k'=1}^{K} \alpha^{\mathrm{d}}_{k',l'} \beta^{\mathrm{d}}_{k',l'}$. Note that user k will receive interference from BS l' iff any user k' is associated to it in the DL, i.e.,

$$Z_{k',l'} = \begin{cases} 1, & \text{if at least one user } k' \in \mathcal{K} \text{ associates to BS } l' \\ 0, & \text{otherwise} \end{cases} \tag{2.2}$$

For example, if a BS has two users associated in the DL, each user will have a 50% chance to access the channel, i.e., $\beta^{\mathrm{d}}_{k',l'} = 0.5$. As a result, $Z_{k',l'}$ will be $1(0.5) + 1(0.5) = 1$.

- *UL-to-DL Interference ($I_{\mathrm{ue}\to\mathrm{ue}}$):* is received from all users that are transmitting in the UL and can be described as

$$I_{\mathrm{ue}\to\mathrm{ue}} = \sum_{k' \neq k} P_{k'} G_{k',k} X_{k',l'}$$

where $X_{k',l'} = \sum_{l'=1}^{L} \alpha^{\mathrm{u}}_{k',l'} \beta^{\mathrm{u}}_{k',l'}$. Note that user k will receive interference from a user k' iff the user k' is associated to any BS $l' \in \mathcal{L}$ and successfully access the channel for UL transmission, i.e.,

$$X_{k',l'} = \begin{cases} 1, & \text{if user } k' \text{ is associated to BS } l' \in \mathcal{L} \text{ in UL} \\ 0, & \text{otherwise} \end{cases} \tag{2.3}$$

Interference incurred at BSs

Interference received at a given BS l associated to user k in the UL is composed of the following two types of interferences, i.e.,

- *DL-to-UL Interference ($I_{\mathrm{bs}\rightarrow\mathrm{bs}}$):* is received from all BSs that are transmitting in the DL and can be described as

$$I_{\mathrm{bs}\rightarrow\mathrm{bs}} = \sum_{l' \neq l} P_{l'} G_{l,l'} Z_{k',l'}$$

- *Traditional UL Interference ($I_{\mathrm{ue}\rightarrow\mathrm{bs}}$):* is received from all users that are transmitting in the UL, i.e.,

$$I_{\mathrm{ue}\rightarrow\mathrm{bs}} = \sum_{k' \neq k} P_{k'} G_{k',l} (1 - \alpha^{\mathrm{u}}_{k',l}) X_{k',l'}.$$

  Note that BS l will receive interference from a given user k' iff k' is associated to a **different BS** $l' \neq l$. Thus the factor $(1 - \alpha^{\mathrm{u}}_{k',l})$ will be one only if user k' is associated with a different BS.

Remark: The considered system model can be extended for the half-duplex scenarios in a straight-forward manner. That is, if users utilize separate frequency channels for UL and DL transmissions, there will be no SI, DL-to-UL interference or UL-to-DL interference, hence $I_{\mathrm{bs}\rightarrow\mathrm{bs}} = 0$ and $I_{\mathrm{ue}\rightarrow\mathrm{ue}} = 0$.

2.2 Decoupled Uplink-Downlink User Association: Rate Maximization

In this section, we present the formulation of the user association problem considering the interference aware utility functions. Each user wants to associate for simultaneous UL and DL transmissions. Each user has a provision for decoupling their association. The utility is calculated as sum of the UL and DL rates attained per user. Each BS has a quota on the maximum number of associated users.

To maximize the overall user rate in both the UL and DL, the problem of decoupled user association in FD two-tier cellular networks can be formulated as follows:

$$\begin{aligned}
\max_{\alpha^{\mathrm{d}}_{k,l},\alpha^{\mathrm{u}}_{k,l}} \quad & \sum_{l=1}^{L}\sum_{k=1}^{K} \alpha^{\mathrm{u}}_{k,l}\beta^{\mathrm{u}}_{k,l}R^{\mathrm{u}}_{k,l} + \alpha^{\mathrm{d}}_{k,l}\beta^{\mathrm{d}}_{k,l}R^{\mathrm{d}}_{k,l} \\
\text{subject to} \quad & C1: \sum_{k=1}^{K}\alpha^{\mathrm{d}}_{k,l} \le q^{\mathrm{d}}_{l}, \sum_{k=1}^{K}\alpha^{\mathrm{u}}_{k,l} \le q^{\mathrm{u}}_{l}, \forall l \in \mathcal{L} \\
& C2: \sum_{l=1}^{L}\alpha^{(.)}_{k,l} \in \{0,1\}, \forall k \in \mathcal{K} \\
& C3: \alpha^{(.)}_{k,l} \in \{0,1\}, 0 \le \beta^{(.)}_{k,l} \le 1
\end{aligned} \tag{2.4}$$

where $\alpha^{(.)}_{k,l} \in \{0,1\}$ is the association variable, i.e., if a user k is associated with a BS l in UL or DL, then its corresponding $\alpha^{(.)}_{k,l} = 1$, $R^{\mathrm{u}}_{k,l}$ is the achievable UL rate of user k associated with BS l, $R^{\mathrm{d}}_{k,l}$ is the achievable DL rate of user k associated with BS l. Constraint C1 indicates that each BS has a predefined quota on the maximum number of users associated to it in either UL or DL. That means a BS can be associated to at most q^{u}_{l} users in UL and q^{d}_{l} users in DL. Constraint C2 indicates that each user can associate with at most one BS in the UL and at most one BS in the DL.

The data rate of a user can be calculated by Shannon's capacity formula

$$R^{(.)}_{k,l} = B\log_2(1+\gamma^{(.)}_{k,l})$$

where $\gamma^{(.)}_{k,l}$ is the SINR of user k associated to BS l in UL or DL, i.e.,

$$\gamma^{\mathrm{u}}_{k,l} = (P_k G_{k,l})/(I_{\mathrm{bs}\to\mathrm{bs}} + I_{\mathrm{ue}\to\mathrm{bs}} + \frac{P_l}{\zeta} + \sigma^2)$$

$$\gamma^{\mathrm{d}}_{k,l} = (P_l G_{k,l})/(I_{\mathrm{bs}\to\mathrm{ue}} + I_{\mathrm{ue}\to\mathrm{ue}} + \frac{P_k}{\zeta} + \sigma^2)$$

where σ^2 is the noise power, $\frac{P_k}{\zeta}$ and $\frac{P_l}{\zeta}$ denote the SI at user and BS, respectively, and ζ denotes the SI cancellation capability of the user or BS.

Note that ζ depends on the nature of the SI cancellation algorithms [?]. For ease of exposition, we consider ζ to be a constant value in this thesis. Since the SI incurred at a given BS l or user k depends on its own transmit power, we can define the residual SI power at the BS and user after performing SI cancellation as $\frac{P_l}{\zeta}$ and $\frac{P_k}{\zeta}$, respectively. The optimization problem given in (1) is a combinatorial mixed-integer non-linear programming problem (MINLP) and thus computationally complex to solve in real-time.

2.2.1 Relaxation of Binary Constraints and Approximations

To simplify the aforementioned centralized problem, we consider following approximations

- a *worst case approximation* of the interference at a given BS l arising from other BSs, i.e., $I_{\text{bs}\to\text{bs}}$. The interference at a given BS l receiving transmissions from user k can be realized from all other BSs that are transmitting in the DL. However, if an interfering BS is not associated to a user in the DL, it will not contribute to the interference $I_{\text{bs}\to\text{bs}}$. In practice, the number of users are much higher then the number of available BSs; therefore, such a case is unlikely to happen. Thus, we approximate $Z_{k',l'} \approx 1$ and thus $I_{\text{bs}\to\text{bs}} \approx \hat{I}_{\text{bs}\to\text{bs}}$ and we get

$$\hat{I}_{\text{bs}\to\text{bs}} = \sum_{l' \in \mathcal{L}, l' \neq l} P_{l'} G_{l,l'}.$$

Similarly, the interference at user k from BSs can also be approximated as

$$\hat{I}_{\mathrm{bs}\to\mathrm{ue}} = \sum_{l' \in \mathcal{L}, l' \neq l} P_{l'} G_{k,l'}$$

That is, user k and BS l will receive interference from all BSs l' excluding l.

- an *average approximation* of the interference at a given BS l arising from the users transmitting in the UL $I_{\mathrm{ue}\to\mathrm{bs}}$. For a network of K users and L BSs, $\frac{K}{L}$ users will be associated to a single BS, on average. But each BS can not accommodate more than q users; therefore, the average load per BS is $\min(q, \frac{K}{L})$. The channel access probability of each user can then be approximated as $\frac{1}{\min(q, \frac{K}{L})}$ and we get

$$\hat{I}_{\mathrm{ue}\to\mathrm{bs}} = \frac{\sum_{k' \in \mathcal{K}, k' \neq k} P_{k'} G_{k',l} \sum_{l' \in \mathcal{L}, l' \neq l} \alpha^{\mathrm{u}}_{k',l'}}{\min(q, \frac{K}{L})}$$

Similarly, the interference received from all users transmitting in the UL can be approximated as

$$\hat{I}_{\mathrm{ue}\to\mathrm{ue}} = \frac{\sum_{k' \in \mathcal{K}, k' \neq k} P_{k'} G_{k',k} \sum_{l' \in \mathcal{L}} \alpha^{\mathrm{u}}_{k',l'}}{\min(q, \frac{K}{L})}$$

Using these approximations in (2.4), the objective function can be written as follows.

$$\max_{\alpha^{\mathrm{d}}_{k,l}, \alpha^{\mathrm{u}}_{k,l}} \frac{B}{\min(q, \frac{K}{L})} \sum_{l=1}^{L} \sum_{k=1}^{K} \alpha^{\mathrm{u}}_{k,l} \log_2(1 + \gamma^{\mathrm{u}}_{k,l}) + \alpha^{\mathrm{d}}_{k,l} \log_2(1 + \gamma^{\mathrm{d}}_{k,l}) \tag{2.5}$$

where

$$\gamma^{\mathrm{u}}_{k,l} = \frac{P_k G_{k,l}}{\hat{I}_{\mathrm{bs}\to\mathrm{bs}} + \hat{I}_{\mathrm{ue}\to\mathrm{bs}} + \frac{P_l}{\zeta} + \sigma^2}$$

$$\gamma_{k,l}^{\mathrm{d}} = \frac{P_l G_{k,l}}{\hat{I}_{\mathrm{bs}\to\mathrm{ue}} + \hat{I}_{\mathrm{ue}\to\mathrm{ue}} + \frac{P_k}{\zeta} + \sigma^2}$$

For ease of exposition, we assume equal quota q for UL and DL; however, this is not a limitation of the solution approach. We also relax the discrete UL and DL association variables as follows :

$$0 \leq \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{d}} \leq 1, \forall k \in \mathcal{K}$$

$$0 \leq \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{u}} \leq 1, \forall k \in \mathcal{K}$$

$$0 \leq \alpha_{k,l}^{(.)} \leq 1$$

Here we can consider the association variables as the association probabilities where each user has a certain probability to associate to a BS. Each user will try to associate to a BS with whom he has maximal association probability. Finally, we approximate $\log(1+\gamma) \approx \log\gamma$ assuming high SINR regime.

2.2.2 Formulation of Geometric Program (GP) and KKT Optimality Conditions

By noting that (2.5) can be reformulated, after high SNR approximation, as follows:

$$\max_{\alpha_{k,l}^{\mathrm{d}}, \alpha_{k,l}^{\mathrm{u}}} \frac{B}{\min(q, \frac{K}{L})} \sum_{l=1}^{L} \sum_{k=1}^{K} \log_2(\alpha_{k,l}^{\mathrm{u}} \gamma_{k,l}^{\mathrm{u}}) + \log_2(\alpha_{k,l}^{\mathrm{d}} \gamma_{k,l}^{\mathrm{d}}), \tag{2.6}$$

This can be equivalently written as :

$$\max_{\alpha^{\mathrm{d}}_{k,l},\alpha^{\mathrm{u}}_{k,l}} \frac{B}{\min(q,\frac{K}{L})}\sum_{l=1}^{L}\sum_{k=1}^{K}\log_2\Big(\frac{\alpha^{\mathrm{u}}_{k,l}P_kG_{k,l}}{\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{l,l'}+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',l}\sum_{l'\in\mathcal{L},l'\neq l}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}+\frac{P_l}{\zeta}+\sigma^2}\Big)+$$
$$\log_2\Big(\frac{\alpha^{\mathrm{d}}_{k,l}P_lG_{k,l}}{\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{k,l'}+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',k}\sum_{l'\in\mathcal{L}}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}+\frac{P_k}{\zeta}+\sigma^2}\Big) \tag{2.7}$$

And as $\log x$ is a monotonically increasing function; maximizing $\log x$ is equivalent to maximizing x. Provided that maximizing the SINR is equivalent to minimizing the interference to signal plus noise ratio, we get

$$\min_{\alpha^{\mathrm{d}}_{k,l},\alpha^{\mathrm{u}}_{k,l}} \frac{B}{\min(q,\frac{K}{L})}\sum_{l=1}^{L}\sum_{k=1}^{K}\log_2\Big(\frac{\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{l,l'}+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',l}\sum_{l'\in\mathcal{L},l'\neq l}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}+\frac{P_l}{\zeta}+\sigma^2}{\alpha^{\mathrm{u}}_{k,l}P_kG_{k,l}}\Big)$$
$$+\log_2\Big(\frac{\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{k,l'}+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',k}\sum_{l'\in\mathcal{L}}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}+\frac{P_k}{\zeta}+\sigma^2}{\alpha^{\mathrm{d}}_{k,l}P_lG_{k,l}}\Big) \tag{2.8}$$

The objective in (2.8) can be formulated as a convex geometric programming (GP) problem as follows:

$$\min_{\alpha^{\mathrm{d}}_{k,l},\alpha^{\mathrm{u}}_{k,l}} \prod_{l=1}^{L}\prod_{k=1}^{K}\left(\frac{A+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',l}\sum_{l'\in\mathcal{L},l'\neq l}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}}{\min(q,\frac{K}{L})\alpha^{\mathrm{u}}_{k,l}\ln(2)P_kG_{k,l}}\right)\left(\frac{B+\frac{\sum_{k'\in\mathcal{K},k'\neq k}P_{k'}G_{k',k}\sum_{l'\in\mathcal{L}}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}}{\min(q,\frac{K}{L})\alpha^{\mathrm{d}}_{k,l}\ln(2)P_lG_{k,l}}\right) \tag{2.9}$$

Where $A=\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{l,l'}+\frac{P_l}{\zeta}+\sigma^2$ and $B=\sum_{l'\in\mathcal{L},l'\neq l}P_{l'}G_{k,l'}+\frac{P_k}{\zeta}+\sigma^2$. In the first term, the denominator is a monomial and the numerator is a posynomial. The ratio of a posynomial to a monomial is also a posynomial [?, ?]. Similarly the second term is also a posynomial. Hence the problem formulated above is a standard GP problem which can be solved to find the optimal association.

By defining the expression in (2.6) as $\mathcal{F}(\alpha^{\mathrm{u}}_{k,l}, \alpha^{\mathrm{d}}_{k,l})$, the Lagrange of the formulated problem can be written as

$$\mathcal{L}(\alpha^{\mathrm{u}}_{k,l}, \alpha^{\mathrm{d}}_{k,l}, \lambda, \mu, \nu, \eta) = \mathcal{F}(\alpha^{\mathrm{u}}_{k,l}, \alpha^{\mathrm{d}}_{k,l}) + \sum_{k=1}^{K} \lambda_k (1 - \sum_{l=1}^{L} \alpha^{\mathrm{u}}_{k,l})$$
$$+ \sum_{k=1}^{K} \mu_k (1 - \sum_{l=1}^{L} \alpha^{\mathrm{d}}_{k,l}) + \sum_{l=1}^{L} \nu_l (q - \sum_{k=1}^{K} \alpha^{\mathrm{u}}_{k,l}) + \sum_{l=1}^{L} \eta_l (q - \sum_{k=1}^{K} \alpha^{\mathrm{d}}_{k,l})$$

where $\lambda = (\lambda_1, ..., \lambda_K), \mu = (\mu_1, ..., \mu_K), \nu = (\nu_1, ..., \nu_L), \eta = (\eta_1, ..., \eta_L)$ are the Lagrange multipliers corresponding to the inequality constraints. The first order necessary conditions (Karush-Kuhn-Tucker (KKT) conditions) for the optimality of the formulated problem can then be obtained by deriving $\frac{\partial \mathcal{L}}{\partial \alpha^{\mathrm{u}}_{k,l}} = 0$, and $\frac{\partial \mathcal{L}}{\partial \alpha^{\mathrm{d}}_{k,l}} = 0$, as shown below.

$$\frac{\partial \mathcal{L}}{\partial \alpha^{\mathrm{u}}_{k,l}} = \frac{1}{\alpha^{\mathrm{u}}_{k,l} \ln(2)} - \sum_{i \in \mathcal{L}, i \neq l} \sum_{j \in \mathcal{K}, j \neq k} \frac{\frac{P_k G_{k,i}}{\ln(2) \min(q, \frac{K}{L})}}{\sum_{l' \neq i} P_{l'} G_{l' i} + \frac{\sum_{k' \neq j} P_{k'} G_{k' i} \sum_{l' \neq i} \alpha^{\mathrm{u}}_{k', l'}}{\min(q, \frac{K}{L})} + \frac{P_i}{\zeta} + \sigma^2}$$
$$- \sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{K}, j \neq k} \frac{\frac{P_k G_{k,j}}{\ln(2) \min(q, \frac{K}{L})}}{\sum_{l' \neq i} P_{l'} G_{l' j} + \frac{\sum_{k' \neq j} P_{k'} G_{k' j} \sum_{l' \in \mathcal{L}} \alpha^{\mathrm{u}}_{k', l'}}{\min(q, \frac{K}{L})} + \frac{P_j}{\zeta} + \sigma^2} - \lambda_k - \nu_l = 0 \tag{2.10}$$

The details of the derivation are provided in **Appendix**. Moreover,

$$\frac{\partial \mathcal{L}}{\partial \alpha^{\mathrm{d}}_{k,l}} = \frac{1}{\ln(2) \alpha^{\mathrm{d}}_{k,l}} - \mu_k - \eta_l = 0$$

and the so-called complementary-slackness conditions can be written as

$$\lambda_k(1-\sum_{l=1}^{L}\alpha^{\mathrm{u}}_{k,l}) = 0, \quad \forall k \in \mathcal{K}$$

$$\mu_k(1-\sum_{l=1}^{L},\alpha^{\mathrm{d}}_{k,l}) = \ 0, \quad \forall k \in \mathcal{K}$$

$$\nu_l(q-\sum_{k=1}^{K}\alpha^{\mathrm{u}}_{k,l}) = 0, \quad \forall l \in \mathcal{L}$$

$$\eta_l(q-\sum_{k=1}^{K}\alpha^{\mathrm{d}}_{k,l}) = 0, \quad \forall l \in \mathcal{L}$$

and $\lambda_k \geq 0, \quad \mu_k \geq 0, \quad \nu_l \geq 0, \quad \eta_l \geq 0 \quad \forall k \in \mathcal{K}, \forall l \in \mathcal{L}$.

Solving these KKT conditions using gradient descent method will lead to optimal solutions. First we write the dual problem as follows:

$$\min_{\lambda,\mu,\nu,\eta\geq 0}\ \max_{\alpha^{\mathrm{u}}_{k,l},\alpha^{\mathrm{d}}_{k,l}\geq 0} \mathcal{L}(\alpha^{\mathrm{u}}_{k,l},\alpha^{\mathrm{d}}_{k,l},\lambda,\mu,\nu,\eta). \tag{2.11}$$

Since the primal problem is a convex optimization problem, the optimal solutions for the primal and dual problem are equal [?]. Therefore, in the following, we solve the dual problem using gradient descent method. That is, given the values of the Lagrange multipliers, the association variables for UL and DL can be updated iteratively as follows.

$$(\alpha^{\mathrm{u}}_{k,l})^{t+1} = \left[(\alpha^{\mathrm{u}}_{k,l})^{t} - \xi_1\frac{\partial\mathcal{L}}{\partial\alpha^{\mathrm{u}}_{k,l}}\right]^{+} \tag{2.12}$$

$$(\alpha^{\mathrm{d}}_{k,l})^{t+1} = \left[(\alpha^{\mathrm{d}}_{k,l})^{t} - \xi_2\frac{\partial\mathcal{L}}{\partial\alpha^{\mathrm{d}}_{k,l}}\right]^{+} \tag{2.13}$$

the notion $[z]^{+}$ represents that z is non-negative number, that is, $z \geq 0$. The optimum values of the Lagrange multipliers that provide the optimum associations can be calculated as follows:

$$\lambda_k^{t+1} = \left[\lambda_k^t - \xi_3 \frac{\partial \mathcal{L}}{\partial \lambda_k}\right]^+ = \left[\lambda_k^t - \xi_3 (1 - \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{u}})\right]^+ \tag{2.14}$$

$$\mu_k^{t+1} = \left[\mu_k^t - \xi_4 \frac{\partial \mathcal{L}}{\partial \mu_k}\right]^+ = \left[\mu_k^t - \xi_4 (1 - \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{d}})\right]^+ \tag{2.15}$$

$$\nu_l^{t+1} = \left[\nu_l^t - \xi_5 \frac{\partial \mathcal{L}}{\partial \nu_l}\right]^+ = \left[\nu_l^t - \xi_5 (q - \sum_{k=1}^{K} \alpha_{k,l}^{\mathrm{u}})\right]^+ \tag{2.16}$$

$$\eta_l^{t+1} = \left[\eta_l^t - \xi_6 \frac{\partial \mathcal{L}}{\partial \eta_l}\right]^+ = \left[\eta_l^t - \xi_6 (q - \sum_{k=1}^{K} \alpha_{k,l}^{\mathrm{d}})\right]^+ \tag{2.17}$$

where ξ_3, ξ_4, ξ_5 and ξ_6 are sufficiently small fixed step size for updating λ, μ, ν, η respectively. The gradient-descent based user association algorithm is given in **Algorithm 1**. Since the optimal association variables are continuous, we can consider them as the association probability of users. After calculating the optimal association variables, each user selects a BS that has the maximal association probability.

Algorithm 1 Algorithm for GP-based Centralized User Association

Initialization : Initialize step size ξ and Maximum number of iterations I
$t = 0$; Initialize $(\alpha_{k,l}^{\mathrm{u}})^t, (\alpha_{k,l}^{\mathrm{d}})^t, \lambda_k^t, \mu_k^t, \nu_l^t, \eta_l^t$
while $\mathcal{F}(\alpha_{k,l}^{\mathrm{u}}, \alpha_{k,l}^{\mathrm{d}})$ does not converge or $t \neq I$ **do**
  Calculate $(\alpha_{k,l}^{\mathrm{u}})^{t+1}, (\alpha_{k,l}^{\mathrm{d}})^{t+1}$ using equation (2.12) and (2.13) respectively.
  Update $\lambda_k^t + 1, \mu_k^t + 1, \nu_l^t + 1, \eta_l^t + 1$ using equation (2.14), (2.15), (2.16) and (2.17) respectively.
  $t = t + 1$
end while
Each user sets the maximal value of optimal association variables to 1 and the others to 0.

Note that, global network information should be provided to a centralized controller to carry out user associations, therefore, it may not be feasible to implement centralized solution in practice. However, it can serve as an efficient offline benchmark for the online distributed user association algorithms presented in later sections of this thesis.

2.3 Simulation Results

In this section, we present numerical results that quantitatively analyze the performance of the centralized GP solution which is attained from **Algorithm 1**.

2.3.1 Simulation Parameters

For our simulations, we consider a single MBS overlaid by randomly deployed small cells, unless stated otherwise. The transmit power of each SBS is 3W and MBS is 20W. The quota is taken as $q_l^{\mathrm{u}} = q_l^{\mathrm{d}} = 2$ for all BSs $l \in \mathcal{L}$. The channel experiences a Rayleigh fading with the path-loss exponent set to $\xi = 2$. Rayleigh fading has been modeled as exponentially distributed random variable with mean 1 and shadow fading is modeled as a log-normal random variable with a mean of 0 dB and a standard deviation of 8 dB. Noise level is assumed to be -151dBW. The users are distributed randomly in the network and each user has a transmit power of 1W. We consider $\zeta = 100$dB SI cancellation for the BSs and the users. All the statistical results are averaged via a large number of runs over the random location of users and BSs and the channel fading coefficients. The unassigned users are given a zero utility throughout the simulations.

2.3.2 Performance of Centralized GP Solution

Fig. 2.2 depicts the aggregate rate of all users in the network considering both UL and DL transmissions as the number of user varies. The centralized solution obtained

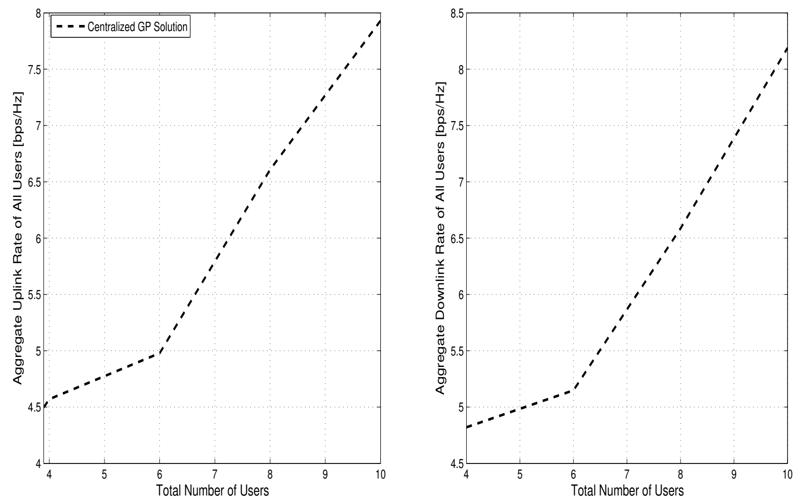

Figure 2.2: UL and DL rate of all users in the network with a MBS and two SBSs as a function of the number of users.

from **Algorithm 1** is presented in the figure. With the increase in number of users in the network the aggregate DL and UL rate increases.

Fig. 2.3 depicts the outage in the network considering UL and DL transmissions as the number of users varies. Outage can be defined as the number of users those remain unassociated. Outage in UL is given as $K - \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{u}}$. Similarly, $K - \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{d}}$ is the outage in DL. As expected, the number of outages increase with the increase in number of users due to increasing competition.

2.4 Summary

In this chapter, we have formulated the problem of user association considering both UL and DL with a provision of decoupling. Our objective is to maximize the sum-rate for UL and DL transmission of all the users in the network. The formulated problem is a non-convex NP hard problem. Therefore, we have performed binary relaxations and interference approximations to convert the problem into a convex Geometric

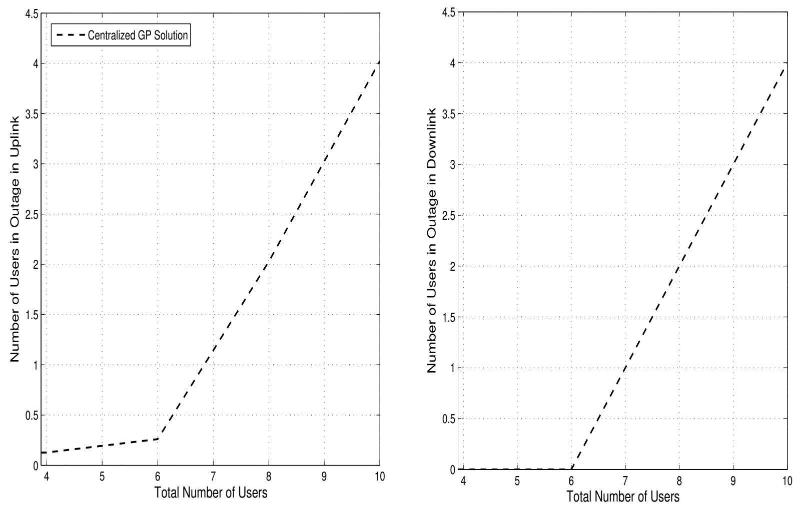

Figure 2.3: Performance, in terms of UL and DL outage in the network with a MBS and two SBSs as a function of the number of users.

Programming (GP) problem. We have derived the KKT optimality conditions and then solved the GP problem using **Algorithm 1**. We have performed simulations to show the performance of the algorithm by varying the number of users in the network.

Chapter 3

Distributed Approach for User Association

3.1 Iterative Matching Game Formulation

Matching theory framework can provide mathematically tractable solutions for combinatorial problems of matching players in two distinct sets, depending on the information and the preferences of each player. A conventional matching game involves the problem of matching multiple agents in two distinct groups, where each of the agents wants to be matched with a partner in the opposite group [?, ?]. Initially, each player makes a preference profile over the players of the opposite group and takes some actions according to the preference profiles they make, i.e., sending, accepting, and rejecting proposals. The matching outcome yields mutually beneficial assignments among players. Nevertheless, in the presence of externalities (preference of one player is dependent on the preference of other players), one player might find it beneficial to change its partner to improve its utility once a matching game is over. In this regard, iterative matching provides a player the opportunity to deviate from a previously agreed decision.

In this section, we use iterative matching theory to solve the considered user association problem where each user associates to a maximum of two BSs for UL and DL transmissions. A BS, however, can associate to multiple users at the same time. The considered user association problem can therefore be formulated as a many-to-many matching game. We first transform the considered user association problem from a many-to-many matching game into a many-to-one matching game. We then describe the method for preference list calculation for different players in the formulated many-to-one matching game. Finally, we describe the implementation details of the proposed iterative matching-based algorithm.

3.1.1 Transformation of Many-to-Many Iterative Matching Game

As has been mentioned before, the considered user association problem can be formulated as a many-to-many matching game where users rank BSs in the UL as well as DL using their predefined utilities and form their preference lists (more details will follow in Section IV.B) [?]. Nonetheless, due to complicated interferences in FD DUDe networks, UL and DL associations impact one another directly. Subsequently, separate preference lists for UL and DL may not capture the interdependency of the DL choice over the UL choice and vice versa. For example, consider a network with two BSs and a single user. Clearly, a user has four possible association options, i.e.,

- UL with BS1 and DL with BS2 (DUDe);
- DL with BS1 and UL with BS2 (DUDe);
- UL and DL with BS1 (Coupled);
- UL and DL with BS2 (Coupled).

In all four association options, the incurred interference and thus the achievable rate utility will be different. Therefore, it is crucial to consider each of the above options as a virtual player (or agent) defined by its unique utility. Note that the initial set of players (two BSs) can be transformed into a set of four virtual players that are represented by the four options listed above. *The transformed game can now be referred as a many-to-one matching game since each user needs to be matched to only one virtual player and these virtual players are referred to as BS agents.* A graphical illustration is provided in Fig. 3.1. Consequently, for a total of L BSs, we have $2\binom{L}{2}$ options for DUDe and L options for coupled association, i.e., a total of $2\binom{L}{2} + L$ players (or BS agents).

Now to define a many-to-one matching game formally, we let $\mathcal{N}$ to be the set of BS agents such that $|\mathcal{N}| = 2\binom{L}{2} + L$. Each element of set $\mathcal{N}$ can then be defined as $n = (l_u, l_d)$, where l_u represents the BS for UL association and l_d represents the BS for DL association, where $l_u, l_d \in \{\mathcal{L}\}$. If User1 gets matched to BS agent1 (e.g., $n = (1, 2)$), we can say BS agent1 is matched to User1. In other words, we can state that BS1 is matched to User1 in UL and BS2 is matched to User1 in DL. Therefore, a matching from a user to BS agent can be interpreted as user to BS matching for UL and DL. Mathematically, the matching and iterative matching can be defined, respectively, as follows.

Definition 3.1 (Matching)**.** *A matching μ is the outcome of the considered association problem and can be defined as a function [?] from the set $\mathcal{K} \cup \mathcal{N}$ into the set $\mathcal{K} \cup \mathcal{N}$ such that*

- $\mid \mu(k) \mid \leq 1$ *for each user k and $\mu(k) \in \mathcal{N} \cup \emptyset$.*

- $|\mu(l_u)| \leq q^{\mathrm{u}}_{l_u}$ *and* $|\mu(l_d)| \leq q^{\mathrm{d}}_{l_d}$ *for each BS agent n.*

- *$k \in \mu(n)$ if and only if $\mu(k) = n$.*

The tuple $(\mathcal{K}, \mathcal{N}, \mathcal{Q}, \succ_{\mathcal{K}}, \succ_{\mathcal{N}})$ determines the cell association matching problem, where $\succ_{\mathcal{K}} = \{\succ_k\}_{k \in \mathcal{K}}$ is the preference set of users, $\succ_{\mathcal{N}} = \{\succ_n\}_{n \in \mathcal{N}}$ is the preference set of BS agents, and $\mathcal{Q}$ is the quota vector.

Definition 3.2 (Iterative Matching). *For a given pair of association $(k, i), (k', j)$ in a matching μ (where $k, k' \in \mathcal{K}$ and $i, j \in \mathcal{N}$), a iterative matching $\mu_{i,j}^k$ can be defined as $\mu_{i,j}^k = \{\mu \setminus (k, i)\} \cup (k, j)$. That is, iterative matching allows a given user k to change its matching iff it is beneficial in terms of its achieved utility. A matching μ with link $(k, i) \in \mu$ is then said to be stable if there does not exist any iterative matching $\mu_{i,j}^k$ such that user k prefers BS agent j to i [$\forall k \in \mathcal{K}$] or BS agent i prefers user k' to k [$\forall i \in \mathcal{N}$].*

3.1.2 Preferences of the Players

To fully describe the matching μ, the preferences of the players (i.e., users and BS agents) need to be well defined. The method of defining preference list for each user and BS agent is described as follows.

Users' preferences

From the users' perspective, each user k seeks to maximize its own utility function which is given by its UL and DL rates, i.e., $\sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{u}} \beta_{k,l}^{\mathrm{u}} R_{k,l}^{\mathrm{u}} + \alpha_{k,l}^{\mathrm{d}} \beta_{k,l}^{\mathrm{d}} R_{k,l}^{\mathrm{d}}$. In order to maximize the UL and DL rate utilities, each user tends to calculate the preferences over the BS agents, as per the formulated game. To illustrate the calculation of preference matrix for the players, let us consider a small network with three BSs and four users. In such a network, we will have nine BS agents.

Table 3.1: UL association table

Table	BS1	BS2	BS3
`User1`	1	0	0
`User2`	0	1	0
`User3`	0	0	1
`User4`	0	0	1

Table 3.2: DL association table

Table	BS1	BS2	BS3
`User1`	0	1	0
`User2`	1	0	0
`User3`	0	0	1
`User4`	0	0	1

- Initially, we can consider a random association for the users to the BSs (see Table 3.1 and Table 3.2). From the tables, we can see that User1 is associated with BS1 in UL and BS2 in DL. User2 is associated with BS2 in UL and BS1 in DL. Moreover, User3 and User4 are associated with the same BS (BS3) for both UL and DL.

- Each user will construct its preference list over the BS agents, i.e., each user will rank the BS agents depending on the value of their utility.

- The utility of a BS agent for a user can be given as the sum of the UL and DL rate it can provide to that user. For instance, if User1 calculates the utility value of BS agent 1, i.e., $n = (1, 2)$, it will calculate the UL rate from BS1 and DL rate from BS2. The summation of these two rates represents the utilty of BS agent 1 for User1. To calculate the DL data rate, User1 calculates the received signal from BS2 and the interference received from all other BSs and users, if scheduled for transmission. Similarly the UL rate from BS1 can also be calculated.

- Each user calculates its utilities for all BS agents and then ranks the agents accordingly in its preference list.

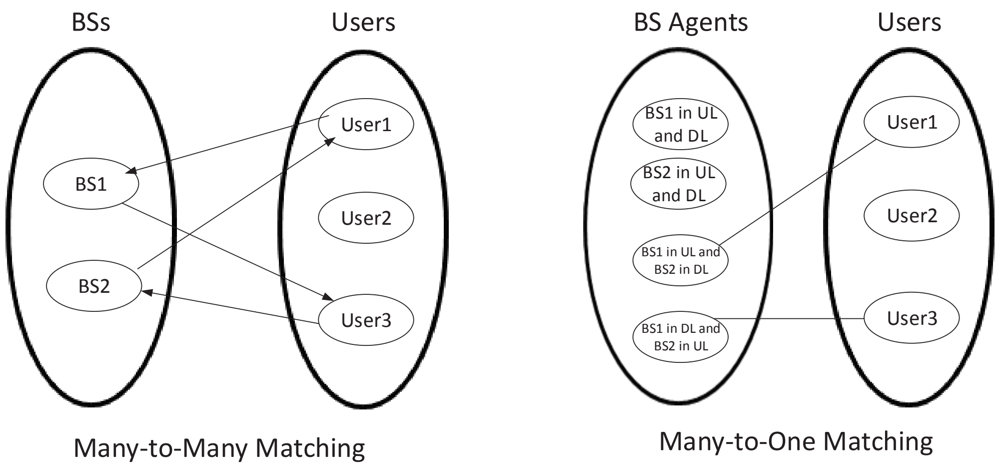

Figure 3.1: Graphical illustration of the considered transformation from many-to-many matching game into a many-to-one matching game.

Preference of BSs

The preference list of BS agents can be computed depending on the rate the BSs (within the BS agent) can provide to the associated users. As each BS agent may be composed of two BSs and the BSs might have different UL and DL quota, the UL and DL preference lists of a BS agent need to be kept separate. Let us consider a BS agent (BS1 UL, BS2 DL). This agent has two BSs, i.e., BS1 and BS2. BS1 will have an UL preference list over the users and BS2 will have a DL preference list over the users. Each BS in a given BS agent calculates the preference profile iff the quota of that BS is violated. For example, if a BS1 has a quota of three users in UL and a 4th user comes in, the preference list over these four users will be calculated. The BS1 will then rank the users according to their achievable UL rate and discard the worst user.

Remark: Each user has a complete, reflexive, and transitive[1] preference over the set of BS agents whereas the preference list of a BS is incomplete as each BS makes up its preference only over a specific set of users who proposed the BS for association. We also assume strict preferences (so that no user is indifferent between two BS agents and vice versa).

3.1.3 Proposed Iterative Matching Algorithm

The proposed iterative matching algorithm is illustrated in **Algorithm 2** where the matching is performed in an iterative manner until the network wide stability is achieved. Initially, each user is assumed to associate with the nearest BS for UL whereas for DL transmission it associates to the BS from which it gets the highest received signal power. Then the BS agents are formed to start the matching game. Each user makes the preference list over the BS agents and checks whether it can get associated to the most preferred BS agent. If the BS agent is not overloaded (i.e., the quota of the BS does not exceed the number of its associated users), then the BS agent accepts the proposal. Otherwise, the BS agent calculates its preference profile and finds out the worst user among the associated users and discards the worst user. Once a user gets discarded from the most preferred BS agent, this user has to update its preference list to remove that BS agent[2]. This user then proposes to the next preferred BS agent in its preference list and tries to get an association. Once the matching game is over for all users, each user rebuilds its preference list. The updated preferences may necessitate changing of the current associations. Therefore, the aforementioned steps

[1] Let $\succeq$ be a binary relation on any arbitrary set $\amalg$. The binary relation $\succeq$ is complete if $\forall i, j \in \amalg$, either $i \succeq j$ or $j \succeq i$ or both. A binary relation is transitive if $i \succeq j$ and $j \succeq i$ implies that $i \succeq k$ $\forall k \in \amalg$.

[2] Depending on the number of rejections, the updating cost of the preference matrix might increase.

continue with the updated preference lists. This iterative process continues until no new changes are required by further updating the preference profiles. Since iterative matching allows room for possible changes after a matching decision has been made, users can update their preferences based on the new interference conditions resulting from the network wide matching. This helps the users to try for a different BS that can provide higher rate than the current association.

Algorithm 2 Iterative Matching Algorithm for User Association

---

Initialization : Each user is associated to its nearest BS for UL and to the BS providing the strongest received signal for DL
Form the set of BS agents $\mathcal{N}$ from the set of BSs $\mathcal{L}$
Each user k forms a preference matrix $\succ k$ over all the BS agents
while there exists a iterative matching $\mu^k_{i,j}$ such that k prefers j to i where $(k, i) \in \mu$ **do**
  each k applies to its most Preferred BS agent n
  if Any BS l in the BS agent n is overloaded **then**
    Step 1 : Calculate the dynamic preference $\succ_l$ of BS l over the currently associated users
    Step 2 : Find the worst user k' in terms of overloaded BS l
    Step 3 : Discard the worst user association in both UL and DL
    Step 4 : Discard the BS agent n from the worst user preference
    Discarded user propose to its next preferred BS agent until association or $\succ k'$ is empty
  end if
  Each user k rebuilds a new preference matrix $\succ k$ based on current matching
end while

In the following, we analyze the performance of distributed iterative matching based user association approach. More specifically, we define and analyze the stability and Pareto-efficiency of the solution.

Definition 3.3 (Stability)**.** *A matching μ is said to be **stable** if there is no user and BS agent pair (k, n) such that $\mu(k) \neq n$ where $n \succ_k \mu(k)$ and $k \succ_n \mu(n)$.*

Proposition 1 (Stability)**.** *The iterative matching algorithm is guaranteed to converge to a stable matching starting from any initial association.*

Proof. Assume that we have a blocking pair (k, n) that blocks our matching μ. Thus $n \succ_k \mu(k)$ and $k \succ_n \mu(n)$. If $n \succ_k \mu(k)$, it means that k has proposed to n before proposing to $\mu(k)$ due to the structure of the preference matrix. That is, k has already been rejected by BS agent n. Now let us assume that k has been discarded by BS agent n due to user k', which means $k' \succ_n k$. Let the utility value provided by k' is $U(k')$. Therefore, in the final matching only someone having utility greater than $U(k')$ can be associated to n which means $\mu(n) \succ_n k$. This contradicts our initial assumption, i.e., there cannot exist any blocking pair (k, n) in the final matching μ. Hence μ is stable. □

Definition 3.4 (Pareto-Efficiency)**.** *We can define a matching to be **Pareto efficient** if there does not exist a Pareto improvement pair. A pair of users (k, k') is called **Pareto improving pair** in a matching μ, if $\mu(k') \succ_k \mu(k)$ and $\mu(k) \succ_{k'} \mu(k')$.*

Proposition 2 (Pareto-Efficiency)**.** *The iterative matching algorithm for the user association is Pareto efficient.*

Proof. Assume that we have a Pareto improvement pair (k, k') in our final matching μ. This implies that we can form a new matching μ', where $\mu' = \mu - (k, \mu(k)), (k', \mu(k')) \cup (k, \mu(k')), (k', \mu(k))$ which will aid in maximizing our objective function. Let the utility of the achieved matching μ be $U(\mu)$ and the utility of the Pareto improved matching μ' be $U(\mu')$. From the definition of preference profile, it is apparent that a user always proposes to the best ranked agent first. Therefore, if k prefers $\mu(k')$, it has already proposed to $\mu(k')$ and got rejected. Same is true for k'. Hence, $U(\mu') < U(\mu)$ and (k, k') cannot be a Pareto improvement pair. Therefore, our proposed matching is Pareto efficient. □

Proposition 3 (Convergence)**.** *Starting from any initial association, the proposed iterative matching algorithm is guaranteed to converge to a final matching.*

3.1.4 Computational Complexity and Signaling Overhead

Worst-case computational complexity

In the iterative matching algorithm, the construction of a preference list is the first step. Since there are $2 \times \binom{L}{2} + L$ BS agents, each user will have a preference profile of size $2 \times \binom{L}{2} + L$. With an efficient sorting algorithm, each user can make up their preference matrix in $(2\binom{L}{2}+L)\log(2\binom{L}{2}+L) = N \log N$ time. For K users, the matrix can be formed with a complexity order $O(KN \log N)$. Now, let us consider the while loop of the algorithm. This loop will be terminated when all users will be associated or when users' preference profiles become empty. If we consider the *worst case*, each user will have to propose to $2 \times \binom{L}{2} + L$ agents to find a suitable association. It is obvious that no user will propose to the same BS agent after rejection; thus, users update their preference profiles and the total attempts made by K users will be atmost $K(2\binom{L}{2} + L)$. At each rejection, a BS recalculates preference profile to find the worst user. Using a good sorting algorithm, each BS can make up the preference list at $q \log q$ cost [?]. As such, the total complexity of the computations within the while loop becomes $O(K(2\binom{L}{2} + L)q \log q) \approx O(K(2\binom{L}{2} + L)) \approx O(KN)$, which is linear with the number of users and BS agents. Since the while loop of the algorithm will be terminated after a finite number of iterations I, the complexity of the while routine is of $O(KNI)$. Finally, with the initial preference profile building, the total complexity of the iterative matching is of $O(KNI \log N)$.

Signaling overhead

Each BS will need to estimate the interference in UL and exchange the information with the users to help building their profiles. Thus, users will need to estimate the interference in the DL to calculate their DL preferences and use the estimated information from the BSs to calculate their UL preferences. Once the preference profiles are made, all users run the matching algorithm independently. Whenever a user proposes to a BS for UL association, the BS will estimate the UL interference and calculate UL preference list over the currently associated users iff the quota is violated. On the other hand, users need to send their interference estimates to BSs in DL so that BSs can build their DL preference profiles accordingly. Once a matching decision is made, a new association is obtained which needs to calculate the preferences all over again and the same overheads listed above will apply.

3.2 Simulation Results

In this section, we present numerical results that quantitatively analyze the performance of matching-based distributed user association schemes compared to the traditional association schemes, i.e.,

- *Coupled UL-DL user association:* In this approach, each user is associated to the BS providing the strongest received signal both in UL and DL.
- *Decoupled UL-DL user association:* In this approach, each user can associate to two different BSs for UL and DL. The association criteria for DL and UL is highest received signal power and shortest distance, respectively.

We also compare the performance of the proposed matching algorithms with the centralized GP solution.

For our simulations, we consider a single MBS overlaid by randomly deployed small cells, unless stated otherwise. The transmit power of each SBS is 3W and MBS is 20W. The quota is taken as $q_l^{\mathrm{u}} = q_l^{\mathrm{d}} = 2$ for all BSs $l \in \mathcal{L}$. The channel experiences

Rayleigh fading with the path-loss exponent set to $\xi = 2$. The channel power gain with Rayleigh fading is modeled as exponentially distributed random variable with mean 1 and that for shadow fading is modeled as a log-normal random variable with a mean of 0 dB and a standard deviation of 8 dB. The noise level is assumed to be -151dBW. The users are distributed randomly in the network and each user has a transmit power of 1W. We consider $\zeta = 100$dB SI cancellation for the BSs and the users. All the statistical results are averaged across a large number of runs over the random location of users and BSs and the channel fading coefficients. The unassigned users are given a zero utility throughout the simulations.

3.2.1 Iterative Matching Vs. Centralized GP Solution

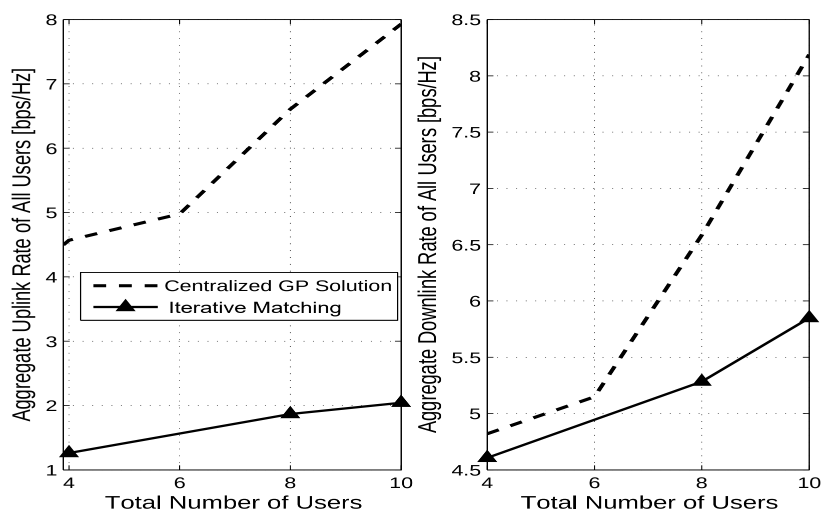

Figure 3.2: UL and DL rate of all users in the network with a MBS and two SBSs as a function of the number of users.

Fig. 3.2 depicts the aggregate rate of all users in the network considering both UL and DL transmissions as the number of users varies. The proposed iterative matching algorithm is compared to the centralized solution which is obtained from

Algorithm 1. The performance of the centralized scheme is higher than the proposed scheme both in UL and DL and the performance gap continues to increase with the increasing number of users. Fig. 3.3 depicts the outage in the network considering UL and DL transmissions as the number of users varies. Outage can be defined in terms of the number of users who remain unassociated. Outage in UL is given as $K - \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{u}}$. Similarly, $K - \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{k,l}^{\mathrm{d}}$ is the outage in DL. As expected, the outage increases with increasing number of users due to increasing competition. Further, the iterative matching is observed to perform nearly the same as the centralized scheme in terms of outage.

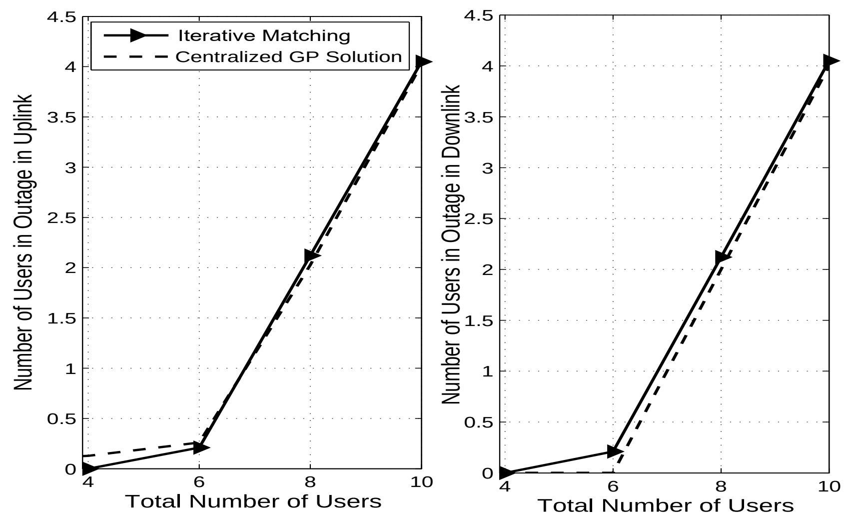

Figure 3.3: Performance, in terms of UL and DL outage in the network with a MBS and two SBSs as a function of the number of users.

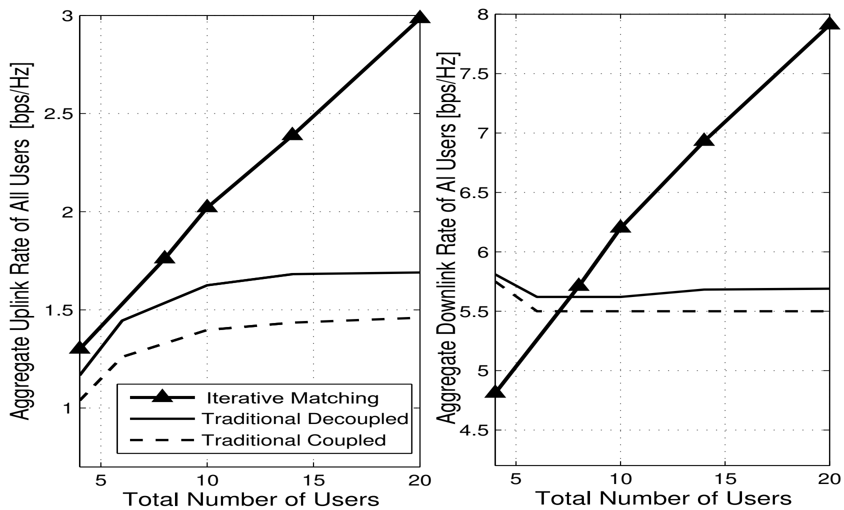

Figure 3.4: UL and DL rate of all users in the network with a MBS and three SBSs as a function of the number of users.

3.2.2 Iterative Matching Vs. Traditional Schemes

Aggregate UL and DL rate of users

Fig. 3.4 depicts the rate of all users in the network considering UL and DL transmissions as the number of users varies. The iterative matching algorithm is compared to both conventional coupled and decoupled association schemes. It can be observed that with the increasing number of users in the network, our algorithm shows noticeable performance gains over the conventional coupled and decoupled association schemes (especially in the UL scenarios). Due to the provisioning of decoupling and consideration of interference-aware utility functions, iterative matching-based association shows significant improvements over the traditional decoupled as well as coupled schemes. Note that the traditional decoupled association is not interference-aware. Further, in case of DL, connecting to a BS that provides the highest received signal is beneficial. Note that the conventional coupled and decoupled (DUDe) association perform nearly the same in the DL since the DL criterion of user association is the same for both schemes. However, as the number of users in the system increases, the interference conditions become more intense; thus the gain of iterative matching becomes evident in DL as well.

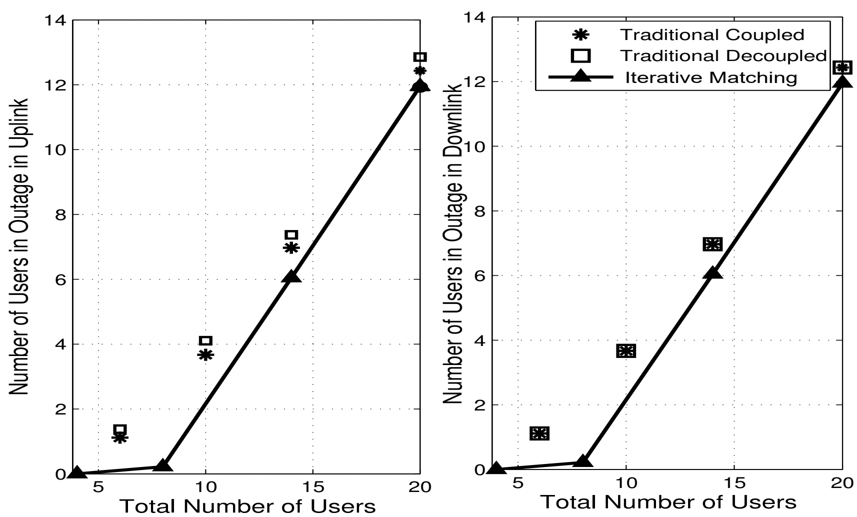

Figure 3.5: Performance in terms of UL and DL outage in the network with a MBS and three SBSs as a function of the number of users.

Outage (number of unassigned users)

Fig. 3.5 depicts the outage in the network considering UL and DL as the number of users varies. From this figure, the reduction of outage in both UL and DL compared to the traditional schemes is evident. In case of coupled/decoupled schemes, users associate to their nearest BSs in UL, and to the BSs from which they receive the maximum power in the DL. However, due to the limited quota of the BSs, all users may not get their desired associations which results in outage. In iterative matching, users have a preference list and if a user gets rejected from the most preferred BS agent it tries to get the next preferred association which increases the number of associated users compared to traditional schemes. Further, considering interference-aware utilities and externalities result in dynamic preferences profiles, which plays an important role in the rate enhancement.

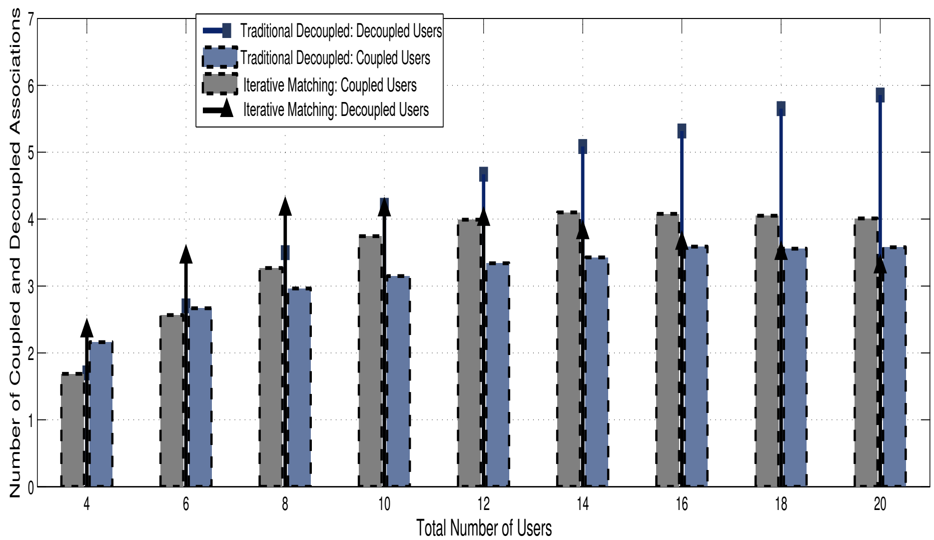

Figure 3.6: Coupled and decoupled associations in the network composed of a MBS and three SBSs as a function of the number of users.

Number of decoupled associations

A user k is said to have a coupled association if $\alpha^{\mathrm{u}}_{k,l} = 1$ and $\alpha^{\mathrm{d}}_{k,l} = 1$ for any $l \in \mathcal{L}$. A user is a decoupled user if $\alpha^{\mathrm{u}}_{k,l} = 1$ and $\alpha^{\mathrm{u}}_{k,l'} = 1$ for any $l, l' \in \mathcal{L}, l \neq l'$. We consider the users as coupled or decoupled users who have both UL and DL associations. The users who are in outage in either UL or DL are not considered to be coupled or decoupled users. With traditional decoupled association, the decoupling of users continues to increase with the increase in the number of users as shown in Fig. 3.6. Thus the rate enhancements (especially in UL) over coupled association can be achieved as shown in Fig. 3.4. However, it may not be wise to continue decoupling of users without taking into account the resulting interferences (as is done in traditional decoupling). Note that more users in the system will lead to higher number of associations and thus interference. As such, it is crucial to control the percentage of decoupled associations in the system to minimize the interference while maximizing the rate. In this context, the proposed iterative matching solution intelligently reduces the number of decoupled associations and allows more coupled associations while enhancing the overall rate in scenarios with high user density and high interference as shown in Fig. 3.4.

3.2.3 Impact of Quota per BS

We analyze the performance of iterative matching in UL and DL with increasing quota per BS in Fig. 3.7, Fig. 3.8. The increase in quota implies a smaller channel access probability per user. If more users associate to the same BS, the chance of getting the channel decreases for a specific user. This deteriorates the rate of individual users which also affects the aggregate rate. On the other side, with the increase in quota, the number of associated users per BS increases with only one user transmitting in UL and DL at maximum. Therefore, the total number of users concurrently receiving or transmitting in the same channel reduces which leads to interference reduction. Thus the gains from matching tends to reduce with high quota as the significance of interference aware utility functions decreases. In other words, when the competition becomes less intense, the usefulness of the matching algorithm starts to decline, which can also be concluded from our previous results. Though the traditional schemes perform well enough with less competition in the network, the outage tends to increase as shown in Fig. 3.8. *Thus the performance of iterative matching is superior from the outage perspective in less competitive scenarios whereas from the rate perspective in highly competitive scenarios.*

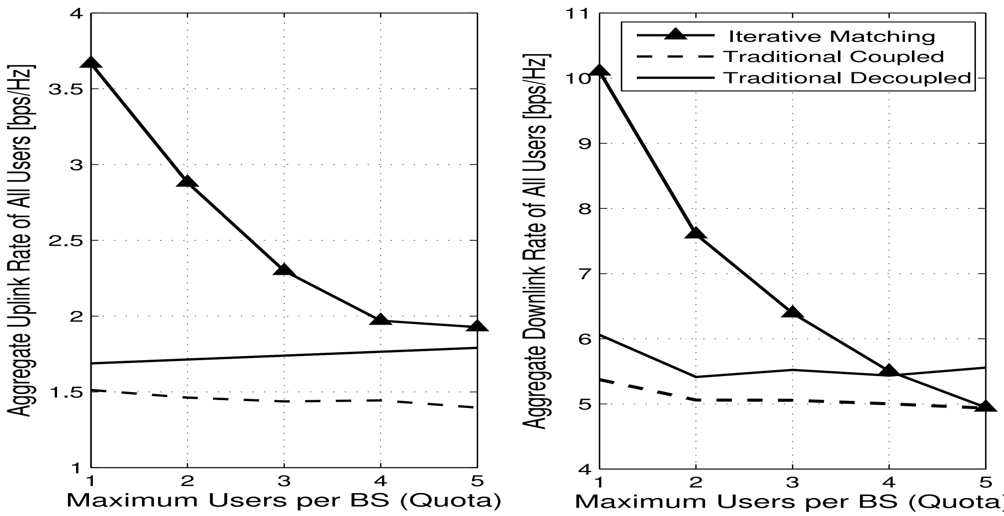

Figure 3.7: Performance in terms of (a) UL and DL rate for all users in the network with a MBS, three SBSs and twenty users as a function of the maximum number of users per BS (quota).

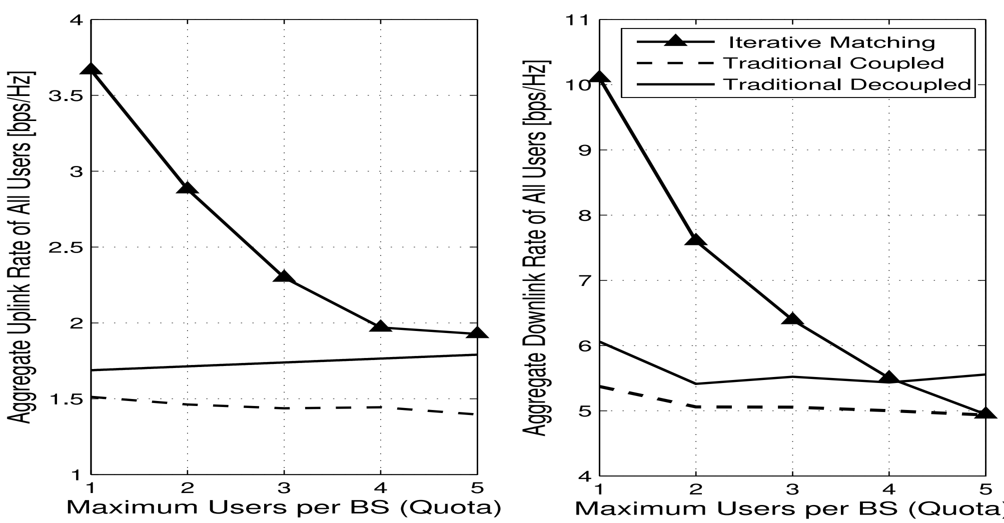

Figure 3.8: Performance in terms of outage (number of unassociated users) for all users in the network with a MBS, three SBSs and twenty users as a function of the maximum number of users per BS (quota).

3.2.4 Number of Iterations to Converge

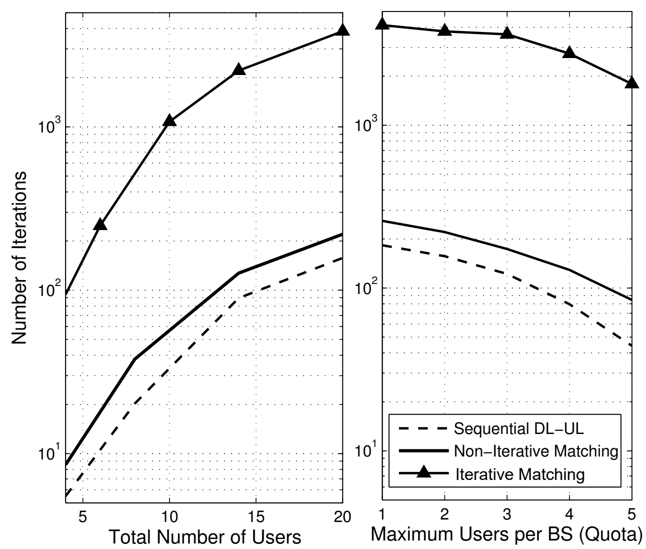

Figure 3.9: Number of iterations needed to converge to a Matching solution in the network with a MBS and three SBSs as a function of (a) the number of users and (b) the maximum number of users per BS (quota).

Fig. 3.9(a) plots the number of iterations needed by the matching algorithms to converge to a stable solution. The proposed non-iterative matching, sequential DL-UL matching, and iterative matching are compared. The number of iterations for convergence increases with the number of users. This is due to the increase in the number of rejections by each BS as the number of users increases (since the competition increases). However, with a fixed number of users, if we increase the quota per BS, the number of iterations reduces (Fig. 3.9(b)). The reason is that each BS can accept more users; thus the competition reduces in the system and the final association decision can therefore be made faster. Finally, compared to non-iterative matching, the sequential DL-UL Matching reduces the complexity even further due to a direct reduction in the number of players (BS agents).

3.3 Summary

In this chapter, we have proposed a iterative matching algorithm to solve the formulated user association problem considering externalities. We have first transformed the game from many-to-many matching to many-to-one matching. We have provided the proof of convergence and stability of the proposed scheme. We have further analyzed the computational complexity of iterative matching and discussed the signaling overhead for real-time implementation of the proposed scheme. Simulation results have demonstrated the efficacy of the proposed algorithm over the traditional association schemes. Our results show the significance of decoupling both in UL and DL for dense scenarios. The performance of the proposed scheme has also been compared to that of the centralized solution presented in Chapter 2. The impact of quota on matching solution has also been evaluated via simulations. To achieve rate maximization in the network, the importance of the choice of percentage of decoupling becomes evident from the simulation results.

Chapter 4

Low-Complexity Matching Algorithms

4.1 Reducing the Complexity of Matching Algorithms

With the increase in number of BSs, the computational complexity of the iterative matching algorithm may increase significantly; thus, the need of light-weight matching algorithms is evident. In this section, we discuss few simplified solutions for the considered user association problem based on matching.

4.1.1 Non-Iterative Matching Algorithm

A simplified version of the iterative matching algorithm can be generated by removing the flexibility of re-generating preference profiles at each iteration. That is, once a stable matching is achieved that fulfills the initial preferences of all users, the algorithm stops. In particular, each user builds a preference profile over the BS agents at the beginning and sequentially proposes its most preferred BS agents. However, once a user gets discarded from the most preferred BS agent, the user has to update its preference list by permanently deleting the BS agent and tries to associate with the next preferred BS agent. Similar to iterative matching, if any UL/DL BS in the BS agent is overloaded (i.e., the quota of BS exceeds either in UL or in DL), then the overloaded BS calculates the preference profile and discards the worst user.

Proposition 4 (Convergence and Stability of Non-Iterative Matching:)**.** *As the preference profile of a user is finite and gets shortened at each rejection by BS agents, this guarantees that a user will never propose an agent twice. As a result, the while loop of the algorithm is guaranteed to terminate once all users are associated or their preference profile gets empty. Note that stability (i.e., neither BSs nor users intend to deviate from their current matching) in this game applies with reference to the initial preferences.*

The complexity of the non-iterative matching algorithm is of $O(KN \log N)$. The signaling overhead remains almost the same as the iterative matching algorithm except that the users do not need to estimate the channel and rebuild the preference profile once the stable association is achieved.

Algorithm 3 Non-Iterative Matching Algorithm

Form the set of BS Agents $\mathcal{N}$ from the set of BSs $\mathcal{L}$
Initialization : $\mu \leftarrow \emptyset$
Calculate Preference Matrix $\succ_k$ for each user $k \in \mathcal{K}$
while an user is not associated and its preference profile is not empty **do**
  Pick an unassociated user k
  k applies to its most Preferred BS agent n
  $\mu \leftarrow \mu \cup \{k, n\}$
  if Any BS l in the BS agent n is overloaded **then**
    Step 1-4 from Algorithm 2
  end if
end while

4.1.2 Sequential Downlink and Uplink Matching

In the iterative and non-iterative matching, the number of BS agents increases exponentially with the number of BSs; thus, the complexity increases with the number of BSs. To reduce this complexity, a sequential matching for DL and UL associations can be performed. That is, a given user gets matched first to a DL BS and then, based on its DL association, selects a suitable UL BS. In particular, each user builds a preference profile over the DL BSs at the beginning and then each user sequentially proposes to its most preferred BS. If the BS is overloaded, then the BS will remove the worst user from the association. If the given user is the worst, it will be discarded and the user will then propose to the next preferred BS. Once the association for DL is complete, the user will calculate a dynamic preference list over the UL BSs and choose the best one. This will continue until all the users are associated or their preference profile gets empty. Here all users will have separate preferences for UL and DL unlike iterative/non-iterative matching.

Algorithm 4 Sequential Downlink-Uplink Matching Algorithm

```
Initialization : Calculate DL Preference Matrix for each user over all the BSs
depending on DL rate
while an user is not associated in DL and its preference profile is not empty do
    Pick an unassociated user k
    k applies to its most Preferred BS l
    if BS l is overloaded then
        Step 1-4 from Algorithm 2
    else
        Calculate the dynamic preference of the user over all the BSs using UL rate
        Connect to the best preferred BS whose quota is not filled
    end if
end while
```

Convergence

The sequential UL-DL matching always converges from any initial association as the convergence is achieved when each user gets associated or their preference list becomes empty. At each rejection by the BS, users update their preferences which guarantees the convergence.

Computational complexity

The length of the preference profile is L instead of $2\binom{L}{2}+L$. Hence in the initialization phase, the DL preference profile can be made with a complexity of $L\log L$ per user. The while loop will terminate when each user is either assigned to a DL BS or its preference profile gets empty. At each rejection, the BS has to make a preference profile which can be made with a complexity of $O(q\log q)$. Each user can be rejected at most L times which takes $O(Lq\log q)$ time. So the total algorithm takes $O(KL\log L)$ time which is a huge improvement over iterative/non-iterative matching.

4.2 Simulation Results

In this section, we present numerical results that quantitatively analyze the performance of the proposed matching schemes compared to the iterative matching scheme.

For our simulations, we consider a single MBS overlaid by randomly deployed small cells, unless stated otherwise. The transmit power of each SBS is 3W and MBS is 20W. The quota is taken as $q_l^{\mathrm{u}} = q_l^{\mathrm{d}} = 2$ for all BSs $l \in \mathcal{L}$. The channel experiences a Rayleigh fading with the path-loss exponent set to $\xi = 2$. Rayleigh fading has been modeled as exponentially distributed random variable with mean 1 and shadow fading is modeled as a log-normal random variable with a mean of 0 dB and a standard deviation of 8 dB. Noise level is assumed to be -151dBW. The users are distributed randomly in the network and each user has a transmit power of 1W. We consider $\zeta = 100$dB SI cancellation for the BSs and the users. All the statistical results are averaged via a large number of runs over the random location of users and BSs and the channel fading coefficients. The unassigned users are given a zero utility throughout the simulations.

4.2.1 Iterative Matching Vs. Low-Complexity Schemes

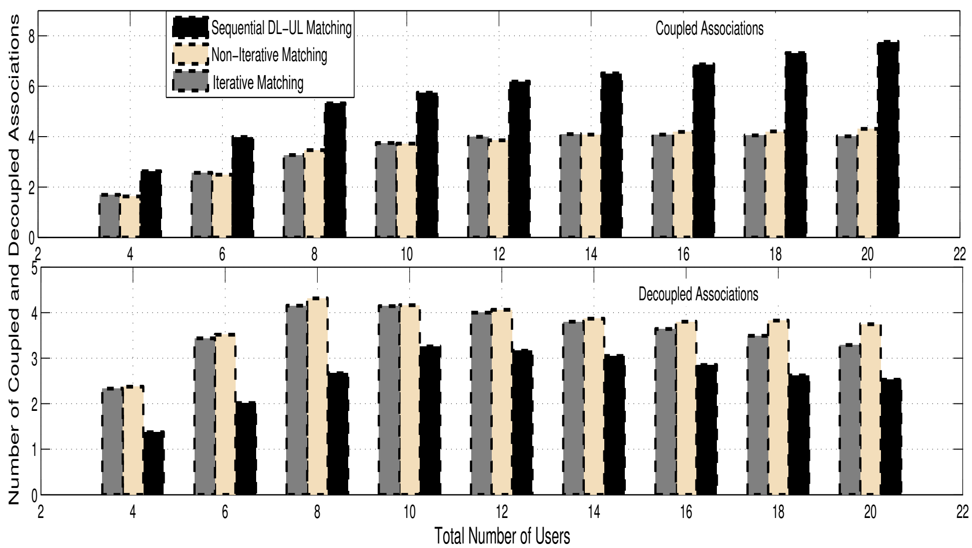

Figure 4.1: Coupled and decoupled associations in the network composed of a MBS and three SBSs as a function of the number of users.

The performances of the proposed low-complexity matching solutions are compared with the proposed iterative matching scheme (Fig. 4.2, 4.3). It is quite clear from Fig. 4.2 that iterative matching performs better compared to the low-complexity solutions in terms of UL and DL rate. The outage is nearly same for all the proposed matching schemes (Fig. 4.3). Unlike iterative matching, the proposed low-complexity matching schemes do not consider externalities. The additional

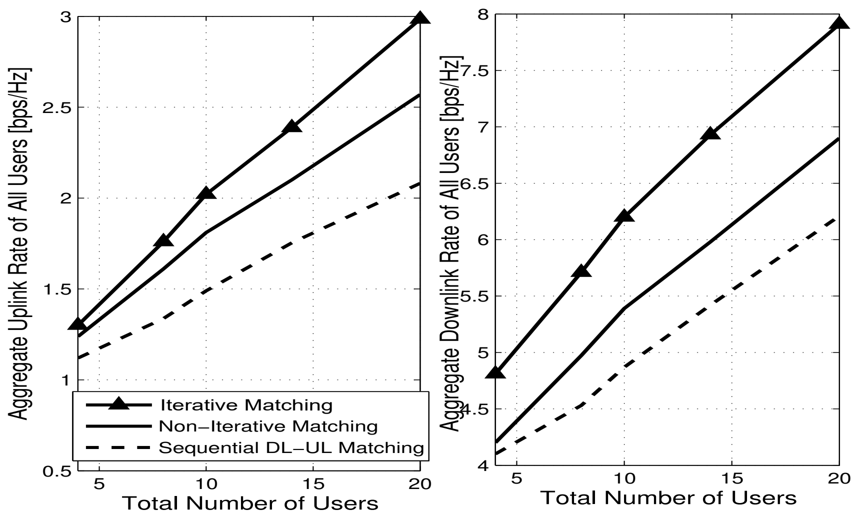

Figure 4.2: Performance in terms of (a) UL and DL rate for all users in the network with a MBS, three SBSs as a function of the number of users.

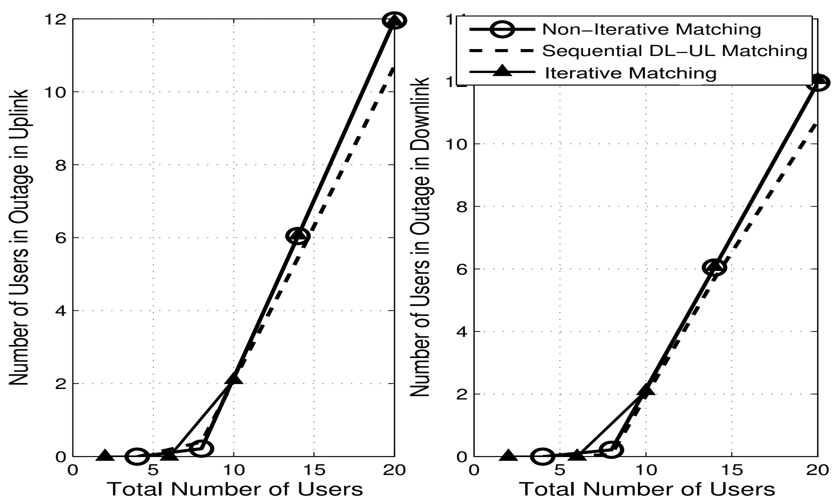

Figure 4.3: Performance in terms of outage (number of unassociated users) for all users in the network with a MBS, three SBSs as a function of the number of users.

changes help in increasing the performance of the proposed solution. However, with the increasing number of users in the network, the low-complexity matching algorithms still show noticeable performance gains. Like iterative matching, with the low-complexity matching schemes, the decoupling of users continues to increase with increasing number of users (Fig. 4.1). But as discussed previously, a careful choice of the percentage of decoupling aids in rate maximization which is perfectly achieved via iterative matching. Nonetheless, non-iterative and sequential DL-UL matching can also be a good alternative of the iterative matching to reduce implementation cost.

4.3 Summary

In this chapter, we have proposed light-weight matching algorithms (i.e., non-iterative matching and sequential UL-DL matching algorithms) to reduce the computational complexity of externalities-aware iterative matching algorithm. We have also discussed their convergence, stability, and complexity. The performances of the light-weight solutions have then been compared to the performance of iterative matching in terms of aggregate UL and DL rates of all users, the number of unassociated users, and the number of coupled/decoupled associations. Although the schemes tend to decrease the rate performance compared to iterative matching, the computational overhead is greatly reduced.

Chapter 5

Conclusion and Future Directions

5.1 Concluding Remarks

We have investigated the decoupled UL-DL user association problem in two-tier full-duplex cellular networks. We have formulated the association problem as a convex GP problem and solved it to find a centralized solution in Chapter 2 which works as a benchmark for distributed schemes. We have then formulated the problem as a distributed many-to-one matching game in which users and BS agents evaluate each other based on their utilities in Chapter 3. Finally, we have proposed low-complexity distributed solutions for the above mentioned association problem in Chapter 4. Simulation results have shown that the proposed approach can provide significant gains over the conventional coupled and decoupled user association schemes. Our results have shown that decoupling the UL association from the DL not only improves the UL performance but also improves the DL performance with interference-aware utility optimization. Further, in high interference scenarios, traditional decoupling may not be needed. Thus, a careful choice of decoupled associations is crucial for rate maximization. Simulation results have revealed the superiority of our proposed matching schemes over the traditional schemes in scenarios of high competition and interferences. High competition scenarios occur when there are fewer number of BSs, more users, and less quota per BS. The work can be extended to develop matching game-based solutions under channel gain uncertainties as well as backhaul constraints.

5.2 Future Research Directions

The user association problem is a fundamental problem in wireless networks. Some of the possible future extensions of the work presented in this thesis are as follows:

- In this work, we have not considered uncertainty in the channel gains. This work can be extended considering channel uncertainty.
- Instead of Matching games, other different game models can also be used to solve the user association problem and the corresponding solutions can be compared with the proposed matching schemes.
- The work can be extended by considering large-scale systems for which different modeling techniques will need to be used.
- Power control may also be considered and the problem of joint user association and power control can be solved.
- The user association problem in out-of-band FD systems is also worth investigating.
- Auction algorithms can be also investigated to solve the problem of user association.
- Fairness-based user association can be also considered instead of rate maximization-based user association.

- In order to develop a complete solution framework, power and sub-channel allocation for the users can also be incorporated in the problem formulation.

Appendix A

A.1 Appendix: Derivative of Lagrangian

For differentiating the Lagrange, we differentiate (2.6) with respect to $\alpha^{\mathrm{u}}_{k,l}$. If we open up the summation, the term for $k = k, l = l$ can be differentiated using trivial calculus and will result in $\frac{1}{\ln(2)\alpha^{\mathrm{u}}_{k,l}}$. However, the other terms of (2.6) need to be observed carefully. Let us consider a toy example with two users and three BSs. If we open up the summations, we can observe that two of the UL terms will have $\alpha^{\mathrm{u}}_{1,1}$ as a denominator and three of the DL terms will have $\alpha^{\mathrm{u}}_{1,1}$ as a denominator. If $k = 2, l = 2$ and $k = 2, l = 3$ we have $\alpha^{\mathrm{u}}_{1,1}$ in the denominator from the UL terms. So, while differentiating (2.6) with respect to $\alpha^{\mathrm{u}}_{1,1}$ we will get five terms of the form $\log_2 \frac{c}{d+e\alpha^{\mathrm{u}}_{1,1}}$. We know $\frac{\partial \log_2(\frac{c}{d+ex})}{\partial x} = -\frac{e}{(d+ex)\ln(2)}$. Hence, we obtain

$$\sum_{i\in\mathcal{L},i\neq 1}\sum_{j\in\mathcal{K},j\neq 1}\frac{\frac{P_k G_{k,i}}{\min(q,\frac{K}{L})\ln(2)}}{\sum_{l'\neq i} P_{l'} G_{l'i} + \frac{\sum_{k'\neq j} P_{k'} G_{k'i} \sum_{l'\neq i}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})} + \frac{P_i}{\zeta} + \sigma^2}.$$

Similarly, we can obtain the DL terms as well.If $k = 2, l = 1$, $k = 2, l = 2$ and $k = 2, l = 3$ we have $\alpha^{\mathrm{u}}_{1,1}$ in the denominator from the DL terms. We can differentiate them with respect to $\alpha^{\mathrm{u}}_{1,1}$ and obtain

$$\sum_{i\in\mathcal{L}}\sum_{j\in\mathcal{K},j\neq 1}\frac{\frac{P_k G_{k,j}}{\min(q,\frac{K}{L})\ln(2)}}{\sum_{l'\neq i}P_{l'}G_{l'j}+\frac{\sum_{k'\neq j}P_{k'}G_{k'j}\sum_{l'\in\mathcal{L}}\alpha^{\mathrm{u}}_{k',l'}}{\min(q,\frac{K}{L})}+\frac{P_j}{\zeta}+\sigma^2}.$$

By observing the terms of the toy example, we can write the general formula and verify the general formula by substituting some toy examples.