UNIVERSITY CARLOS III OF MADRID

Department of Telematics Engineering

Master of Science Thesis

Opportunistic cellular communications with clusters of dual-radio mobiles

Author: **Arash Asadi**
Ms.Eng. in Telecommunications

Supervisor: **Pablo Serrano Yáñez-Mingot, Ph.D.**
Co-supervisor: **Vincenzo Mancuso, Ph.D.**

Leganés, September 2012

Abstract

Opportunistic scheduling was initially proposed to exploit user channel diversity for network capacity enhancement. However, the achievable gain of opportunistic schedulers is generally restrained due to fairness considerations which impose a tradeoff between fairness and throughput. In this dissertation, we show via analysis and simulation that opportunistic scheduling not only increases network throughput dramatically, but also can be fair to the users when they cooperate, in particular by forming clusters. We propose to leverage smartphone's dual-radio interface capabilities to form clusters among mobile users, and we design simple and scalable cluster-based opportunistic scheduling strategies which would incentivize mobile users to form clusters. We use a coalitional game theory approach to analyze the cluster formation mechanism, and show that proportional fair-based intra-cluster payoff distribution would bring significant incentive to all mobile users regardless of their channel quality.

Table of Contents

Chapter 1

Introduction

Opportunistic schedulers have become a promising solution to cope with the mobile consumer traffic boom in cellular networks. This class of schedulers exploit multiuser diversity to reorder transmissions so that each user is served, with high probability, when it is in a good channel state. However, the achievable opportunistic gain is restrained by user's fairness requirements, and by limited memory and computational resources at the base station. In particular, schedulers that achieve a good tradeoff between throughput and fairness, e.g., the renowned Proportional Fair scheduler (PF) [30], are too complex for the centralized architecture of the cellular networks.

Within last decade, smartphones improved in terms of processing power, memory size and they are well adapted to today's needs of users by providing more functionalities (e.g., Internet connectivity, multimedia support, and entertainment). Nowadays, Internet connectivity feature is a must in every smartphone which can be obtained by using the data service provided by cellular operators (cellular radio interface) or by connecting to popular and widely accessible local area networks using WiFi capabilities (IEEE 802.11-based radio interface). The WiFi interface also allow mobile users to connect to each other using 802.11 interfaces, e.g., endowed with WiFi-Direct capabilities [25]. The dual-radio interface creates the opportunity to integrate cooperative communication capabilities in cellular networks in order to enhance the performance of cellular communication by cooperative techniques (e.g., cluster formation). Interestingly, many mobile users are switching from conventional mobile phones (i.e. phones that are only meant for voice call and texting) to smartphones which indicates that the potential to use cooperative communications already exists. Fig. 1.1 illustrates a possible scenario in which we exploit the dual-radio interface to form clusters among users in a cellular network.

In this dissertation, we propose to use the multi-radio capabilities of newly designed mobile devices to form cooperative clusters. The presence of clusters simplifies the scheduling operation because the number of entities to be scheduled reduces (the scheduler considers the users in the same cluster as a single user with extended demand). Moreover, clustering enables efficient radio resource utilization due to the fact that the scheduler has the freedom to choose the user with the best channel quality among cluster members. We design a multi-layer cluster-based scheduling mechanism in which the base station *schedules clusters* instead of users, while intra-cluster resource distribution is left to cluster members.

Note that scheduling clusters instead of users means that the cluster connects to the base

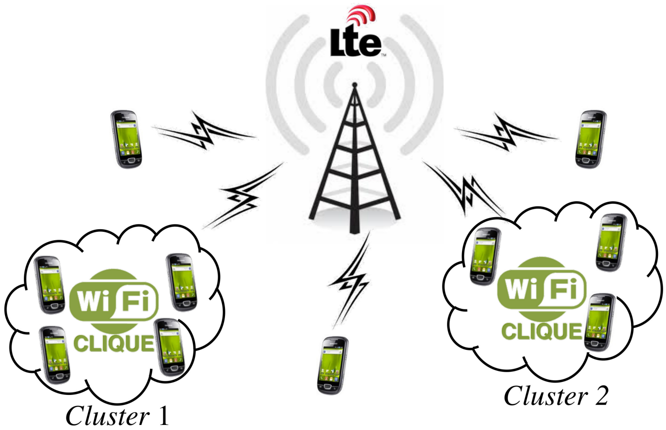


Figure 1.1: Cellular network with clusters of dual-radio mobiles.

station via a *cluster head*. However, unlike existing clustering approaches, we propose to select the cluster head *opportunistically* in each frame. The resulting scheduling mechanism consists of two elements: an algorithm to schedule clusters, and an algorithm to select cluster heads opportunistically within each cluster.

The main contributions of this work are as follows: (i) we design a novel network architecture based on cooperative communications with clusters of mobile users and opportunistic scheduling in cellular networks with dual-radio mobile users; (ii) we design three novel cluster scheduling algorithms, and present a mathematical analysis of these schemes; (iii) we show that inter-cell clusters are feasible, in which clusters members belongs to multiple base stations; (iv) we provide a game theory-based description of the clustering formation and gain; (v) via extensive numerical simulations, we evaluate the performance of the proposed scheduling solutions and show that they allow to achieve dramatic throughput gain and extremely fair throughput distributions among mobile users.

The remainder of this dissertation is organized as follows. In Chapter 2, we discuss the most relevant works to our proposal. The system model is presented in Chapter 3. Chapter 4 introduces the scheduling mechanisms that we propose for cluster-oriented opportunistic scheduling. We evaluate the clustering gain over a variety of scenarios in Chapter 5. In Chapter 6, we propose a coalitional game theory-based approach to form clusters. In addition, we evaluate the payoff of our opportunistic clustering scheduling against the conventional cellular network architecture in a realistic scenario with mobile users. Finally, we conclude the work in Chapter 7.

Chapter 2

Related Work

Since our proposal integrates opportunistic scheduling with cooperative communications, here we review the literature related to both topics.

Opportunistic scheduling. Proposals on opportunistic scheduling are very mature. Indeed, a simplified version of PF is already implemented in 3G systems [30]. However, there are other schedulers proposed in the literature, which promise better throughput performance than PF, at the expenses of either fairness or increased complexity.

Knopp and Humblet proposed the so called MaxRate opportunistic scheduler in [11], which always schedules the user in the best channel condition. Since opportunistic gain of MaxRate relies on multiuser channel diversity, opportunistic beamforming was proposed in order to increase the user diversity [27], [24]. MaxWeight [2] is another opportunistic scheduler that selects the user with the highest product of queue length and transmission rate. *Exp-rule* schedulers [13] are throughput-optimal schedulers that prioritize users based on an exponential formula using queue size and transmission rate of every user.

Our proposal leverages the MaxRate scheduler for communications between base station and users in a cluster, thus achieving the maximum utilization of the airtime allotted to each cluster. However, we will show that *cluster* scheduling can be operated by means of different schemes which impact on fairness in the throughput distribution among clusters.

User cooperation. Research on cooperative communications in cellular networks has investigated different aspects of cooperation, such as base station-level cooperation [6] and user-level cooperation [10].

Relaying is an example of cooperation, in which stations act as base stations with limited functionalities, hence increasing capacity and/or coverage without the need for setting up additional cells [12,29]. Interestingly, Wu *et al.* [29] propose to use dual-radio relay stations (cellular and ad hoc) to perform load balancing among different cells. Their approach does not consume cellular radio resource for relaying but it introduces extra delay.

Another example of user cooperation is represented by clustering techniques. Clustering has been well studied in wireless sensor networks for energy saving, routing and coverage improvement purposes [5, 9]. The work in [7, 15, 21] studied clustering in WLANs and cellular networks. In particular, Lin *et al.* [15] proposed clustering to form robust multi-hop networks. In [7, 21], mobile users are clustered to form a virtual antenna array which emulates a MIMO device. Furthermore, Dohler *et al.* [7] proposed to use a second wireless interface (e.g. bluetooth or WiFi) for intra-cluster communications. Differently from our work, these proposals do not exploit opportunistic scheduling.

Eventually, game theory has been used to model cooperative clustering. Saad *et al.* [19] give a thorough treatment on clustering schemes using coalitional game theory. In [28], the authors use coalition formation game to obtain the optimal solution of the tradeoff between outage performance and network life time in clustered wireless sensor networks. In a recent work, the authors of [1] propose a cooperative network in hybrid wireless systems based on a carry and forward structure. They use social networking techniques to identify the users that can form a coalition. Using Markov chain, they calculate the supported delay and coalition formation cost of a coalition based of the probability that mobile nodes help each other. These probabilities are obtained using Nash bargaining solution that has Pareto-optimal properties (i.e., the solution is beneficial for all users and it is not possible to obtain a better solution without affecting other users). The stability of possible coalition structures are verified using the Nash bargaining solution, supported delay and incurred cost. If a coalition is unstable a new coalition is evaluated until an stable coalition is found.

To the best of our knowledge, there is no previous work proposing an opportunistic scheduling framework by integrating opportunistic scheduling with cooperative communications using independent radios for intra-cluster and inter-cluster communications in cellular networks.

Chapter 3

System model

Here, we model downlink transmissions from base stations to mobile devices using both legacy user-based schedulers, and our proposed cluster-based scheduling algorithms.

Clustering assumptions. Mobiles can form clusters and receive downlink traffic through one or more *cluster heads*, i.e., nodes enabled to exchange data with the base station (see Fig. 1.1). Note that each node is a potential candidate to act as cluster head, and cluster heads are selected on a per-frame basis. A cluster consists of several mobiles that formed a local wireless network, e.g., a WiFi clique. Hence, all intra-cluster communications take place over the local wireless network. After cluster formation, the base station is notified of clustering decisions. Thus, whenever a packet is destined to a cluster member, the base station simply sends it to the cluster member that maximize the throughput at that epoch.

Note that our clustering proposal does not conflict with the scheduler deployed at the base station. In fact, from the base station point of view, clusters are seen as users (characterized by higher demand than regular users). We assume that the user selected for transmission represents the cluster head, therefore, it can receive traffic for any other user in the cluster. As a consequence, in this work we focus on the aggregate per-cluster throughout rather than on the per-user throughput. Note that per-user throughput can be derived from the aggregate per-cluster throughput if the cluster resources are divided equally among users. Indeed, through this dissertation, we assume that cluster resources are shared equally among users unless otherwise specified.

Model assumptions. The downlink channel in between the base station and mobile node i is characterized by stationary Rayleigh fading. Therefore, the SNR can be described as a r.v. C_i with average SNR γ_i, and pdf and CDF of the SNR have the following expressions, respectively:

$$f_i(z) = \frac{1}{\gamma_i} e^{-\frac{z}{\gamma_i}} u(z), \quad F_i(z) = \left[1 - e^{-\frac{z}{\gamma_i}}\right] u(z); \tag{3.1}$$

where $u(z)$ is the unit step function.[1] We assume that user channels are independently distributed but not identically, and the channel state information (CSI) is available at the base station. Transmissions occur at different rates according to available modulation and coding schemes (MCS's). We assume that the MCS for a user is selected as a function of the

[1]In this work, we use $f_x(.)$ to indicate the pdf of the r.v. X, while $F_x(.)$ denotes the CDF of X.

instantaneous SNR, i.e.:

$$MCS_i = k \quad \Longleftrightarrow \quad C_i \in [th_k; th_{k+1}[\,, \quad k = 1..M; \tag{3.2}$$

$$th_1 = 0; \quad th_p < th_q \iff p < q; \quad th_{M+1} = \infty.$$

Therefore, the probability that a scheduled user i receives a frame encoded according to the kth MCS is as follows:

$$\pi_k^{(i)} = \int_{th_k}^{th_{k+1}} f_i(z)dz = e^{\frac{th_k}{\gamma_i}} - e^{\frac{th_{k+1}}{\gamma_i}}. \tag{3.3}$$

The bit rate corresponding to the kth MCS is denoted by b_k, and the value of b_k is proportional to the bits per symbol reported in the rightmost column of Table 3.1. The Table shows the list of possible MCS's with their corresponding SNR thresholds for LTE-like networks [23]. In particular, we assume a network based on LTE-like specifications in FDD mode [26]. However, we report throughputs achieved in the network after normalizing them to the cell downlink capacity. Therefore, our results apply to a variety of configurations in terms of frequency bandwidths and frame durations. The implementation margin (IM) in Table 3.1 is a value that represents the effects of non-ideal receiver. For the sake of tractability, we assume that mobile users belong to one of three predefined SNR *classes*, which correspond to *poor*, *average*, and *good* mean SNR. The designated SNR for different classes are chosen in a manner that the mean achievable rates for *poor*, *average*, and *good* users are 20%, 50%, and 80% of the maximum transmission rate achievable in the system, respectively. With the thresholds and MCS values reported in Table 3.1, the designated SNR values are 7dB, 16dB and 23dB, respectively for *poor*, *average*, and *good* users.

Table 3.1: Modulation and coding schemes and their thresholds

Modulation	**Coding Rate**	**SNR** (dB)	**IM** (dB)	**SNR+IM** (dB)	**Bits per symbol**
QPSK	1/8	-5.1	2.5	-2.6	0.25
	1/5	-2.9		- 0.4	0.4
	1/4	-1.7		0.8	0.5
	1/3	-1		1.5	0.67
	1/2	2		4.5	1
	2/3	4.3		6.8	1.3
	3/4	5.5		8.0	1.5
	4/5	6.2		8.7	1.6
16QAM	1/2	7.9	3	10.9	2
	2/3	11.3		14.3	2.66
	3/4	12.2		15.2	3
	4/5	12.8		15.8	3.2
64QAM	2/3	15.3	4	19.3	4
	3/4	17.5		21.5	4.5
	4/5	18.6		22.6	4.8

Chapter 4

Scheduling algorithms

In the following, we review conventional schedulers and their performance when clusters come into play. We then introduce a new class of schedulers, namely *cluster-based schedulers*, which are benchmarked against widely-adopted conventional user-centric schedulers.

4.1 User-Based Schedulers

Round Robin Scheduling (RR). In round robin scheduling, with one base station and N users, each user is scheduled for an equal amount of resources (e.g., *equal time* or *equal rate*) [8]. Although equal rate achieves complete fairness, its throughput performance decreases drastically in the presence of *poor* users. Therefore, we use equal time RR, in which the throughput of each user only depends on the total number of users in the system and on the probability to transmit with a given MCS:

$$T_i = \frac{1}{N}\sum_{k=1}^{M}\pi_k^{(i)} b_k, \forall i \in \{1..N\}. \tag{4.1}$$

Proportional Fair Scheduling (PF). Since proportional fair scheduling is an opportunistic scheduler that is already implemented in 3G systems, it is a good benchmark to evaluate our proposal. Here we show an adaptation from the analytical model in [16], in which we plug discrete values for the achievable rates. The expected throughput achieved by proportional fair scheduler for the ith user, $i \in \{1..N\}$, is given by [16]:

$$\begin{aligned} T_i = \; & E[R_i]/N. \left(1 - \left[F_{(0,1)}\left(-E[R_i]/\sigma_{R_i}\right)\right]^N\right) \\ & +\sigma_{R_i} \int_{-M_j}^{\infty} y f_{(0,1)}(y). \left[F_{(0,1)(y)}\right]^{N-1} dy. \end{aligned} \tag{4.2}$$

In Eq. (4.2) $E[R_i]$ and σ_{R_i} are the achievable rate and its standard deviation, respectively. In our discrete case, they are computed as follows:

$$E[R_i] = \sum_{k=1}^{M} \pi_k^{(i)} b_k, \tag{4.3}$$

$$\sigma_{R_i}^2 = \sum_{k=1}^{M} \pi_k^{(i)} \left(b_k - E[R_i]\right)^2. \tag{4.4}$$

$F_{(0,1)}(.)$ and $f_{(0,1)}(.)$ are the CDF and pdf of a Gaussian distribution with zero mean and unit variance, respectively, and $M_i = E[R_i]/\sigma_{R_i}$.

MaxRate Scheduling (MR). Here we consider that case of N non-clustered users and one base station. The base station transmits according to the MaxRate scheme: each frame is completely allotted to the user with the best channel, i.e., the user with the highest MCS in the current frame.

The probability that a user U_i with SNR C_i is scheduled is then as follows:[1]

$$P(i) = Pr(U_i \text{ is scheduled}) = Pr(C_i > \max\{C_j\}, j \neq i). \tag{4.5}$$

Similarly, the probability that a user U_i with SNR C_i is scheduled and its MCS is k is given by:

$$\begin{aligned} P(i|k) &= Pr(U_i \text{ is scheduled} | MCS_i = k) \\ &= Pr(C_i > \max\{C_j\}, j \neq i | MCS_i = k). \end{aligned} \tag{4.6}$$

Considering that channels are independent, the random variable $Y_i = \max\{C_j\}, j \neq i$, exhibits the following CDF:

$$F_{Y_i}(z) = \prod_{j \neq i} F_j(z) = u(z) \prod_{j \neq i} \left(1 - e^{-\frac{z}{\gamma_j}}\right). \tag{4.7}$$

Therefore, the pdf of Y_i is:

$$f_{Y_i}(z) = u(z) \sum_{j \neq i} \frac{1}{\gamma_j} e^{-\frac{z}{\gamma_j}} \prod_{l \neq i, l \neq j} \left(1 - e^{-\frac{z}{\gamma_l}}\right). \tag{4.8}$$

The CDF of C_i, subject to $MCS = k$, is as follows:

$$F_i(z|MCS = k) = u(z - th_k) \frac{e^{-\frac{th_k}{\gamma_i}} - e^{-\frac{\min(z, th_{k+1})}{\gamma_i}}}{\pi_k^{(i)}}. \tag{4.9}$$

Since C_i and Y_i are independent, the following relation holds:

$$\begin{aligned} Pr(C_i > Y_i | Y_i = z, MCS_i = k) &= Pr(C_i > z | MCS_i = k) \\ &= 1 - F_i(z|MCS = k). \end{aligned} \tag{4.10}$$

Therefore, using the total probability formula and (4.10), we can rewrite Eq. (4.6) as follows:

$$\begin{aligned} P(i|k) &= Pr(C_i > Y_i | MCS_i = k) \\ &= \int_0^\infty \left[1 - F_i(z|MCS_i = k)\right] f_{Y_i}(z) dz. \end{aligned} \tag{4.11}$$

Plugging Eqs. (4.8) and (4.9) in Eq. (4.11), it is possible to compute the probability that a scheduled user i receives a frame with $MCS = k$. This is the building block to compute user's throughput, i.e.:

$$T_i = \sum_{k=1}^{M} P(i|k) \pi_k^{(i)} b_k t_f, \quad \forall i \in \{1..N\}. \tag{4.12}$$

[1] We neglect the probability that two or more users have the same channel quality, which occurs with infinitesimal probability.

4.2 Cluster-Based Schedulers

Round Robin Between Clusters (CL(RR)). Let's now consider a single cell with two clusters, CL_1 with N_1 users and CL_2 with N_2 users. Assume that the base station uses opportunistic scheduling within each cluster, and clusters are scheduled in a round robin fashion. Accordingly, the scheduler alternates transmissions between the user with the best channel in CL_1 and the user with the best channel in CL_2.

The described system is equivalent to a round robin system with 2 users, each representing a cluster. From a base station's point of view, channel condition of a cluster is equivalent to the channel condition of the cluster member with the best channel quality. Hence, an equivalent cluster channel can be defined as that channel whose SNR is the max of the SNR values of the cluster members. Namely, defining X_i as the SNR of cluster i, we have:

$$X_i = \max\{C_j, j : U_j \in CL_i\}, \quad i \in \{1, 2\}. \tag{4.13}$$

The CDF of X_i, $i \in \{1, 2\}$, can be readily computed considering that the random variables C_j are all independent:

$$F_{X_i}(z) = \prod_{j:U_j \in CL_i} F_j(z); \tag{4.14}$$

the corresponding pdf $f_{X_i}(z)$ can be obtained by derivation from $F_{X_i}(z)$.

The MCS scheme adopted by the base station for each transmission only depends on the instantaneous SNR of the best channel in the scheduled cluster, i.e., it only depends on X_i at the time of scheduling cluster i:

$$\pi_k^{(CL_i)} = \int_{th_k}^{th_{k+1}} f_{X_i}(z)dz. \tag{4.15}$$

Because of round robin, the probability to schedule each cluster is $1/2$. More in general, in case that N_c clusters are present and scheduled in round robin, the cluster scheduling probability is $1/N_c$.

The throughput of each cluster is then:

$$T_{CL_i} = \frac{1}{N_c} \sum_{k=1}^{M} \pi_k^{(CL_i)} b_k, \quad i \in \{1..N_c\}. \tag{4.16}$$

Finally, the average per-node throughput is obtained by dividing the throughput of the ith cluster by the number of users in the cluster, namely N_i:

$$T_{j:U_j \in CL_i} = \frac{1}{N_c N_i} \sum_{k=1}^{M} \pi_k^{(CL_i)} b_k, \quad i \in \{1..N_c\}. \tag{4.17}$$

Weighted Round Robin Between Clusters (CL(WRR)). Here we consider the case in which each cluster is scheduled with a frequency which is proportional to the number of its members. Hence, the per-cluster scheduling probability is:

$$Pr(\text{Cluster } i \text{ is scheduled}) = \frac{N_i}{\sum_{j=1}^{N_c} N_j}, \tag{4.18}$$

where N_c is the total number of clusters, and N_i, $i \in \{1..N_c\}$, represents the number of users which are members of the ith cluster CL_i.

Throughput expressions for each cluster and for each user are similar to Eqs. (4.16) and (4.17), respectively:

$$T_{CL_i} = \frac{N_i}{\sum_{j=1}^{N_c} N_j} \sum_{k=1}^{M} \pi_k^{(CL_i)} b_k, \quad i \in \{1..N_c\}; \tag{4.19}$$

$$T_{j:U_j \in CL_i} = \frac{1}{\sum_{j=1}^{N_c} N_j} \sum_{k=1}^{M} \pi_k^{(CL_i)} b_k, \quad i \in \{1..N_c\}. \tag{4.20}$$

MaxRate Between Clusters (CL(MR)). Here, we use a MaxRate scheduler for both intra-cluster and inter-cluster scheduling. Using MaxRate among clusters, each frame is allotted to the cluster that has the user with the best channel. The probability that CL_i is scheduled and its MCS is k is given by:

$$P(CL_i|k) = Pr(X_i > Y_i | MCS_i = k), \tag{4.21}$$

where $Y_i = \max\{Cj\}, j \notin CL_i$, and X_i represents the SNR of cluster i (see Eq. (4.13)). The CDF of X_i, subject to $MCS_{CL_i} = k$, is:

$$F_{CL_i}(z|MCS_{CL_i}{=}k) = u(z{-}th_k) \frac{f_{X_i}(\min(z,th_{k+1})) - f_{X_i}(th_k)}{\pi_k^{(CL_i)}}, \tag{4.22}$$

where f_{X_i} is obtained from derivation of F_{X_i} (see Eq. (4.14)). Now we can rewrite (4.21) as follows:

$$\begin{aligned} P(CL_i|k) &= Pr(X_i > Y_i | MCS_{CL_i} = k) \\ &= \int_0^{\infty} [1 - F_{CL_i}(z|MCS_{CL_i} = k)]\, f_{Y_i}(z) dz. \end{aligned} \tag{4.23}$$

Finally, the average per-cluster throughput can be computed using the following formula:

$$T_{CL_i} = \sum_{k=1}^{M} P(CL_i|k) \pi_k^{(CL_i)} b_k. \tag{4.24}$$

Chapter 5

Clustering gain

The potential clustering gain versus the conventional architecture is discussed in this section. We use the analysis presented in Section 4 to numerically simulate different network scenarios and thus illustrate the advantages of cluster-based scheduling techniques. Initially, we illustrate the motivation for introducing clustering by means of simple numerical calculations. Then, we proceed with the evaluation of throughput and fairness in the network with realistic scenarios.

5.1 Clustering Effect

The incentive behind clustering can be easily observed by comparing the user's channel state probabilities. Fig. 5.1 shows the impact of clustering on user's with good, average, and bad channel quality. The clustering impact is depicted in terms of MCS probabilities π_k. As shown in the figure, cluster formation highly boosts the transmission rate of *poor* and *average* users, but it may be not that helpful for *good* users. Nonetheless, we will show that with our proposal the throughput of *good* users improves as well by a non-negligible quantity. Therefore, *good users* are incentivized to help users with lower channel qualities. In practice, *good* users can be encouraged to participate in clustering by receiving an extra quota for the portion of traffic that they forward for others users, as discussed later in Section 6.

Fig. 5.1 illusterate how the channel state probabilities are improved by clustering. It should be noted that the throughput received by each cluster also depends on the scheduling policy. Fig. 5.2(a) and Fig. 5.2(b) depict the effect of clustering when a cluster of *poor* users (C2) is competing against a cluster with one *good* user (C1). Since CL(RR) does not account for cluster size, per user throughput is descending as the number of users increases and as expected, per cluster throughput is not affected by the cluster size. Because CL(WRR) considers the cluster size as a parameter in scheduling, both per user and per cluster throughput increase with cluster size. Hence, we can see the throughput distribution received by users in different clusters become more fair as the cluster size of *poor* users increases. The cluster of *poor* users does not receive much throughput under CL(MR) scheduler which indicates that a group of *poor* users, no matter how big is the group, will never be able to compete with a *good* user. It should be noted whether the *poor* users can compete with *good* ones or not depends on the SNR associated with every class.

Now, Let's see how does a cluster of *average* users (C2) compete with a cluster of one

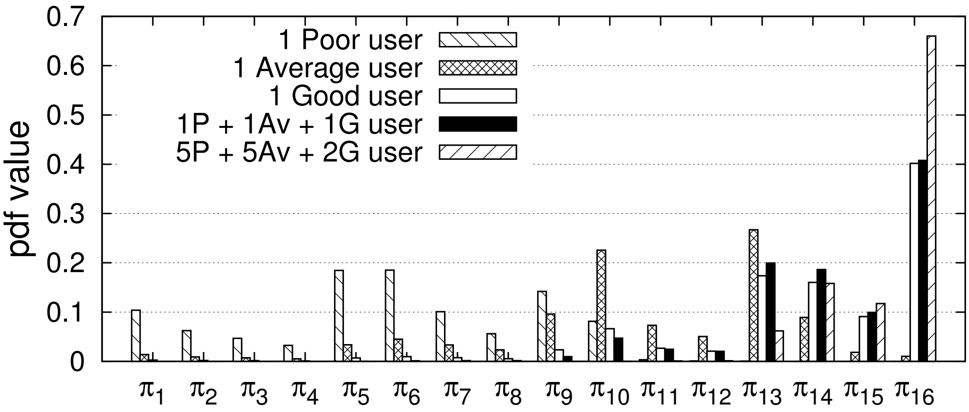


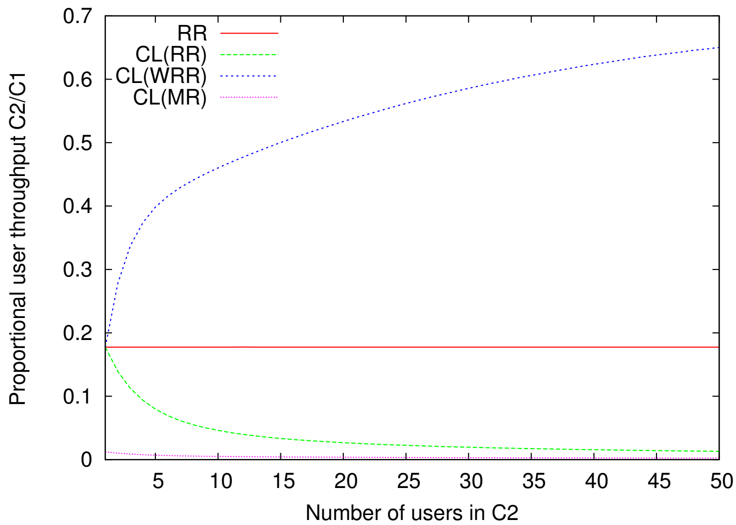
Figure 5.1: Impact of clustering on channel state (MCS) pdf.

good user (C1). In Fig. 5.3(a) and Fig. 5.3(b), we observe the same trend as scenario with a cluster of *poor* users with a few differences. In general, users have more throughput under all scheduling policies which is expected since they have higher SNR. Under CL(WRR), the *average* users achieve the same throughput as the good users when the cluster size reaches 5. In addition, the throughput of the cluster with *average* users increases under CL(MR) that indicates clustering *average* users can increase the throughput received by the cluster when competing with a good user.

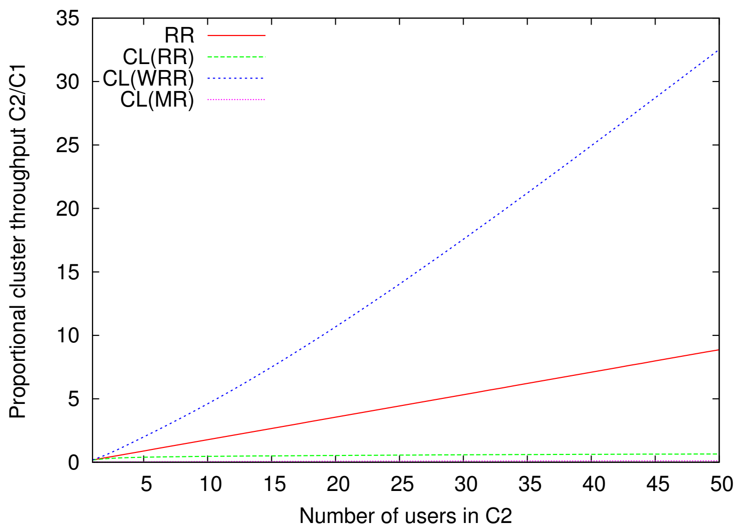
5.2 Clustering in a Cell

Let us begin the evaluation of throughput and fairness in the network by numerically simulating a simple scenario including 3 clusters with fixed number of members, all of them belonging to a single cell, see Fig. 5.4. In this scenario, clusters C1, C2, and C3 have 4, 8 and 12 users, respectively. We use a uniform distribution to select the SNR classes of users in each cluster. The experiment results include the mean, $5th$ and $95th$ percentiles over 2000 simulation runs. Note that clusters have no effect on user-based scheduler results as users are scheduled individually under RR and PF schedulers. Since it is not practical to show the throughputs of all users in one graph, we computed the average throughput for every cluster. When we show *per-user* throughputs, we report *per-cluster* throughputs normalized to the number of cluster members. Therefore, the *per-user* throughput can be interpreted as the average throughput received by a cluster member or, equivalently, as the amount of resources allotted to the cluster for each member forming the cluster.

In Fig. 5.5(a), we observe that users receive the least throughput under RR due to the fact that RR does not take the user channel qualities into consideration upon scheduling. The performance improvement due to PF is remarkable which is the result of user channel state consideration of this scheduler. However, PF schedules the users irrespective of cluster



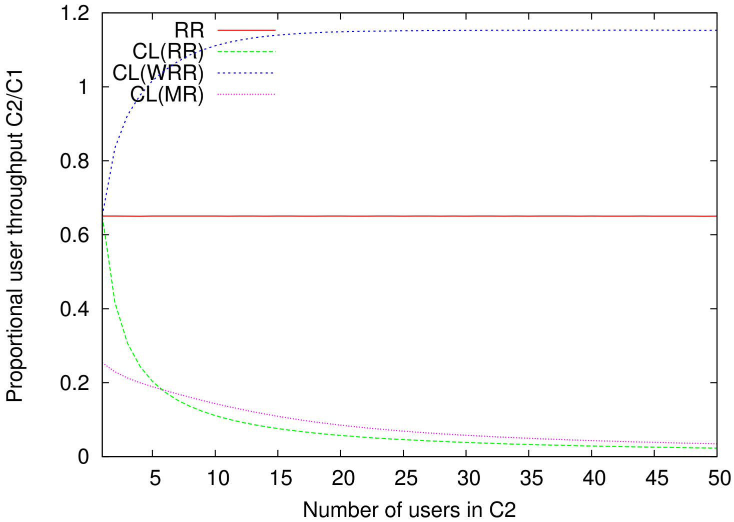
(a) User proportional throughput.



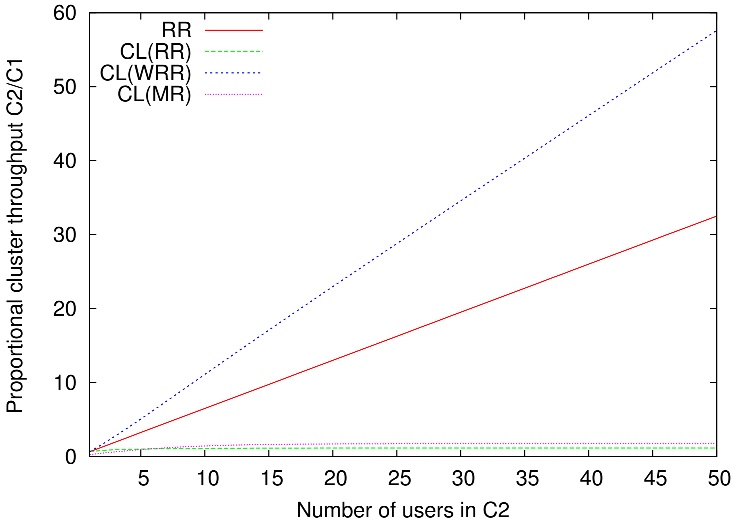
(b) Cluster proportional throughput.

Figure 5.2: A cluster of *poor* users is competing with a cluster that consists of one *good* user.

sizes. Cluster-based schedulers have different performances. First, CL(RR) exhibits an unfair distributions of per-user throughputs, due to the fact that it allocates equal airtime to all clusters regardless of their size. This behavior explains the reason why cluster C1, with the smallest size, has the highest per-user throughput. On the contrary, CL(WRR) allots airtime to clusters according to their size, which explains why users in all three clusters have almost the same throughput. Small differences in throughput distribution are due to the fact that clustering gain grows with cluster size. Eventually, CL(MR) operates based on the cluster's equivalent channel state CDF and does not take into account the size of clusters in scheduling decision, like in CL(RR). The maximum throughput is achieved under CL(MR), since it is a pure opportunistic scheduler. However, throughput distribution across users is



(a) User proportional throughput.



(b) Cluster proportional throughput.

Figure 5.3: A cluster of *average* users is competing with a cluster that consists of one *good* user.

unfair because it always serves the cluster with the best channel state. Moreover, the high throughput variation observed for cluster C1 is due to the random user channel distribution within a cluster, which has higher impact on clusters with small number of users.

Fig. 5.5(b) illustrates the aggregate throughput achieved in clusters, for the same scenario of Fig. 5.4. As it can be noticed, under CL(RR) all clusters receive similar throughput regardless of their sizes, whereas with CL(WRR) the clusters with bigger size obtains more resources. CL(MR) achieves the best throughput, but also the highest variability.

The total cell throughput is shown in Fig. 5.6(a), from which it is clear how RR and PF are both outperformed by cluster-based schedulers. As expected, CL(MR), that always

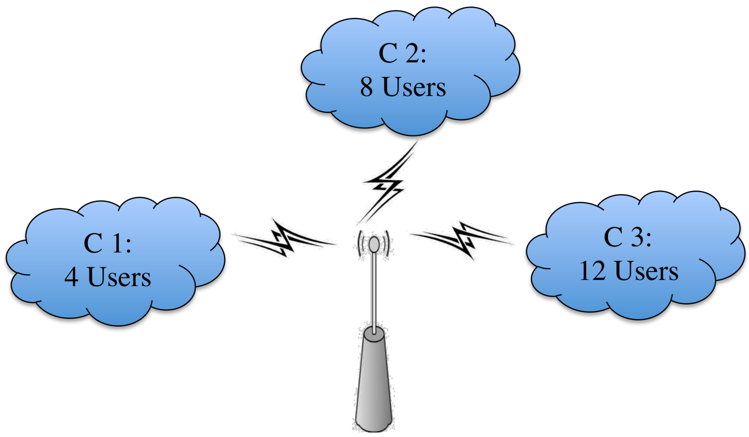


Figure 5.4: Clustering with users belonging to the same cell.

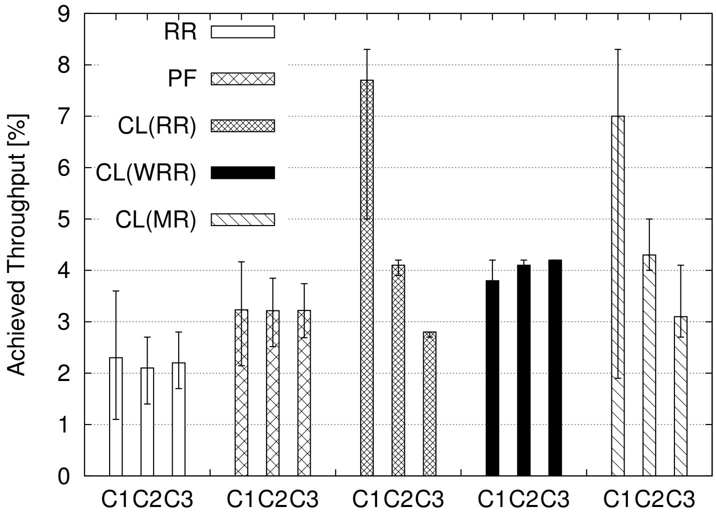
serves the cluster in the best channel, has the highest throughput. However, CL(RR) and CL(WRR) achieve comparable performance to CL(MR). Note that the difference between RR and CL(RR) consists in the clustering gain which in this scenario amounts to 45% of the total cell capacity.

Overall, while CL(RR) is fair with respect to clusters as a whole, CL(WRR) results in fairer throughput distributions among users. CL(MR) achieves the best throughput, but it is neither cluster-fair nor user-fair. Fig. 5.6(b) gives insights into the levels of fairness achieved by the different schedulers. In the figure, we report the Jain's fairness index among per-user throughputs. It is interesting to observe that our clustering proposal not only increases the throughput, but also it increases the fairness level. In particular, CL(WRR) advantages are three folds: (i) it provides nearly perfect fairness among users; (ii) it offers the possibility to gain a high throughput with respect to legacy RR and PF schedulers; (iii) it allows each cluster to exploit the clustering gain proportionally to its size.

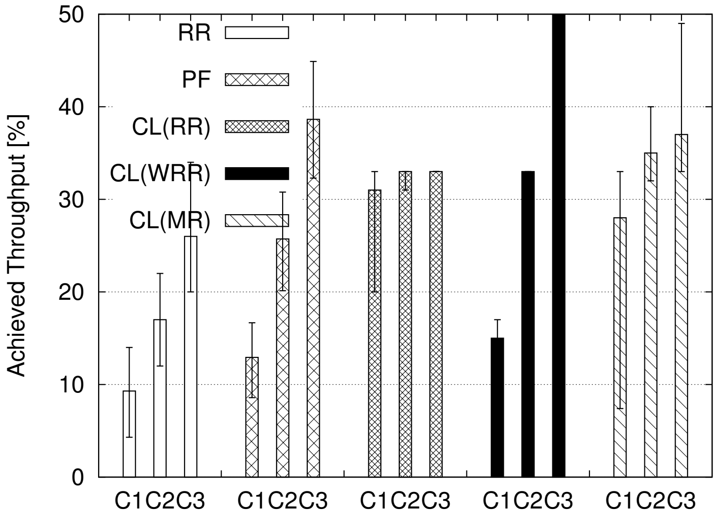
5.3 Clustering across Cells

Another interesting scenario in which clustering can be beneficial is the case of clusters formed by users associated to different base stations. This scenario is particularly interesting for users located at the edge of their cell, whose channel can suffer deep fading fluctuations. Indeed, opportunistic scheduling gives the best performance gain under such conditions [11]. Assume a scenario as in Fig. 5.7, where n_i represents the number of users in cluster Ci. In the figure, cluster C2 is the merger of two clusters formed by users at the edge of the cells, namely *sub-clusters* C2a and C2b, which are connected to BS1 and BS2, respectively. Users at the edge of each cell connect to their corresponding base stations, but share their resources within the entire cluster. Accordingly, note that cluster C2 has two cluster heads at each frame.

In this scenario, we first study the cluster throughput under different scheduling mechanisms with fixed cluster sizes. Second, we randomize cluster sizes in order to show that our proposal performs well under generic distributions of users across clusters.



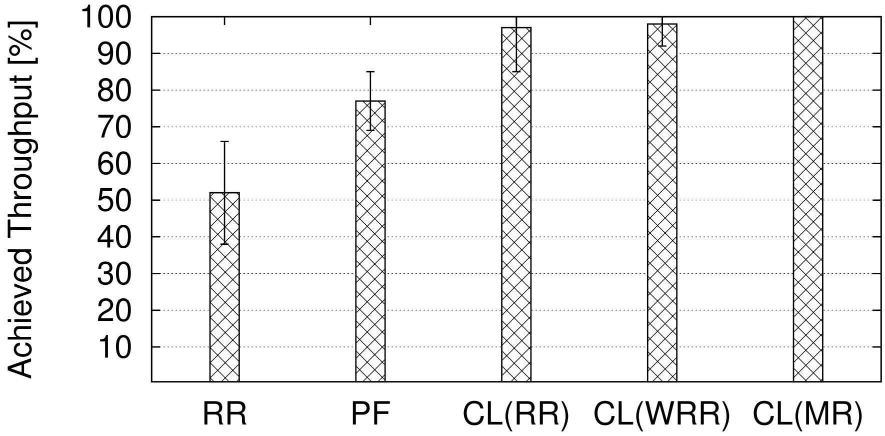
(a) Average per-user throughput



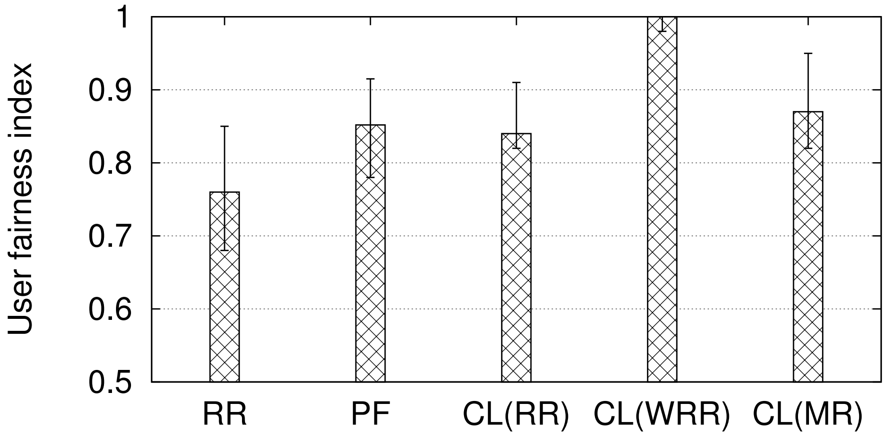
(b) Average per-cluster throughput

Figure 5.5: Throughput under different scheduling mechanisms in a single cell scenario (See Fig. 5.4).

Fixed cluster sizes. Let us assume that the number of cluster members is fixed as follows: $n_1 = 10$; $n_{2a} = 5$; $n_{2b} = 3$; $n_3 = 12$. In Fig. 5.8(a), which depicts the per-cluster throughput achieved with different schedulers, we can see that clustering is very beneficial for clusters spanning two cells. In particular, cluster C2 is an example of dual-head cluster, since it has one cluster head connected to base station BS1 and another cluster head connected to BS2. Thanks to its dual cellular connectivity, C2 receives almost double throughput under CL(RR) than under CL(WRR). Notably, the former scheduler allots half of the airtime to cluster C2 in each cell, irrespective of the throughput received by C2 from the other cell. In contrast, as shown in Fig. 5.8(b), CL(WRR) behaves fairly on a per-user basis,



(a) Aggregate cell throughput



(b) Jain's fairness indexes

Figure 5.6: Throughput and fairness under different scheduling mechanisms in a single cell scenario (See Fig. 5.4).

irrespective of the number of cells to which its members belong to.

Variable Cluster Size. We now address the case of variable-size clusters for the scenario

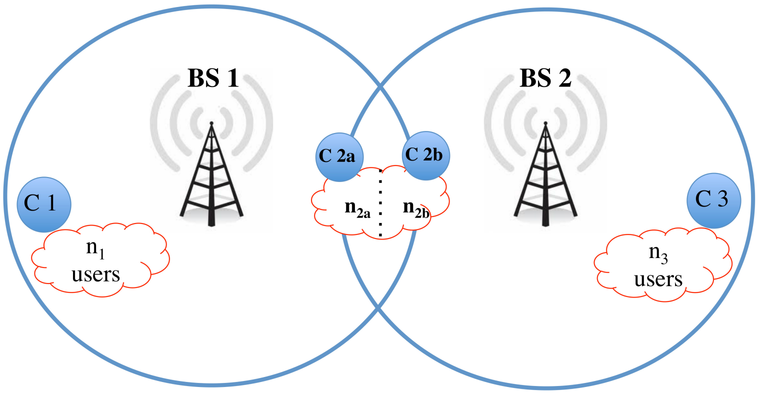
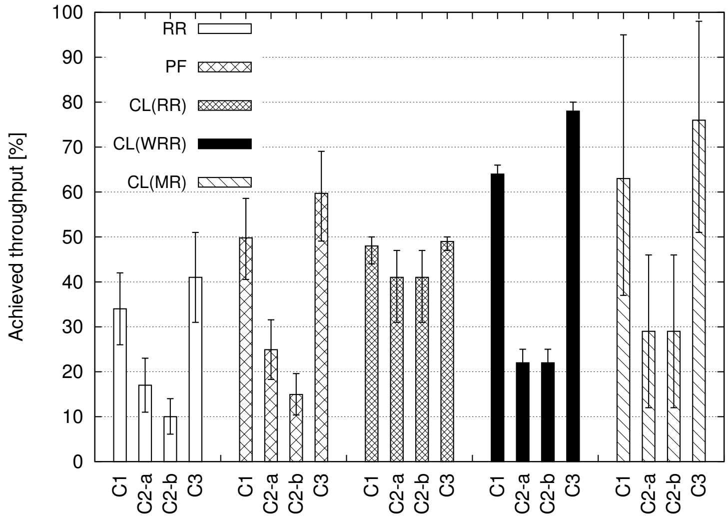


Figure 5.7: Two base stations with three clusters. Cluster C2 is composed by two sub-clusters belonging to two adjacent cells. Clusters 2a and 2b which are connected to BS1 and BS2, respectively.

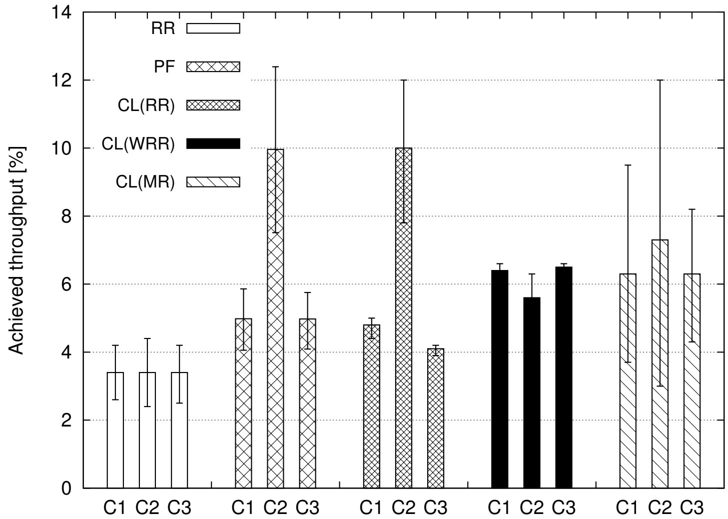
depicted in Fig. 5.7. Specifically, in our numerical simulations, we allow the cluster size to vary between 2 to 10 members, and repeat the experiment for 2000 configurations selected at random. The results obtained in this case are similar to the ones achieved with fixed cluster sizes. However, the variation of the results is magnified due to variability of cluster sizes. Specifically in the case of small cluster size, random user assignment leads to highly different results. Fig. 5.9 confirm the merits of cluster-based schedulers. In addition, we can conclude that CL(WRR) exhibits the best tradeoff between throughput and fairness per-user.

5.4 Discussion

Numerical simulation results indicate that cluster scheduling provides better fairness and higher throughput in comparison to conventional schedulers. Although CL(MR) achieves the maximum throughput, its results are unreliable (i.e., highly variable) even for the case of fixed cluster sizes. Among cluster scheduling schemes, the best tradeoff between throughput and fairness is exhibited by CL(WRR) with a throughput close to maximum and nearly perfect user fairness. Since we were interested in the average cluster performance, so far, we did not differentiate the performance among users in different SNR classes. However, intra-cluster resource distribution is important to incentivize users to join clusters. Therefore, in the next section we tackle such issue and present a simple coalitional game that describes the cluster formation process.

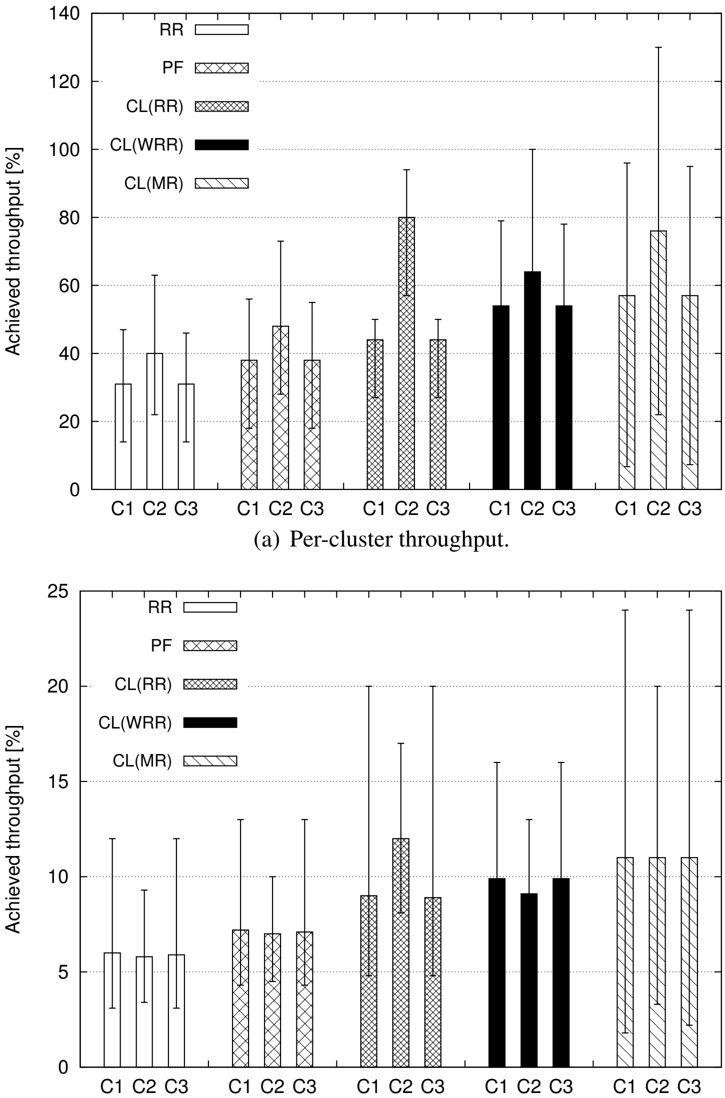


(a) Per-cluster throughput



(b) Per-user throughput

Figure 5.8: Throughput under different scheduling mechanisms for the scenario depicted in Fig. 5.7, normalized to the capacity of a *single* cell (so that, with two cells, aggregate throughput can reach 200%). Cluster sizes are fixed as follows: $n_1 = 10$; $n_{2a} = 5$; $n_{2b} = 3$; $n_3 = 12$.



(a) Per-cluster throughput.

(b) Per-user throughput.

Figure 5.9: Throughput with variable cluster sizes under different scheduling mechanisms for the scenario depicted in Fig. 5.7, normalized to the capacity of a *single* cell (so that, with two cells, aggregate throughput can reach 200%). Cluster sizes vary form 2 to 10 users.

Chapter 6

Cluster Formation: A game theory approach

The goal of this section is to provide a simple model for the cluster formation process, and shed light on the impact of clustering when users experience non-stationary channel qualities, e.g., due to mobility. For the sake of clarity, we only describe the case of CL(WRR) cluster scheduling, which is the method that yields the best tradeoff between throughput and fairness (see Section 5).

Our proposed clustering scheme can be modeled using *coalitional game theory* [19]. Coalitional games are a class of games studied in cooperative game theory and a coalition is simply a group of entities that agree on cooperating to increase their *social welfare*. In our case, a coalition is a group of users that agree on forming a cluster and acting as a single mobile user. Here, we use a simple dynamic coalition formation game that accounts for the basic cost to form a cluster, namely the transmission power. Clearly, a big cluster in which members are placed far from each other is not attractive for a mobile user with power constraints. Therefore, we need a model defining which users should form a cluster and which user are better off alone. As in [18], we assume that each user has a fixed power budget per frame, and translate power constraints into distance constraints.

6.1 Definition of the game

In the following, $N = \{u_1, u_2, ..., u_n\}$ denotes the set of users in the network and $S := \{S_1, S_2, ..., S_l\}$ is a partition of N, i.e., $\bigcup_{i=1}^{l} S_i = N$ and $S_i \cap S_i = \emptyset$ if $i \neq j$. The utility function $\nu(.)$ defines the value of a coalition (i.e., cluster) as follows:

$$\nu\left(S_i\right) = \begin{cases} \sum\limits_{j=1}^{M} \pi_j^{(S_i)} \cdot b_j \cdot t_{S_i} & \text{if } D_{S_i} \leq D_{\max}, \\ 0 & \text{otherwise;} \end{cases} \tag{6.1}$$

where t_{S_i} is a quantity proportional to the amount of resources allocated to the cluster S_i—which depends on the selected scheduling policy—and $\pi_j^{(S_i)}$ is the probability that the best MCS available within the members of cluster S_i is the ith MCS. D_{S_i} and $D_{\max}$ are the distance between the two farthest users in cluster S_i, and the maximum allowable distance among cluster members, respectively. In particular, $D_{\max}$ accounts for power consumption overhead by avoiding cluster formations in which cluster members are placed far from each other, thus exceeding their power budget. Eq. (6.1) can be used to guarantee that all intra-cluster communications are single hop (i.e., any users inside a cluster can directly reach the rest of the cluster members).

6.2 Cluster formation algorithm

The problem of finding optimal coalitions is NP-complete because it requires evaluating all possible partitions of the set of users N in the network [17]. Obviously, the existing base stations with limited computational resources are not able to handle an NP-complete problem involving a few tens of users. Similarly, the cluster formation problem does not scale in case of distributed approaches in which enough resources might be available, since it could not be solved in polynomial time and would require high traffic overhead in the network.

Hence, we adapt the simple *merge and split* algorithm to solve the coalition formation problem with low complexity [20]. Although merge and split is a trivial method for dynamic cluster formation, it was shown to be a good alternative when computational overhead is of concern [4,18]. The merge and split rules are defined as follows: merge any set $\{S_{a_1}, .., S_{a_k}\}$ into a unique coalition (i.e., cluster), if the following inequality holds:

$$\sum_{i=1}^{k} \nu(S_{a_i}) < \nu\left(\cup_{i=1}^{k} S_{a_i}\right). \tag{6.2}$$

Similarly, if the previous inequality does not hold for a coalition that can be described as $\cup_{i=1}^{k} S_{a_i}$, then split it into its components (i.e., split the big cluster into smaller clusters). The authors of [3] have proven that the merge and split algorithm terminates and the result is D_{hp} stable, i.e., the system reaches a state in which there are no cluster members willing to perform a merge or a split operation. Intuitively speaking, in the merging phase, the merge and split algorithm clusters a given set $\{S_{a_1}, .., S_{a_k}\}$ if the clustering gain is higher than the cost of clustering. This helps us to make sure that coalition is beneficial to all, although it does not guarantee to form optimal coalitions. In the split phase, the algorithm searches for the clusters with negative gain and splits them.

6.3 Payoff allocation

So far we have not investigated on how resources should be distributed among cluster members. We have generically assumed that cluster throughput was equally shared by cluster members. However, in a realistic scenario, it is natural to think that only extra revenues due to clustering (i.e., the clustering gain) should be redistributed among cluster members. We formalize this concept in what follows.

We term *payoff* the amount of utility allotted to a member from the total available resources allotted to its cluster by the scheduling process. Let $G \in S$ be a cluster of size $|G|$. The payoff vector $\bar{x} = \{x_1, x_2, \dots, x_{|G|}\}$ describes the portion of cluster utility received by any user $i \in G$. A payoff vector is called cost efficient if $\sum_{i \in G} x_i = \nu(G)$ [18]. Of course, we are only interested in cost efficient payoff vectors.

As for the payoff distribution method, we chose to compare two mechanisms proposed in the literature, namely equal share and weighted share [18,22]. These two mechanisms are simple and would allow us to easily illustrate how clustering can be made attractive for all classes of users.

Equal share is the simplest approach, in which the clustering gain is equally divided among members. The cost efficient payoff distribution used under equal share is formally expressed as follows:

$$x_i = \frac{\nu(G) - \sum_{j \in G} \nu(\{j\})}{|G|} + \nu(\{i\}), \quad i \in \{G\}. \tag{6.3}$$

With the weighted share method, the cost efficient payoff distribution is computed based on the positive weights w_i:

$$x_i = \frac{w_i}{\sum\limits_{j \in G} w_j} \cdot \left(\nu(G) - \sum_{j \in G} \nu(\{j\}) \right) + \nu(\{i\}),\ i \in \{G\}. \tag{6.4}$$

As shown in Section 4, the clustering gain is mainly due to the presence of *good* users, whereas the channel state probability distribution of a cluster does not dramatically improve with the addition of a *poor* user (see Fig. 5.1). Hence, equal share may not strongly motivate users with good channel quality to cluster with users with poor channel quality. In contrast, adjusting w_i in Eq. (6.4), we can make sure that users with better channel quality receive more resources. Specifically, in our numerical simulation, we use values of w_i which are proportional to the user non-cooperative throughput, so that the clustering gain is shared proportionally to user's performance achieved without clustering.

6.4 Numerical evaluation

So far, we have shown that clustering gives substantial throughput increment. We also defined the rules to form clusters and distribute the resources in the cluster. Our proposal can be discouraging for good users, if the channel quality diversity of cluster members is high and most of the cellular transmission is carried on by the good users. Hence, power consumption of these users would increase. Now the question is: *Is there enough motivation for the users in good channel quality to participate in clustering?*

To answer this question, we simulate a scenario with 50 users randomly placed in cell area of $2.5km^2$ with varying channel quality according to their distance from the base station. In order to have a more realistic scenario, we assume that mobile users move on an average pedestrian speed between 0 to 5 km/h [14]. A cluster can have a maximum radius of $100m$.

From Table 6.1, we see that per-user relative throughput over RR and PF improves for all classes under all payoff schemes. The advantage of cluster-based scheduling with respect to RR is huge, and it is remarkable also when comparing to PF results. As for the distribution of gain among users, Table 6.1 shows that, under equal share payoff, *poor* users obtain

Table 6.1: Average per-user throughput improvement achieved with CL(WRR) over RR and PF with different payoff schemes

User type	**RR**		**PF**	
	Equal share	**Weighted share**	**Equal share**	**Weighted share**
Poor	199%	142%	37.9%	17.1%
Average	77.9%	136%	13%	15.7 %
Good	47.2%	139%	9.8%	19.2%

almost 20% more increment compared to *good* users. Differently, all classes of users receive comparable gain under weighted share payoff distribution. Therefore, our results testify the fact that weighted share payoff better incentivize *good* users to cluster while providing a reasonable improvement to *poor* and *average* users. More importantly, all users are highly encouraged to participate in cluster formation, regardless of their SNR class, especially under weighted share payoff scheme.

Chapter 7

Conclusions

In this paper, we introduced novel cluster-based scheduling schemes that avoid the need of trading off fairness and throughput by integrating the concepts of opportunistic scheduling and cooperative communications. We have shown that cluster-based scheduling substantially ameliorates the throughput (up to 50%) while maintaining high fairness among users. In particular, CL(WRR)—which assigns resources to the clusters in round robin and selects clusters heads opportunistically—achieves throughputs close to the ones achieved by the MaxRate scheduler, but with nearly perfect fairness among users. The result of our numerical simulations confirmed that cluster-based scheduling benefits all users irrespective of their channel qualities. Our proposal enhances the throughput of users in poor channel conditions by leveraging users with good channel qualities which are motivated for clustering by substantial throughput improvements, about 20% higher than legacy per-user opportunistic schedulers. Considering the diffusion of multi-radio devices, we conclude that cluster-based scheduling is a simple approach that has the potential to be embedded into cellular technologies, and provides higher scalability in comparison to conventional schedulers, since it reduces the individuals to be taken care of from the base station point of view.

References

[1] K. Akkarajitsakul, E. Hossain, and D. Niyato. Cooperative packet delivery in hybrid wireless mobile networks: A coalitional game approach. *IEEE Transactions on Mobile Computing*, (99):1–1, 2012.

[2] M. Andrews, K. Kumaran, K. Ramanan, A. Stolyar, R. Vijayakumar, and P. Whiting. Scheduling in a queuing system with asynchronously varying service rates. *Probability in the Engineering and Informational Sciences*, 18:191–217, April 2004.

[3] K. Apt and T. Radzik. Stable partitions in coalitional games. *Arxiv preprint cs/0605132*, 2006.

[4] K. Apt and S. Witzel. A generic approach to coalition formation. 2006.

[5] S. Bandyopadhyay and E. Coyle. An energy efficient hierarchical clustering algorithm for wireless sensor networks. In *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies*, volume 3, pages 1713–1723. IEEE, 2003.

[6] W. Choi and J. Andrews. The capacity gain from base station cooperative scheduling in a MIMO DPC cellular system. In *IEEE International Symposium on Information Theory*, pages 1224 –1228, July 2006.

[7] M. Dohler et al. *Virtual antenna arrays*. PhD thesis, University of London, 2004.

[8] E. Hahne. Round-robin scheduling for max-min fairness in data networks. *IEEE Journal on Selected Areas in Communications*, 9(7):1024–1039, 1991.

[9] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan. Energy-efficient communication protocol for wireless microsensor networks. In *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*, pages 10–pp. IEEE, 2000.

[10] K. Khalil, M. Karaca, O. Ercetin, and E. Ekici. Optimal scheduling in cooperate-to-join cognitive radio networks. In *Proceedings of IEEE INFOCOM*, pages 3002 –3010, April 2011.

[11] R. Knopp and P. Humblet. Information capacity and power control in single-cell multiuser communications. In *Proceedings of IEEE ICC*, volume 1, pages 331 –335 vol.1, June 1995.

[12] L. Le and E. Hossain. Multihop cellular networks: Potential gains, research challenges, and a resource allocation framework. *Communications Magazine, IEEE*, 45(9):66–73, 2007.

[13] J.-W. Lee, R. Mazumdar, and N. Shroff. Opportunistic power scheduling for multi-server wireless systems with minimum performance constraints. In *Proceedings of IEEE INFOCOM*, volume 2, pages 1067 – 1077 vol.2, March 2004.

[14] S. Lee, K. Kim, K. Hong, D. Griffith, Y. Kim, and N. Golmie. A probabilistic call admission control algorithm for WLAN in heterogeneous wireless environment. *IEEE Transactions on Wireless Communications*, 8(4):1672–1676, 2009.

[15] C. Lin and M. Gerla. Adaptive clustering for mobile wireless networks. *IEEE Journal on Selected Areas in Communications*, 15(7):1265–1275, 1997.

[16] E. Liu and K. Leung. Proportional fair scheduling: analytical insight under rayleigh fading environment. In *Proceedings of IEEE WCNC*, pages 1883–1888. IEEE, 2008.

[17] D. Ray. *A game-theoretic perspective on coalition formation*. OUP Oxford, 2007.

[18] W. Saad, Z. Han, M. Debbah, and A. Hjorungnes. A distributed merge and split algorithm for fair cooperation in wireless networks. In *Proceedings of IEEE ICC Workshops*, pages 311–315. Ieee, 2008.

[19] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar. Coalitional game theory for communication networks. *Signal Processing Magazine, IEEE*, 26(5):77–97, 2009.

[20] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar. Coalitional games for distributed collaborative spectrum sensing in cognitive radio networks. In *INFOCOM 2009, IEEE*, pages 2114–2122. IEEE, 2009.

[21] A. Sendonaris, E. Erkip, and B. Aazhang. User cooperation diversity. part i. system description. *Communications, IEEE Transactions on*, 51(11):1927–1938, 2003.

[22] M. Sereno. Cooperative game theory framework for energy efficient policies in wireless networks. pages 1 –9, May 2012.

[23] S. Sesia, I. Toufik, and M. Baker. *LTE-the UMTS long term evolution: from theory to practice*. Wiley, 2011.

[24] N. Sharma and L. Ozarow. A study of opportunism for multiple-antenna systems. *IEEE Transactions on Information Theory*, 51(5):1804 – 1814, May 2005.

[25] W.-F. A. Specification. Wi-Fi Peer-to-Peer (P2P) Specification v1.1, 2011.

[26] Third Generation Partnership Project (3GPP). Physical layer procedures (Release 10) for Evolved Universal Terrestrial Radio Access (E-UTRA). 3GPP TR 36.213 v 10.5.0, March 2012.

[27] P. Viswanath, D. Tse, and R. Laroia. Opportunistic beamforming using dumb antennas. In *IEEE Transactions on Information Theory*, page 449, June 2002.

[28] D. Wu, Y. Cai, L. Zhou, and J. Wang. A cooperative communication scheme based on coalition formation game in clustered wireless sensor networks. *IEEE Transactions on Wireless Communications*, (99):1–11, March 2012.

[29] H. Wu, C. Qiao, S. De, and O. Tonguz. Integrated cellular and ad hoc relaying systems: iCAR. *Selected Areas in Communications, IEEE Journal on*, 19(10):2105–2115, 2001.

[30] J. Yang, Z. Yifan, W. Ying, and Z. Ping. Average rate updating mechanism in proportional fair scheduler for hdr. In *Global Telecommunications Conference, 2004. GLOBECOM'04. IEEE*, volume 6, pages 3464–3466. IEEE, 2004.