

Doctoral Thesis

Modeling and Analysis of Interactions
in Wireless Resource Allocation

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Preface

This thesis primarily aims to analyze resource allocation in wireless communication systems. Specifically, the behavior of competing transmitters in systems and the resulting performance of resource allocation are analyzed using mathematical models. Resource allocation problems in wireless communication systems essentially involve mutual interactions because the available bandwidth for each system is limited; thus, mutual interactions should be considered for modeling and analyzing target systems.

The wireless systems discussed in this thesis include two major systems, wireless local area networks (WLANs) and cellular systems, where the resource allocation for each system is different. A crucial factor for mutual interaction in WLANs is the spatial co-channel cell overlapping, and that in cellular systems is user scheduling and interference. This thesis focuses on two topics: the first topic is transmission power control (TPC) and channel allocation in WLANs, and the second topic is the analysis of channel-adaptive user scheduling in uplink cellular networks. Each topic is described in detail below.

The first part of this thesis discusses the resource allocation in WLANs, wherein decentralized algorithms that are suitable for WLANs are proposed. In a densely deployed WLAN environment, the unorganized deployment of access points (APs) can cause significant cell overlaps among APs. In such a situation, because of the carrier sense multiple access with collision avoidance (CSMA/CA) mechanism, APs and/or stations (STAs) are supposed to time-share the channel with all their neighboring APs. Therefore, in a dense environment where an appropriate resource allocation is lacking, transmitters only have limited transmission opportunities.

This thesis proposes coverage adaptation based on TPC to mitigate

coverage overlaps. When performing TPC, the connectivity between STAs and serving APs should be maintained. In other words, the regions not covered by any AP should be eliminated; these regions are referred to as coverage holes in this thesis. To detect coverage holes, STAs and/or APs are used as sensors that inform each AP of the coverage in the areas they exist. Moreover, the effect of maintaining the transmission power of specific APs at their maximum values is investigated; this is achieved by focusing on the APs that are at the outer boundary of the network, which are expected to significantly contribute to the coverage as compared to more central APs.

In addition to TPC, a decentralized channel selection method in WLANs is also discussed. Typically, multiple channels are available in WLANs, and simultaneous transmissions in different channels do not conflict with each other. Therefore, appropriate channel allocation is also useful in the context of coverage overlap mitigation. However, because decentralized channel selection inherently involves the mutual interaction among APs, the best channel for an AP considering minimum coverage overlap is dependent on the channels that other APs select. In such a situation, the channel selection dynamics in which each AP selects a channel locally do not necessarily converge to a stable state. This thesis captures the mutual interaction by the game-theoretical formulation. Particularly, the payoff functions for APs are designed such that the resulting game has a potential function, which is called potential game; this formulation ensures that the decentralized channel selection dynamics converge to a Nash equilibrium, which is a stable solution concept in game theory.

The latter half of this thesis is dedicated to channel-adaptive scheduling in uplink cellular networks, where the corresponding signal-to-interference-plus-noise power ratio (SINR) distribution is analyzed. Generally, the irregular locations of interferers, typical to cellular networks, complicate the analysis of SINR; therefore, conventional methods for performance evaluation are limited to Monte Carlo simulations. Stochastic geometry can provide a direct and often tractable mathematical expression of the SINR distribution in a general form with the help of point process theory; therefore, it has developed into a widespread methodology for analyzing various types of wireless networks. In this thesis, the SINR distribution and av-

erage data rate for uplink user scheduling are provided in a general form using stochastic geometry. In the context of user scheduling, the number of candidate users is a crucial factor in analyzing the gain by user scheduling because of the effects of multi-user diversity. Based on this insight, the process of deriving the complete expression of the uplink SINR distribution is divided into two stages: In the first stage, the conditional SINR distribution is derived using stochastic geometry, when the number of candidate users is given. In the second stage, the conditional SINR distribution is averaged with respect to the number of candidate users. The above averaging requires the distribution of the number of candidate users in a Poisson cellular network, in which the locations of base stations form a Poisson point process. This thesis provides the distribution of the number of candidate users in a general form, while considering the TPC per user in uplink cellular networks. Based on these results, this study successfully obtains the uplink SINR distribution under channel-adaptive user scheduling.

The chapters of this thesis are as follows. Chapter 1 provides the background and overview of this thesis. Chapter 2 introduces related technologies to this work. Chapters 3 and 4 present a TPC and a channel allocation scheme to mitigate coverage overlaps in WLANs, respectively. Chapter 5 presents the stochastic geometry analysis of channel-adaptive scheduling in uplink cellular networks. Finally, Chapter 6 concludes this thesis.

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Notations

Notation	Description
$\mathbb{R}$	Real numbers
$\mathbb{R}^n$	n -dimensional Euclidean space
$\mathbb{N}$	Natural numbers not including 0
$\mathbb{N}_0$	Natural numbers including 0
$A \setminus B$	Set difference of A and B
$\bigcup_{i \in I} A_i$	Union of sets in $\{A_i\}_{i \in I}$
$\bigcap_{i \in I} A_i$	Intersection of sets in $\{A_i\}_{i \in I}$
$\prod_{i \in I} A_i$	Cartesian product of sets in $\{A_i\}_{i \in I}$
$\emptyset$	Empty set
$\#\{\cdot\}$	Number of elements of a set
$ A $	Area of a region for $A \subset \mathbb{R}^2$
$g \circ f$	Composite function of f and g
$\min_{\text{condition}}$	Minimum operator under the condition
$\max_{\text{condition}}$	Maximum operator under the condition
$\mathbb{P}(A)$	Probability of event A
$\mathbb{P}(A B)$	Conditional probability of A given B
$\mathbb{E}[\cdot]$	Expectation operator
$\mathbb{E}[\cdot \text{condition}]$	Conditional expectation given the condition
$f_x(\cdot)$	pdf of a continuous random variable x , pmf of a discrete random variable x
$\mathcal{L}_x(\cdot)$	Laplace transform of the pdf of x
$B(\cdot, \cdot)$	Beta function
$\gamma(\cdot, \cdot)$	Lower incomplete gamma function
${}_1F_1(\cdot; \cdot; \cdot), {}_2F_1(\cdot, \cdot; \cdot; \cdot)$	Hypergeometric function

Abbreviations

Abbreviation	Description
5G	fifth generation
EHT	extremely high throughput
WLAN	wireless local area network
WSN	wireless sensor network
MAC	medium access control
CSMA/CA	carrier sense multiple access with collision avoidance
TDD	time-division duplex
AP	access point
BS	base station
STA	station
BSS	basic service set
OBSS	overlapping BSS
IoT	Internet of Things
TPC	transmission power control
BRD	best response dynamics
SAP	spatial adaptive play
BSI	bilateral symmetric interaction
SNR	signal-to-noise power ratio
SINR	signal-to-interference-plus-noise power ratio
i.i.d.	independently and identically distributed
pmf	probability mass function
pdf	probability density function
cdf	cumulative distribution function
ccdf	complementary cdf

Abbreviations

Abbreviation	Description
pgfl	probability generating functional
PPP	Poisson point process
CSI	channel state information

Chapter 1

Introduction

1.1 Background

Wireless communication technologies have experienced remarkable growth in the past two decades. The demand brought by cellular systems has been steadily growing and is expected to rise continuously [1]. Currently, with the explosive demand for wireless communication, wireless communication technologies have been steadily evolving. Furthermore, the development of future 5G wireless networks has become a real possibility. Concurrently, the IEEE 802.11 Extremely High Throughput Study Group (EHT Study Group) has been established to initiate discussion on new IEEE 802.11 features for bands between 1 and 7.125 GHz [2], which has led to the IEEE 802.11be Task Group [3].

To cope with the exponential growth of mobile broadband data traffic, improvement in the efficiency of spectrum utilization remains a significant challenge. For example, in wireless local area networks (WLANs), due to the carrier sense multiple access with collision avoidance (CSMA/CA) mechanism, access points (APs) and/or stations (STAs) are supposed to time-share the wireless channel with all neighboring APs. Therefore, transmitters have limited transmission opportunities in a densely deployed environment of APs if appropriate wireless resource allocation is lacking. The primary focus of this thesis is to consider effective resource allocation schemes from the perspectives of transmission power and wireless channel control. For

the efficient utilization of bandwidth among multiple users, it is vital to control the transmission power and channel allocation to reduce contention among different users, and to select an appropriate user according to a given environment.

Additionally, given a specific resource allocation method, the methodology for evaluating the performance of resource allocation is also critical. This performance analysis is typically conducted using Monte Carlo simulations, which are often time-consuming; for example, when seeking appropriate system parameter settings. Another focus of this thesis is to evaluate the performance under the assumption of specific resource allocation. Currently, wireless systems and related technologies are evolving; therefore, a general understanding of the performances of wireless communication systems is essential because it is difficult to evaluate all possibilities by simulations or experiments.

Based on these viewpoints, this thesis presents two main topics that are associated with wireless resource allocation. First, the resource allocation in WLANs, particularly, the design of distributed algorithms that can show the stability of the channel update dynamics, is discussed. Second, the analysis of channel-adaptive scheduling in uplink cellular networks, particularly, the method to obtain the analytical expression of performance metrics is elucidated under the assumption of uplink channel-adaptive user scheduling.

In wireless resource allocation, mutual interaction is typically observed; therefore, capturing the mutual interactions gives us an important insight. In the first topic, we observe that spatial co-channel overlaps among APs are determined not only by an AP making a decision but by other APs as well. This thesis captures such mutual interactions in a channel selection problem with the help of game theory, and succeeds in analyzing the behavior of competing transmitters in the system. In the second topic, by focusing on the distribution of the number of candidate users to be scheduled, we note that the multi-user diversity depends on the number of candidate users. This thesis successfully gives the signal-to-interference-plus-noise power ratio (SINR) distribution of a scheduled user through the derivation of the distribution of the number of candidate users, which is useful for a link

budget with the consideration of the multi-user diversity in uplink cellular networks. Furthermore, the interference signals can be considered as interactions in wireless networks, which is well elucidated using point process theory and stochastic geometry.

A detailed background of each topic is provided in the following sections.

1.1.1 Transmission Power Control and Channel Allocation in Dense WLANs

The dissemination of IEEE 802.11 WLANs has been rapidly growing because of their ease of deployment and low cost. For wireless Internet access, personal users and WLAN operators install numerous APs such that multiple basic service sets (BSSs) coexist in the same spectrum (i.e., several *overlapping BSSs (OBSSs)* exist) in a variety of places such as hotels, cafes, hospitals, and restaurants [1, 4]. Globally, there will be nearly 549 million public Wi-Fi hotspots by 2022, up from 124 million hotspots in 2017, which is a fourfold increase [1]. These aim to meet the increasing demand for bandwidth (e.g., consumer video use). Moreover, it is expected that many terminals including Internet of Things (IoT) devices will be connected [1]; hence, user terminals will also be densely deployed.

In such an environment, an exposed terminal problem [5, 6] becomes more serious, in which unnecessary transmission suppression frequently occurs. Without appropriate resource allocation, dense deployment of APs and user terminals would accelerate this problem. Therefore, wireless resource management becomes increasingly important in densely deployed WLANs. As mentioned earlier, transmitters have limited transmission opportunities in a dense environment without appropriate resource allocation. This kind of channel contention over the same frequency degrades the throughput and other performance indicators, resulting in the inefficient use of wireless bandwidth. To improve the spectral efficiency, this thesis discusses the decentralized control of transmission power and channels for APs, which are arbitrarily arranged.

1.1.2 Stochastic Geometry Analysis of Uplink Channel-Adaptive Scheduling

The methodology by which the performance analysis of a wireless network is conducted has changed significantly during the past decade because of the emergence of stochastic geometry [7–9]. This type of performance analysis is typically conducted using Monte Carlo simulations, which are often time-consuming, for example, when an appropriate system parameter setting is sought. In contrast, stochastic geometry provides direct and often tractable mathematical expressions of performance metrics (e.g., signal-to-interference-plus-noise power ratio (SINR) distribution and the average rate) for different types of wireless networks [7]. Specifically, the modeling of random topologies based on a point process, typically a Poisson point process (PPP), results in a simple and tractable form of the SINR distribution.

Stochastic geometry analysis has been extensively applied to downlink cellular networks [9, 10]. Andrews *et al.* [11] proposed a basic framework for downlink cellular analysis and derived the SINR distribution as a simple result, which was in good agreement with the Monte Carlos simulations. Moreover, owing to the recent emergence of symmetric traffic applications (e.g., video streaming and cloud-based tasks [12]), analysis of uplink cellular networks has become more critical. Therefore, the framework of downlink analysis has been extended to an uplink case [13, 14], and their extensions have appeared in a wide variety of scenarios [15–18].

Despite the widespread popularity of stochastic geometry analysis for cellular networks, most analytical results lack the perspective of channel-adaptive user scheduling. In other words, these studies analyze SINR distribution under the assumption that each transmitting or receiving user is selected uniformly randomly in each cell. However, in modern cellular systems, the transmitting user is not selected uniformly randomly but rather selected on the basis of specific channel-adaptive scheduling [19] such as the proportional fair scheduler [20]. This thesis will discuss the SINR distribution and the average data rate of users that are selected according to normalized SNR-based scheduling [21].

Main subject	Modeling and analysis of interactions in wireless resource allocation	
Main topics	Decentralized resource allocation in WLANs	Uplink channel-adaptive user scheduling
Communication systems	IEEE 802.11 WLAN	Uplink cellular network
Inherent interactions	Spatial co-channel overlaps are determined not only by an AP itself but also by other APs.	- Interfering signal power varies depending on realization of locations of interferers. - Number of candidate users affects the multiuser diversity.
Targets	Chapter 3 Transmission power control Chapter 4 Channel allocation	Chapter 5 SINR distribution and average data rate
Approaches	Monte Carlo simulations, Game theory	Stochastic geometry analysis

Figure 1.1: Chapter overview.

1.2 Chapter Overview

Fig. 1.1 shows a chapter overview of this thesis. The main subject of this thesis is the modeling and analysis of the resource allocation in wireless communication. This thesis discusses this subject with regards to two topics, decentralized resource allocation in WLANs and uplink channel-adaptive user scheduling.

The vital interactions of the first topic are described because the spatial co-channel overlaps are determined not only by an AP that selects a channel but by other APs as well. This thesis captures such mutual interactions with the help of game theory, which enables the analysis of the behavior of competing transmitters in the system and/or the resulting performance of decentralized channel allocation. The essential interactions of the second topic are explained from two perspectives: the interfering signal power varies depending on the locations of interferers, which are considered as a random element in a Poisson cellular network; the multi-user diversity increases as the number of candidate users increases. We observe that a randomized source of interference is formulated with a point process, and these random

factors are averaged using stochastic geometry. Furthermore, the way in which the number of candidate users affects the SINR distribution of a scheduled user is captured with the help of order statistics. The foundations of such mathematical models are given in Chapter 2.

1.3 Contributions of This Thesis

The contributions of the first topic (i.e., resource allocation in WLANs) are summarized as follows:

- the proposal of an autonomous transmission power control (TPC) scheme that treats APs and STAs as sensors, which detect the coverage domains of APs,
- the proposal of a potential game-based channel selection scheme, which is based on coverage overlaps.

Notably, by designing a channel selection scheme based on a potential game, the behavior of the system that includes competing transmitters can be analyzed by considering the stability of decentralized channel selection. Furthermore, the total coverage overlaps that are achieved by decentralized dynamics are shown to be upper bounded by the potential function. It is also significant that the proposed TPC significantly contributes to the tightness of the upper bound.

The contributions of the latter topic (i.e., the stochastic geometry analysis of uplink channel-adaptive user scheduling) are summarized as follows:

- This thesis provides the general method for deriving the SINR distribution and the average data rate under channel-adaptive user scheduling in an uplink cellular network, which is achieved with the help of stochastic geometry. This thesis assumes the TPC per user in a general form, which includes the channel inverse power control and the fractional power control; this is aimed at achieving wide applicability for the given framework to be utilized in a typical uplink network.
- By noticing that the multi-user diversity depends on the number of candidate users, this thesis successfully gives the SINR distribution

of a scheduled user through the derivation of the distribution of the number of candidate users. Furthermore, it is also shown that the analytical expression is reduced to a closed-form expression in special cases.

The further detailed contributions will be given in each chapter. Here, it should be emphasized that the scopes of these methods are not limited to specific standards; these can be regarded as versatile methods. Therefore, I believe that the proposed methods and frameworks are useful, regardless of technological trends.

Chapter 2

Related Technologies

2.1 Game Theory

First, the basic game-theoretic framework [22–24] is introduced. Then, an important class of the strategic form game, the potential game, is introduced. Note that the channel selection schemes proposed in this thesis are based on a potential game-theoretic framework. In addition, learning algorithms in a game-theoretic situation are described, which provides the way of deciding a strategy for each player and plays an important role in Section 4.4.

2.1.1 Theoretical Basis

A *strategic form game* is defined as a triplet $G = (\mathcal{N}, (\mathcal{A}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$, where $\mathcal{N}$ is the finite index set of *players*, $\mathcal{A}_i$ is the set of *strategies* associated with player $i \in \mathcal{N}$, and $u_i: \prod_{i \in \mathcal{N}} \mathcal{A}_i \rightarrow \mathbb{R}$ is the *payoff* function. Payoff function u_i represents a preference ordering of the strategies of player $i \in \mathcal{N}$. Note that u_i depends on not only player i 's strategy but also the other players' strategies. In other words, a player varies his/her strategy to take according to the other players' strategies. Let $\prod_{i \in \mathcal{N}} \mathcal{A}_i$ be denoted by $\mathcal{A}_{\mathcal{N}}$, and $\prod_{j \in \mathcal{N} \setminus \{i\}} \mathcal{A}_j$ by $\mathcal{A}_{-i}$.

A fundamental solution concept for strategic form games is a *Nash equilibrium*.

Definition 2.1 (Nash equilibrium). A Nash equilibrium of game $G = (\mathcal{N}, (\mathcal{A}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$ is defined by a strategy profile $\mathbf{a}^* = (a_i^*, \mathbf{a}_{-i}^*) \in \mathcal{A}_{\mathcal{N}}$ that satisfies

$$u_i(a_i^*, \mathbf{a}_{-i}^*) \geq u_i(a_i, \mathbf{a}_{-i}^*) \quad (2.1)$$

for every $i \in \mathcal{N}$ and every $a_i \in \mathcal{A}_i$.

At the Nash equilibrium, no player has an incentive to deviate from the equilibrium because his/her current strategy is the optimal with respect to his/her payoff as long as the other players do not change their strategies. In general, a strategic form game does not always have a Nash equilibrium. In addition, even if a Nash equilibrium exists, how players achieve the Nash equilibrium is not obvious.

The important class of strategic form games is a *potential game* [25] as follows.

Definition 2.2 (Potential game). A strategic form game $G = (\mathcal{N}, (\mathcal{A}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$ is a potential game if there exists a *potential function* $V: \mathcal{A}_{\mathcal{N}} \rightarrow \mathbb{R}$ such that

$$u_i(a'_i, \mathbf{a}_{-i}) - u_i(a_i, \mathbf{a}_{-i}) = V(a'_i, \mathbf{a}_{-i}) - V(a_i, \mathbf{a}_{-i}), \quad (2.2)$$

for every $i \in \mathcal{N}$, $a_i, a'_i \in \mathcal{A}_i$, and $\mathbf{a}_{-i} \in \mathcal{A}_{-i}$.

In a potential game, the improvement of each player's payoff results in the improvement of some sort of total performance called a potential function. It is known that if a strategic form game is a potential game with finite strategy sets, then unilateral improvement dynamics are guaranteed to converge to a Nash equilibrium in a finite number of steps [25].

In addition, a necessary and sufficient condition for a strategic form game to be a potential game is introduced. A strategic form game is a potential game if and only if there exists an interaction potential.

Theorem 2.1 (Interaction potential [26]). A strategic form game $G = (\mathcal{N}, (\mathcal{A}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$ is a potential game if and only if there exists a family of functions $\{\Phi_{\mathcal{L}} \mid \Phi_{\mathcal{L}}: \mathcal{A}_{\mathcal{N}} \rightarrow \mathbb{R}, \mathcal{L} \subseteq \mathcal{N}\}$ such that

$$u_i(\mathbf{a}_{\mathcal{N}}) = \sum_{\mathcal{L} \subseteq \mathcal{N}: i \in \mathcal{L}} \Phi_{\mathcal{L}}(\mathbf{a}_{\mathcal{L}}), \quad (2.3)$$

for every $i \in \mathcal{N}$ and $\mathbf{a}_{\mathcal{N}} \in \mathcal{A}_{\mathcal{N}}$. A potential function is given by

$$V(\mathbf{a}_{\mathcal{N}}) = \sum_{\mathcal{L} \subseteq \mathcal{N}} \Phi_{\mathcal{L}}(\mathbf{a}_{\mathcal{L}}). \quad (2.4)$$

A family of functions $\{\Phi_{\mathcal{L}}\}_{\mathcal{L} \subseteq \mathcal{N}}$ is called an *interaction potential* [26]. This theorem is used in Section 4.3 to show that the proposed channel selection games are potential games.

2.1.2 Learning Algorithm

A learning algorithm provides the way of deciding a strategy for each player. One of the most frequently used algorithms is *spatial adaptive play (SAP)* [27, 28], which is introduced here. In addition, *best response dynamics (BRD)* is introduced as a special case of SAP.

To explain the algorithm, some symbols are required. The set of players is denoted by $\mathcal{N} := \{1, 2, \dots, N\}$. Discrete variable $t \geq 0$ is used to denote time index, and let $a_i[t] \in \mathcal{A}_i$ denote the strategy of player $i \in \mathcal{N}$ at step t .

In SAP, each player decides his/her strategy according to the following rules: At each step t , each player $i \in \mathcal{N}$ unilaterally updates his/her strategy in turn. For simplicity, the way of selecting a player is assumed to be in turn according to the order of indices in $\mathcal{N}$. When player $i \in \mathcal{N}$ updates his/her strategy, he/she randomly selects next strategy $a_i[t+1] \in \mathcal{A}_i$ according to the following distribution,

$$x_i(a_i | \mathbf{a}_{-i}[t]) = \frac{\exp[\beta u_i(a_i, \mathbf{a}_{-i}[t])]}{\sum_{a'_i \in \mathcal{A}_i} \exp[\beta u_i(a'_i, \mathbf{a}_{-i}[t])]}, \quad (2.5)$$

$$\mathbf{a}_{-i}[t] := (a_1[t+1], \dots, a_{i-1}[t+1], a_{i+1}[t], \dots, a_N[t]) \in \mathcal{A}_{-i},$$

where $\beta \geq 0$ is the exploration parameter. When all players have finished updating their strategies at step t , the dynamics continue to the next step $t+1$.

If β is as small as zero, each player selects every strategy with nearly equal probability. In contrast, in the limit $\beta \rightarrow \infty$, SAP approaches the BRD [28], where at each step t , player $i \in \mathcal{N}$ unilaterally changes its channel from $a_i[t]$ to $a_i[t+1] \in \arg \max_{a_i} u_i(a_i, \mathbf{a}_{-i}[t])$. As an appropriate β depends on

an order of magnitude of a payoff function, parameter β should be carefully chosen.

By applying SAP to a potential game, the probability of taking a specific strategy profile is obtained.

Theorem 2.2 ([27]). In the potential game with finite strategy space $\mathcal{A}_N$ and potential function $V(\mathbf{a})$, the SAP has the unique stationary distribution of a strategy profile:

$$\pi(\mathbf{a}) = \frac{\exp[\beta V(\mathbf{a})]}{\sum_{\mathbf{a}' \in \mathcal{A}_N} \exp[\beta V(\mathbf{a}')]} \quad (2.6)$$

This theorem means that the SAP has more possibilities to select strategy profiles so that a potential function is larger regardless of the initial players' strategies. Note that if using SAP in a potential game, the potential function can be maximized with arbitrarily high possibility by an appropriate development of exploration parameter β [27].

2.2 Stochastic Geometry

2.2.1 Foundation of General Point Process

Consider measurable space $(\mathbb{R}^d, \mathcal{B}^d)$, where $\mathbb{R}^d$ is the d -dimensional Euclidean space and $\mathcal{B}^d$ is the Borel σ -algebra of $\mathbb{R}^d$.

A *counting measure* on $\mathbb{R}^d$ is defined as a mapping $\varphi : \mathcal{B}^d \rightarrow \mathbb{N}_0 \cup \{\infty\}$ from a Borel subset $B \in \mathcal{B}^d$ to the number of points falling in the set B .

Let $\mathcal{N}$ be the set of all the counting measures on $\mathbb{R}^d$. A basic event $E_{B,k} \subset \mathcal{N}$ is defined as the event that there are exactly k points in the region B , for compact $B \subset \mathbb{R}^d$ and $k \in \mathbb{N}_0$:

$$E_{B,k} := \{ \phi \in \mathcal{N} \mid \varphi(B) = k \}. \quad (2.7)$$

Let the σ -algebra of subsets of $\mathcal{N}$ generated by $\{E_{B,k} \mid (B,k) \in \mathfrak{P}(\mathbb{R}^d) \times \mathbb{N}_0, B \text{ is compact}\}$ be denoted by $\mathfrak{N}$, i.e., $\mathfrak{N}$ is the intersection of all σ -algebras containing $\{E_{B,k} \mid (B,k) \in \mathfrak{P}(\mathbb{R}^d) \times \mathbb{N}_0, B \text{ is compact}\}$. An ordered pair $(\mathcal{N}, \mathfrak{N})$ is called a *canonical space*.

A point process Φ is defined as a measurable map $N : \Omega \rightarrow \mathcal{N}$ from a probability space $(\Omega, \mathcal{A}, \mathbb{P})$ to the canonical space $(\mathcal{N}, \mathfrak{N})$. In this sense, a canonical space $(\mathcal{N}, \mathfrak{N})$ is also called as the outcome space for a point process in $\mathbb{R}^d$.

We denote $N^\omega = N(\omega)$ for each sample $\omega \in \Omega$. Given a compact $B \subset \mathbb{R}^d$, $N^\omega(B)$ is a random variable. Actually, noting that N is measurable and $\mathcal{A}$ is a σ -algebra, we have

$$\begin{aligned} \{\omega \in \Omega \mid N^\omega(B) \leq x\} &= \bigcup_{k \in \mathbb{N}_0 : k \leq x} \{\omega \in \Omega \mid N^\omega(B) = k\} \\ &= \bigcup_{k \in \mathbb{N}_0 : k \leq x} N^{-1}(E_{B,k}) \in \mathcal{A}. \end{aligned} \quad (2.8)$$

Hereinafter, for ease of notation, we let $N(B)$ always represent a random variable, whose realization corresponds to $\varphi(B)$.

A point process N on a metric space $\mathbb{R}^d$ is said to be *locally finite* if $\mathbb{P}(N(B) < \infty) = 1$ for every bounded $B \in \mathcal{B}^d$. In fact, for any locally finite point process N , there exist random variables $x_1, x_2, \dots$ in $\mathbb{R}^d$ and a random variable κ over $\mathbb{N}_0 \cup \{\infty\}$ such that almost surely $N = \sum_{n=1}^{\kappa} \delta_{x_n}$, where δ_x is the Dirac measure at a point $x \in \mathbb{R}^d$, which returns 1 if $x \in B$ and 0 otherwise. The above decomposition gives us the intuitive notion of a point process as a random set of points, rather than a counting measure. That is, a point process can be interpreted as a countable random set of points in $\mathbb{R}^d$. In that sense, we also use the notation Φ to denote a random set on $\mathbb{R}^d$. In the context of wireless communications, a point process is used for modeling the locations of nodes randomly scattered in $\mathbb{R}^d$.

A primary interest is in the expectation of functions depending on locations of nodes with respect to a point process. Given a measurable function $f : \mathcal{N} \rightarrow \mathbb{R}$, the expectation of f over the point process is given by

$$\mathbb{E}[f(\Phi)] := \int_{\Omega} f(N^\omega) d\mathbb{P}(\omega). \quad (2.9)$$

Letting the distribution of Φ be denoted by $\mathbf{P}$, i.e.,

$$\mathbf{P}(E) := \mathbb{P} \circ N^{-1}(E) = \mathbb{P}(\{\omega \in \Omega \mid N^\omega \in E\}), \quad \forall E \in \mathfrak{N} \quad (2.10)$$

we can rewrite the above expectation as follows:

$$\int_{\Omega} f(N^{\omega}) d\mathbb{P}(\omega) = \int_{\mathcal{N}} f(\varphi) d\mathbf{P}(\varphi) \quad (2.11)$$

Note that $\mathbf{P}$ is the probability measure pertaining to the outcome space.

As seen in the following subsection, the *intensity measure* plays an important role in calculating the expectation over a PPP. The intensity measure Λ is defined as

$$\Lambda(B) := \int_{\Omega} N^{\omega}(B) d\mathbb{P}(\omega) = \int_{\mathcal{N}} \varphi(B) d\mathbf{P}(\varphi) \quad (2.12)$$

2.2.2 Poisson Point Process

A PPP is introduced by identifying the distribution of $N^{\omega}(B)$. Specifically, a homogeneous PPP is characterized by the following two properties:

- For any compact $B \subset \mathbb{R}^2$,

$$\mathbb{P}(\{\omega \in \Omega \mid N^{\omega}(B) = k\}) = \frac{(\lambda|B|^k)e^{-\lambda}}{k!}. \quad (2.13)$$

- For any disjoint compact subsets B_1 and B_2 of $\mathbb{R}^d$, and for any 1-dimensional Borel subsets A_1 and A_2 ,

$$\begin{aligned} & \mathbb{P}(\{\omega \in \Omega \mid N^{\omega}(B_1) \in A_1, N^{\omega}(B_2) \in A_2\}) \\ &= \mathbb{P}(\{\omega \in \Omega \mid N^{\omega}(B_1) \in A_1\}) \cdot \mathbb{P}(\{\omega \in \Omega \mid N^{\omega}(B_2) \in A_2\}). \end{aligned} \quad (2.14)$$

We can understand the first property as $N(B)$ follows a Poisson distribution, and the second property as $N(B_1)$ and $N(B_2)$ are independent. Note that the intensity measure of a homogeneous PPP is $\Lambda(B) = \lambda|B|$, and parameter λ is called a density.

For validating an expression derived by stochastic geometry, the derived analytical result is often compared to the evaluation value obtained through Monte Carlo simulations. To conduct Monte Carlo simulations properly, it is required to simulate a PPP on a certain region. We can simulate the PPP with intensity λ on a region A as follows: draw a sample from a Poisson distribution with mean $\lambda|A|$, call it n , and then place n points uniformly randomly in A . The above mentioned process is used in the numerical evaluation part in Chapter 5.

2.2.3 Campbell's Theorem and Probability Generating Functional for Poisson Point Process

When we consider the expectation of measurable function $f : \mathcal{N} \rightarrow \mathbb{R}$ with respect to a PPP Φ , the following two expectations are fundamental:

$$\mathbb{E} \left(\sum_{x \in \Phi} f(x) \right) := \int_{\mathcal{N}} \sum_{x \in \varphi} f(x) d\mathbf{P}(\varphi), \quad (2.15)$$

$$\mathbb{E} \left(\prod_{x \in \Phi} f(x) \right) := \int_{\mathcal{N}} \prod_{x \in \varphi} f(x) d\mathbf{P}(\varphi), \quad (2.16)$$

i.e., the sum of $f(x)$ over a point process Φ and the product of $f(x)$ over Φ , where we regard φ as a deterministic point set.

The Campbell's theorem says that

$$\int_{\mathcal{N}} \sum_{x \in \varphi} f(x) d\mathbf{P}(\varphi) = \int_{\mathbb{R}^d} f(x) d\Lambda(x), \quad (2.17)$$

and it is shown by using this theorem that

$$\int_{\mathcal{N}} \prod_{x \in \varphi} f(x) d\mathbf{P}(\varphi) = \exp \left(- \int_{\mathbb{R}^d} (1 - f(x)) d\Lambda(x) \right). \quad (2.18)$$

Note that the expectations are converted into the integral over the measure space $(\mathbb{R}^d, \mathcal{B}^d, \Lambda)$.

The second expectation is called a probability generating functional (pgfl) of PPP, and is used in this thesis to derive an SINR distribution.

2.3 Order Statistics

As an another topic, the order statistics of random variables is introduced in this section. In particular, we derive the i th largest of n random variables that follow exponential distribution with mean one.

Consider random variables $x_1, x_2, \dots, x_n$, which are independently and identically distributed (i.i.d.) with a distribution F . The goal of this section is to obtain the distribution of the i th largest random variable of $x_1, x_2, \dots, x_n$. At first, letting the k th smallest of $x_1, x_2, \dots, x_n$ be denoted

by $x_{(k)}$, we consider the distribution of $x_{(k)}$. Let $\lambda_1, \lambda_2, \dots, \lambda_j$ be an arbitral subset of $\{1, 2, \dots, n\}$ with j elements that satisfies $\lambda_1 < \lambda_2 < \dots < \lambda_n$. Considering that the random variables are i.i.d., we have

$$\begin{aligned} & \mathbb{P}(x_{\lambda_1} < x, \dots, x_{\lambda_j} < x, x_{\lambda_{j+1}} \geq x, \dots, x_{\lambda_n} \geq x) \\ &= \mathbb{P}(x_{\lambda_1} < x) \cdots \mathbb{P}(x_{\lambda_j} < x) \mathbb{P}(x_{\lambda_{j+1}} \geq x) \cdots \mathbb{P}(x_{\lambda_n} \geq x) \\ &= F(x)^j (1 - F(x))^{n-j}. \end{aligned} \quad (2.19)$$

As we can choose $\lambda_1, \lambda_2, \dots, \lambda_j$ in $\binom{n}{j}$ ways, we obtain the probability of the event $E_j^n(x)$ that j of n random variables are less than x and the remainings are more than or equal to x as follows:

$$\mathbb{P}(E_j^n(x)) = \binom{n}{j} F(x)^j (1 - F(x))^{n-j}. \quad (2.20)$$

The event $x_{(k)} < x$ is the union of exclusive events $E_k^n(x), E_{k+1}^n(x), \dots, E_n^n(x)$; thus we have

$$\mathbb{P}(x_{(k)} < x) = \sum_{j=k}^n \mathbb{P}(E_j^n(x)) = \sum_{j=k}^n \binom{n}{j} F(x)^j (1 - F(x))^{n-j}. \quad (2.21)$$

Note that we can obtain the distribution of the i th largest of $x_1, x_2, \dots, x_n$ by letting $k = n - i + 1$. Note that, if the common distribution F is continuous, the probability density function (pdf) of $x_{(k)}$ is also obtained by differentiating $F_{(k)}(x)$.

As a special case, we consider the i th largest of i.i.d. random variables $h_1, h_2, \dots, h_n$ following the exponential distribution with mean one. The distribution of a random variable h_i ($i = 1, 2, \dots, n$) is given by

$$\mathbb{P}(h_i < x) = 1 - e^{-x}. \quad (2.22)$$

Letting $F(x) = 1 - e^{-x}$ and $k = n + i - 1$ in (2.21), we obtain the distribution of the i th largest of i.i.d. random variables following the exponential distribution with mean one as follows:

$$\sum_{j=n-i+1}^n \binom{n}{j} (1 - e^{-x})^j (e^{-x})^{n-j} = \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j (-1)^k e^{-(n+k-j)x}. \quad (2.23)$$

In particular, letting $i = 1$, we have the distribution of the largest random variable as follows:

$$\mathbb{P}(\max\{h_1, h_2, \dots, h_n\} < x) = (1 - e^{-x})^n = \sum_{k=0}^n (-1)^k e^{-kx}. \quad (2.24)$$

Chapter 3

Coverage Adaptation without Coverage Holes in WLANs

3.1 Introduction

3.1.1 Overview

In densely deployed WLAN environments, the arbitrary deployment of WLAN APs can cause serious cell overlaps among APs. In such situations, the ability to realize adaptable coverage using TPC is effective for improving the area spectral efficiency. Meanwhile, it should be guaranteed that no coverage holes occur and that connectivity between APs and wireless STAs is maintained. In this chapter, the self-organization of coverage domains of APs using TPC is proposed. The proposed technique reduces the incidence of coverage overlaps without generating area coverage holes. To detect coverage holes, STAs and/or APs are used as sensors that inform each AP of whether or not the points at which they exist are covered by the APs. However, there is a problem with this approach in that when the density of STAs is not sufficiently large, the occurrence of area coverage holes is inevitable because the points at which the sensors do not exist are not guaranteed to be covered by APs. This study overcomes the problem by focusing APs that belong to network's outer boundary (boundary APs) and keeping the transmission power levels of the APs at their maximum

levels, the idea being that the coverage domains of such APs always include the region covered by only those APs. The boundary APs are determined by performing Delaunay triangulation [29] of the set of points at which all APs exist. Simulation results confirm the effectiveness of the proposed TPC scheme in terms of its ability to reduce the total overlap area while avoiding the occurrence of area coverage holes.

3.1.2 Motivations and Contributions

In order to improve spectral efficiency, it is important to reduce overlaps in time, frequency, and spatial domains. In particular, in WLANs, the reduction in the spatial overlap area using TPC is effective for improving the area spectral efficiency. This is because the medium access control (MAC) protocol of IEEE 802.11 WLAN is based on CSMA/CA [30], and spatial overlap among multiple AP cells may reflect the number of contentions among transmitters. Monks et al. [31] proposed a TPC scheme for CSMA/CA networks that enables APs or STAs to simultaneously transmit frames by reducing their transmission power levels. For densely deployed WLANs, Mhatre et al. [32] proposed the joint adjustment of transmission power levels and carrier sense thresholds, which increases spatial reuse in the spectrum while maintaining the fairness.

Meanwhile, coverage holes should be considered to ensure connectivity maintenance between APs and STAs. In the field of wireless sensor networks (WSNs), efficient spatial coverage has been discussed [33, 34]. In WSNs, coverage problems can be classified in terms of the coverage policy [33]. The term *point coverage* refers to the policy in which the objective is to cover a set of points (targets), and the term *area coverage* refers to the policy in which the objective is to cover (monitor) an area. In WLAN systems, an operator aims to realize the area coverage of the overall region under consideration by his/her APs. On the other hand, the coverage planning carried out to eliminate area coverage holes typically requires manual site surveys, which require much effort and time.

Therefore, the ultimate goal of coverage adaptation is self-organization, where no *area coverage hole* exists while having minimal spatial overlap

areas among APs. This thesis proposes a self-organization technique that reduces the spatial overlap region through TPC without generating coverage holes. This thesis first describes the in-plane framework to model spatial overlap regions, and then defines the *total coverage overlap* and *coverage hole* in the framework. Moreover, this thesis formulates the optimization problem in which the objective function to be minimized is the *total coverage overlap*. Subsequently, this thesis proposes the TPC in an autonomous manner. The basic mechanism employed to reduce the spatial overlap regions is to limit any adjustment of transmission power levels to monotonous decreases. On the other hand, in order to prevent the occurrence of coverage holes, each AP is required to know the exact coverage regions of all APs. In order to confirm whether each point in the target region is covered by at least one AP, this thesis uses STAs and/or APs as sensors that provide information about the coverage of their positions by each AP.

However, there is a problem with this approach in that although the points at which sensors exist are guaranteed to be covered by at least one AP, regions in which there is no sensor are not necessarily guaranteed to have coverage, resulting in the occurrence of area coverage holes. To overcome this problem, this thesis proposes to focus on a network's outer boundary, which is determined by performing a Delaunay triangulation [29] of all APs, and keeping the transmission power levels of APs at the outer boundary at the maximum power level. This approach is based on the idea that each AP belonging to a network's outer boundary always includes a region that is covered by itself alone [35]. This limitation in the TPC scheme is expected to prevent the occurrence of area coverage holes.

In the field of WSNs, there is an approach that focuses on a network's outer boundary, which is called *boundary detection* [36–38]. Cărbunar et al. [36] reported a problem involving the detection and reduction of redundant sensors, with the aim of improving energy efficiency while preserving the network's coverage in WSNs. Saukh et al. [38] proposed boundary detection only based on the connectivity information.

Moreover, to confirm the validity of the proposed TPC scheme in a propagation model that closely models a realistic scenario, this thesis considers the spatially correlated shadowing as well as the distance-dependent

path loss. Ai et al. [34] used a similar formulation to that employed in this chapter from the perspective of managing the in-plane coverage overlap among multiple cells, while they also assumed the circular coverage in their simulations.

The contributions of this chapter are: 1) to establish an autonomous TPC scheme that treats STAs as sensors that detect APs' coverage domains; 2) to prevent the occurrence of area coverage holes while focusing on the network's outer boundary; and 3) to evaluate the performance of the proposed scheme under the effect of spatially correlated shadowing by performing simulations.

The remainder of this chapter is organized as follows. Section 3.2 describes the framework to consider in-plane coverage overlaps, in which coverage adaptation is formulated as an optimization problem. In Section 3.3, the TPC scheme is proposed. This section includes a practical algorithm of the TPC and a discussion of the idea to address the network's outer boundary. Section 3.4 shows the simulation setup and results, taking into account spatially correlated shadowing. Section 3.5 concludes this chapter.

3.2 Problem Formulation

To establish a planer framework for formulating a coverage overlap problem, this section first introduces two important definitions, total coverage overlap and coverage hole. Then, the problem is formulated as an optimization problem. The objective of TPC can be divided to two parts, to minimize the *total coverage overlap* and to eliminate the *coverage holes*.

The notation used in this chapter is shown in Table 3.1. Let $\mathcal{N} := \{1, 2, \dots, N\}$ be the index set of all APs under consideration. Let $\mathcal{L}_{\text{AP}} := \{l_i\}_{i \in \mathcal{N}}$ be the set of locations of APs, where $l_i \in \mathbb{R}^2$ is the point at which AP $i \in \mathcal{N}$ exists. For each AP $i \in \mathcal{N}$, let $\mathcal{P}_i$ denote a finite set of configurable transmission power levels, and let $p_i \in \mathcal{P}_i$ represent the current transmission power level. Let $\mathcal{P}$ denote $\mathcal{P}_1 \times \mathcal{P}_2 \times \dots \times \mathcal{P}_N$ and let $\mathbf{p} \in \mathcal{P}$ denote $(p_i)_{i \in \mathcal{N}}$. We use $\mathbf{p}_{\text{max}} \in \mathcal{P}$ to denote the case in which all APs use the maximum transmission power levels, i.e., $\mathbf{p}_{\text{max}} := (\max\{\mathcal{P}_i\})_{i \in \mathcal{N}}$. To evaluate the interference over the same frequency channel, it is assumed that all APs use

Table 3.1: Notations.

$\mathcal{N}$	Index set of APs
N	Number of APs, $N = \#\{\mathcal{N}\}$
$\mathcal{M}$	Index set of STAs
M	Number of STAs, $M = \#\{\mathcal{M}\}$
$\mathcal{P}_i$	Set of configurable transmission levels of AP i
p_i	Transmission power level of AP i , $p_i \in \mathcal{P}_i$
$\mathcal{P}$	Product set of $\{\mathcal{P}_i\}_{i \in \mathcal{N}}$
$\mathbf{p}_{\max}$	Element of $\mathcal{P}$ such that $p_i = \max\{\mathcal{P}_i\}, \forall i$
p_{STA}	Transmission power level of STAs
$\mathcal{S}_i(p_i)$	Cell of AP i , (3.1)
T	Required signal power
G_{ij}	Average link gain between points $i, j \in \mathbb{R}^2$
$\mathcal{S}_{\mathcal{N}}(\mathbf{p})$	System-wide coverage, (3.2)
$\mathcal{O}_i(\mathbf{p})$	Overlap region of AP i , (3.3)
$\mathcal{I}(\mathbf{p})$	Total coverage overlap, (3.4)
$\mathcal{H}(\mathbf{p})$	Coverage hole, (3.5)
$\mathcal{W}$	Region that is required to be covered
$\mathcal{L}_{\text{AP}}$	Set of points in which APs exist
$\mathcal{L}_{\text{STA}}$	Set of points in which STAs exist
$\mathcal{M}_i(p_i)$	Subset of $\mathcal{M}$ whose locations are in $\mathcal{S}_i(p_i)$, (3.12)
$\mathcal{N}_i(p_i)$	Subset of $\mathcal{N}$ whose locations are in $\mathcal{S}_i(p_i)$, (3.13)

the same channel. Note that the channel assignment is outside of the scope of this chapter because coverage holes in this system (given by (3.5)) do not depend on channels that are operated by each AP $i \in \mathcal{N}$ [39].

Let $\mathcal{W}$ be a connected subset of $\mathbb{R}^2$, which represents the physical space that the operator attempts to cover using his/her APs. In order to model the coverage domain of AP $i \in \mathcal{N}$, cell $\mathcal{S}_i(p_i) \subset \mathcal{W}$ formed by AP $i \in \mathcal{N}$ is defined as the region in which the received signal power level of the signal transmitted by AP $i \in \mathcal{N}$ is higher than the required signal power level T ,

i.e.,

$$\mathcal{S}_i(p_i) := \{z \in \mathcal{W} \mid G_{z l_i} p_i \geq T\}, \quad (3.1)$$

where G_{zi} represents the average link gain between the points $l_i \in \mathcal{L}_{\text{AP}}$ and $z \in \mathbb{R}^2$. Assume that each AP controls its transmission power level according to an average value of the received signal strength, i.e., fast fading is averaged out, and the link gain is due to distance-dependent path loss and shadowing. It should be pointed out that as we can regard WLAN systems in a given channel as time-division duplex (TDD)-based systems, each AP can make channel measurements based on the signal received along the opposite link due to channel reciprocity in TDD systems [40]. Therefore, we can use the approximation $G_{z l_i} \simeq G_{l_i z}$, which indicates the link gain of the downlink is approximately equal to that of the uplink. Note that, however, each AP $i \in \mathcal{N}$ cannot know the exact region of its cell $\mathcal{S}_i(p_i)$ because it requires to measure received signal power of frames from the AP at each point $z \in \mathbb{R}^2$. We define the *system-wide coverage* as

$$\mathcal{S}_{\mathcal{N}}(\mathbf{p}) := \bigcup_{i \in \mathcal{N}} \mathcal{S}_i(p_i), \quad (3.2)$$

which represents the region covered by at least one cell.

Next, *coverage overlap* is introduced for considering the overlap among multiple cells. Before that, *overlap region* $\mathcal{O}_i(\mathbf{p}) \subseteq \mathcal{S}_i(p_i)$ of AP $i \in \mathcal{N}$ is defined by

$$\mathcal{O}_i(\mathbf{p}) := \bigcup_{j \neq i} (\mathcal{S}_i(p_i) \cap \mathcal{S}_j(p_j)), \quad (3.3)$$

where $\bigcup_{j \neq i}$ denotes $\bigcup_{j \in \mathcal{N} \setminus \{i\}}$. We define *total coverage overlap* $\mathcal{I}(\mathbf{p})$ as the region that are covered by more than two APs, i.e.,

$$\mathcal{I}(\mathbf{p}) := \bigcup_{i \in \mathcal{N}} \mathcal{O}_i(\mathbf{p}). \quad (3.4)$$

The first objective of this chapter is to minimize the area of total coverage overlap $|\mathcal{I}(\mathbf{p})|$, where $|\cdot|$ is Lebesgue measure on $\mathbb{R}^2$, i.e., area. We call $|\mathcal{I}(\mathbf{p})|$ by *total overlap area*. It should be noted that $|\mathcal{I}(\mathbf{p})|$ can be decreased by the reduction in transmission power level of each AP.

At the same time, in order to consider a region that is not covered by any APs, *coverage hole* is introduced as follows:

$$\mathcal{H}(\mathbf{p}) := \mathcal{S}_{\mathcal{N}}(\mathbf{p}_{\max}) \setminus \mathcal{S}_{\mathcal{N}}(\mathbf{p}). \quad (3.5)$$

The coverage hole is defined as the subset of $\mathcal{S}_{\mathcal{N}}(\mathbf{p}_{\max})$ because the region $\mathbb{R}^2 \setminus \mathcal{S}_{\mathcal{N}}(\mathbf{p}_{\max})$ cannot be covered by any APs for any $\mathbf{p} \in \mathcal{P}$. The second objective of this chapter is to eliminate coverage holes $\mathcal{H}(\mathbf{p})$. Condition $|\mathcal{H}(\mathbf{p})| = 0$ indicates that all locations in the physical space of interest are covered by at least one AP.

Consequently, we obtain the following optimization problem:

$$\begin{aligned} & \underset{\mathbf{p}}{\text{minimize}} && |\mathcal{I}(\mathbf{p})|, \\ & \text{subject to} && \mathbf{p} \in \mathcal{P}, |\mathcal{H}(\mathbf{p})| = 0. \end{aligned} \quad (3.6)$$

3.3 Transmission Power Control (TPC)

The objective of TPC is to seek an appropriate vector $\mathbf{p}$ for which total overlap area $|\mathcal{I}(\mathbf{p})|$ is as small as possible without generating coverage holes in a distributed manner. This section describes the heuristic algorithm of TPC, in which the transmission power level of each AP is suppressed as long as no coverage holes are generated. One of the essential features of the proposed scheme is that STAs and/or APs are used as sensors that inform each AP of whether or not the positions in which they are located are covered by the AP. In addition, by focusing on network's outer boundary, this study prevents the occurrence of area coverage holes that are generated in regions in which STAs and/or APs do not exist.

3.3.1 Transmission Power Suppression

First, this section describes the TPC algorithm that is employed to reduce total overlap area $|\mathcal{I}(\mathbf{p})|$ without generating any coverage holes $|\mathcal{H}(\mathbf{p})|$. The basic mechanism of the algorithm used to reduce $|\mathcal{I}(\mathbf{p})|$ is to limit any adjustment of transmission power levels to monotonous decreases so that $|\mathcal{I}(\mathbf{p})|$ also monotonously decreases. The following scheme decreases $|\mathcal{I}(\mathbf{p})|$

by suppressing the transmission power level of each AP as long as there are no coverage holes. Assume that the set of configurable transmission power levels $\mathcal{P}_i$ is finite and consists of $P_i^1, P_i^2, \dots, P_i^{\#\{\mathcal{P}_i\}}$, which satisfies $P_i^1 < P_i^2 < \dots < P_i^{\#\{\mathcal{P}_i\}}$, where $\#\{\cdot\}$ is a counting measure, i.e., the number of elements. Assume that the initial transmission power level vector of all APs is $\mathbf{p} = \mathbf{p}_{\max}$, and the current transmission power level of AP $i \in \mathcal{N}$ is $p_i = P_i^k$. Assume that no more than two APs simultaneously change their transmission power levels. Each AP $i \in \mathcal{N}$ reduces its transmission power level p_i from P_i^k to P_i^{k-1} ($k \geq 2$) if

$$\mathcal{S}_i(P_i^k) \setminus \mathcal{S}_i(P_i^{k-1}) \subset \bigcup_{j \neq i} \mathcal{S}_j(p_j) \quad (3.7)$$

until $p_i = P_i^1$. The left-hand side of (3.7) represents the region not covered by AP $i \in \mathcal{N}$ when $p_i = P_i^{k-1}$, but which is covered when $p_i = P_i^k$. The right-hand side of (3.7) represents the region covered by all APs except AP i . This inclusion relation means that the other APs $\mathcal{N} \setminus \{i\}$ are able to make up the deficit of the transmission power decrease of AP $i \in \mathcal{N}$. As (3.7) regulates the transmission power decrease that causes $\mathcal{H}(\mathbf{p}) \neq \emptyset$, this scheme keeps the condition of $\mathcal{H}(\mathbf{p}) = \emptyset$. As each AP $i \in \mathcal{N}$ monotonously decreases the transmission power level p_i and $\mathcal{P}_i$ is finite, the dynamics of TPC is guaranteed to converge.

Note that this thesis does not consider the order of TPC because each AP in general is considered to change its transmission power level asynchronously in a decentralized system.

3.3.2 Practical Method of TPC

In order to use the above scheme, each AP $i \in \mathcal{N}$ needs to have accurate information about all APs' cells $\{\mathcal{S}_j(p_j)\}_{j \in \mathcal{N}}$. In other words, each AP has to know the inclusion relation between the cells and any points in the region to be covered. However, it is difficult for each AP $i \in \mathcal{N}$ to know whether or not each point $z \in \mathcal{W}$ belongs to each cell because it requires a manual site survey. This section proposes an approximate method for estimating the region of each cell, which uses STAs and/or APs as the sensors that inform each AP of the index of STAs and/or APs that exist in its cell.

Let $\mathcal{M} := \{1, 2, \dots, M\}$ be the index set of STAs in the system. Let $\mathcal{L}_{\text{STA}} := \{l'_i\}_{i \in \mathcal{M}} \subset \mathcal{W}$ be the set of locations of STAs, where l'_i is the point at which STA $i \in \mathcal{M}$ exists. This study considers the set of locations in which STAs exist in cell $\mathcal{S}_i(p_i)$, which is denoted by $\mathcal{S}'_i(p_i)$. The relation between $\mathcal{S}_i(p_i)$ and $\mathcal{S}'_i(p_i)$ is as follows:

$$\begin{aligned} \mathcal{S}_i(p_i) &= \{z \in \mathcal{W} \mid G_{z l_i} p_i \geq T\} \\ &\simeq \{z \in \mathcal{W} \mid G_{l_i z} p_i \geq T\} \\ &\supset \{l' \in \mathcal{L}_{\text{STA}} \mid G_{l_i l'} p_{\text{STA}} p_i / p_{\text{STA}} \geq T\} \\ &=: \mathcal{S}'_i(p_i), \end{aligned} \tag{3.8}$$

where p_{STA} is the transmission power level of STAs. Note that the approximation $G_{z l_i} \simeq G_{l_i z}$ is valid because of the channel reciprocity as discussed in Section 3.2. In addition to STAs, this study considers a set of locations in which APs exist as follows:

$$\mathcal{S}''_i(p_i) := \{l_j \in \mathcal{L}_{\text{AP}} \mid j \neq i, G_{l_i l_j} p_j p_i / p_j \geq T\}. \tag{3.9}$$

The exclusion of l_i is also required for the following TPC scheme, i.e., if $\mathcal{S}''(p_i)$ includes l_i , all APs can operate at their minimum transmission power levels according to the following TPC scheme. It should be noted that each AP i learns whether or not a sensor belongs to $\mathcal{S}_i(p_i)$ by using the received signal power of the frame from the sensor, $G_{l_i l'} p_{\text{STA}}$ and/or $G_{l_i l_j} p_j$, and the transmission power levels of both the sensor and the AP, (p_{STA}, p_i) and/or (p_j, p_i) . Note that $\mathcal{S}'_i(p_i)$ and $\mathcal{S}''_i(p_i)$ are discrete subsets of $\mathcal{S}_i(p_i)$.

In the following method, each AP approximately evaluates (3.7) based on $\mathcal{S}'_i(p_i)$ and/or $\mathcal{S}''_i(p_i)$ instead of $\mathcal{S}(p_i)$. The criterion for TPC (3.7) is rewritten as follows:

$$\begin{aligned} \mathcal{S}'_i(P_i^k) \setminus \mathcal{S}'_i(P_i^{k-1}) &\subset \bigcup_{j \neq i} \mathcal{S}'_j(p_j), \\ \mathcal{S}''_i(P_i^k) \setminus \mathcal{S}''_i(P_i^{k-1}) &\subset \bigcup_{j \neq i} \mathcal{S}''_j(p_j). \end{aligned}$$

Algorithm 3.1 Algorithm of TPC with (3.10)

```
1: initialization:
2:   set the initial transmission power  $p_i[0] \leftarrow \max\{\mathcal{P}_i\}$  for each AP  $i \in \mathcal{N}$ , the initial transmission power profile as  $\mathbf{p}[0] \leftarrow (p_1[0], \dots, p_N[0])$ , and the iteration index  $t \leftarrow 0$ .
3:   for AP  $i$  in 1 to  $N$  do
4:     share  $\mathcal{M}_i(p_i[0])$  with the other APs.
5:   end for
6: do
7:   for AP  $i$  in 1 to  $N$  do
8:     Assume  $p_i[t] = P_i^k \in \mathcal{P}_i$ .
9:     if  $k = 1$  then
10:      set  $p_i[t+1] \leftarrow P_i^k$ .
11:    else
12:      count  $\leftarrow 0$ 
13:      for each index  $m \in \mathcal{M}_i(P_i^k) \setminus \mathcal{M}_i(P_i^{k-1})$  do
14:        for each neighboring AP  $j$  do
15:          if  $m \in \mathcal{M}_j(p_j)$  then
16:            set count  $\leftarrow$  count + 1.
17:          break
18:        end if
19:      end for
20:    end for
21:    if count =  $\#\{\mathcal{M}_i(P_i^k) \setminus \mathcal{M}_i(P_i^{k-1})\}$  then
22:      set  $p_i[t+1] \leftarrow P_i^{k-1}$ .
23:      share  $\mathcal{M}_i(P_i^{k-1})$  with the other APs.
24:    else
25:      set  $p_i[t+1] \leftarrow P_i^k$ .
26:    end if
27:  end if
28: end for
29: set transmission power selection profile as  $\mathbf{p}[t+1] \leftarrow (p_1[t+1], \dots, p_N[t+1])$ , and the iteration index  $t \leftarrow t+1$ .
30: while  $\mathbf{p}[t+1] \neq \mathbf{p}[t]$ 
```

These are equivalent to the following relations:

$$\mathcal{M}_i(P_i^k) \setminus \mathcal{M}_i(P_i^{k-1}) \subset \bigcup_{j \neq i} \mathcal{M}_i(p_j), \quad (3.10)$$

$$\mathcal{N}_i(P_i^k) \setminus \mathcal{N}_i(P_i^{k-1}) \subset \bigcup_{j \neq i} \mathcal{N}_i(p_j), \quad (3.11)$$

where for each AP $i \in \mathcal{N}$, $\mathcal{M}_i(p_i)$ and $\mathcal{N}_i(p_i)$ are defined respectively as follows:

$$\mathcal{M}_i(p_i) := \{m \in \mathcal{M} \mid l'_m \in \mathcal{S}'_i(p_i)\}, \quad (3.12)$$

$$\mathcal{N}_i(p_i) := \{n \in \mathcal{N} \mid l_n \in \mathcal{S}''_i(p_i)\}. \quad (3.13)$$

These criteria (3.10) and (3.11) will be used for TPC. We can consider three types of TPC schemes, i.e., TPC with (3.10), with (3.11), and with both (3.10) and (3.11). Assume that each AP $i \in \mathcal{N}$ has knowledge about the transmission power levels of STAs p_{STA} and/or APs $\{p_i\}_{i \in \mathcal{N}}$ and the received signal powers of the frames that are transmitted from them, so that the AP can obtain $\mathcal{M}_i(p_i)$ and/or $\mathcal{N}_i(p_i)$. Assume that each AP shares $\mathcal{M}_i(p_i)$ and/or $\mathcal{N}_i(p_i)$ with the other APs so that each AP decides whether or not (3.10) and/or (3.11) attain. The details of the algorithm of TPC with (3.10) are shown in Algorithm 3.1, where $p_i[t]$ is used to denote the transmission power level of AP i at iteration index t . The algorithm is extendable to the other two cases: TPC with (3.11) and that with both (3.10) and (3.11).

Hereinafter, the validity of the above TPC schemes is discussed. Let $\mathcal{S}'''_i(p_i)$ be the union of the sets $\mathcal{S}'_i(p_i)$ and $\mathcal{S}''_i(p_i)$, i.e., $\mathcal{S}'''_i(p_i) := \mathcal{S}'_i(p_i) \cup \mathcal{S}''_i(p_i)$. For a simple explanation, $\widehat{\mathcal{S}}_i(p_i)$ is used to denote either $\mathcal{S}'_i(p_i)$, $\mathcal{S}''_i(p_i)$, or $\mathcal{S}'''_i(p_i)$. We call $\widehat{\mathcal{S}}_i(p_i)$ by *point coverage* of AP $i \in \mathcal{N}$. Using the notion of point coverage, the *point coverage hole* can be defined as follows:

$$\widehat{\mathcal{S}}_{\mathcal{N}}(\mathbf{p}) := \bigcup_{i \in \mathcal{N}} \widehat{\mathcal{S}}_i(p_i), \quad (3.14)$$

$$\widehat{\mathcal{H}}(\mathbf{p}) := \widehat{\mathcal{S}}_{\mathcal{N}}(\mathbf{p}_{\max}) \setminus \widehat{\mathcal{S}}_{\mathcal{N}}(\mathbf{p}). \quad (3.15)$$

With the TPC scheme based on (3.10) and/or (3.11), the point coverage hole is always kept at zero, i.e., $\#\{\widehat{\mathcal{H}}(\mathbf{p})\} = 0$. Note that the above TPC scheme decreases the total overlap area $|\mathcal{I}(\mathbf{p})|$ because any adjustment of transmission power levels is limited to a monotonous decrease.

If $\mathcal{L}_{\text{STA}}$ and $\mathcal{L}_{\text{AP}}$ follows a homogeneous PPP [8] with intensity ρ , the following asymptotic approximation holds:

$$\frac{|\mathcal{H}(\mathbf{p})|}{|\mathcal{S}_{\mathcal{N}}(\mathbf{p}_{\max})|} \simeq \frac{\#\{\widehat{\mathcal{H}}(\mathbf{p})\}}{\#\{\widehat{\mathcal{S}}_{\mathcal{N}}(\mathbf{p}_{\max})\}}, \rho \rightarrow \infty. \quad (3.16)$$

This means that we can regard the point coverage in the same way as the area coverage when the number of STAs is sufficiently large because of the principle of the Monte Carlo integration [41]. Therefore, if there is no point coverage hole ($\#\{\widehat{\mathcal{H}}(\mathbf{p})\} = 0$), then there is no area coverage hole ($|\mathcal{H}(\mathbf{p})| = 0$).

3.3.3 TPC Restriction for Boundary APs

There is a problem associated with the scheme introduced in the previous subsection. When either the number of sensors is not sufficiently large or the distribution of sensors' locations is not uniformly random, the scheme does not work well. In other words, $|\mathcal{H}(\mathbf{p})| \neq 0$ even when $\#\{\widehat{\mathcal{H}}(\mathbf{p})\} = 0$. However, area coverage hole $|\mathcal{H}(\mathbf{p})|$ should also be decreased as much as possible in order to ensure connectivity maintenance over the target region. In this section, the TPC-based method that focuses on the boundary of a set of APs is proposed with the idea that each AP that belongs to the network's outer boundary always contains the region covered by it alone [35]. This enables reducing the area coverage hole $|\mathcal{H}(\mathbf{p})|$. The key idea of this scheme is keeping the transmission power levels of *boundary APs* at their maximum levels.

APs whose transmission power decreases are restricted are determined as follows. *First-boundary* APs are defined as vertices of the convex hull [29] of APs. In addition, *second-boundary* APs are defined as the vertices whose neighboring two vertices in the Delaunay triangulation [29] of the set of APs belong to first-boundary APs. The first-boundary APs and second-boundary APs are represented by the blue APs and the green APs in Fig 3.1, respectively.

This study considers two types of boundary restrictions, namely the scheme by which first-boundary APs are restricted and the scheme by which

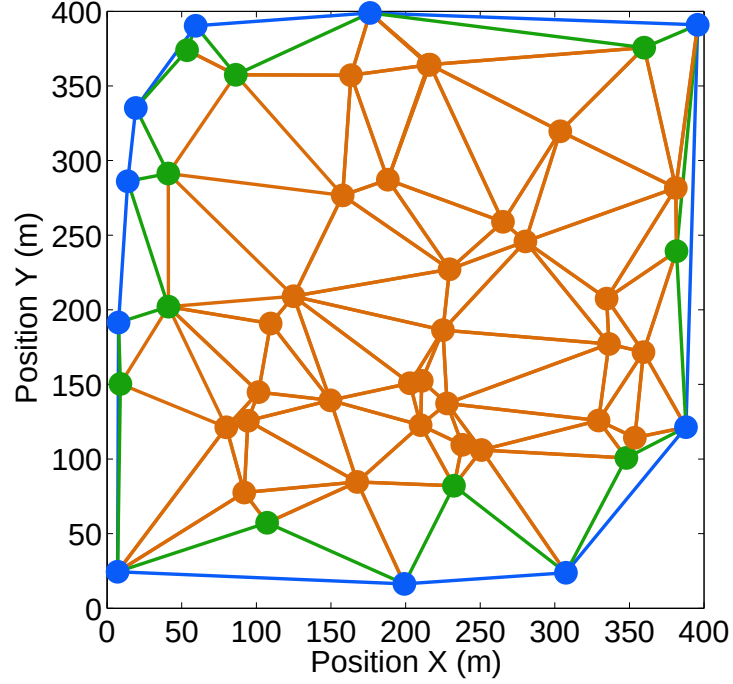


Figure 3.1: First boundary (blue nodes) and second boundary (green nodes).
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both first-boundary APs and second-boundary APs are restricted. They are called *first-restriction* and *second-restriction*, respectively.

3.4 Numerical Evaluation

The performance of the proposed scheme is evaluated by simulations. The results of the simulations reveal the following three points: 1) the exclusive coverage ratio of the first-boundary APs and second-boundary APs introduced in Section 3.3.3 to show that these APs should not reduce their transmission power levels; 2) the impact of the boundary restriction on the area coverage hole and the total overlap area; 3) the impact of the number of sensors on the area coverage hole and the total overlap area. The remarkable feature of the simulations is that it considers spatially correlated shadowing.

Table 3.2: Parameters in simulations.

Parameter	Value
Breakpoint distance, r_{BP}	5 m
Center frequency, f	2.45 GHz
Number of sinusoids, N_c	200
Shadowing standard deviation, σ_s	5 dB
Decorrelation distance, d_{cor}	20 m
Required signal power level, T	-75 dBm
Number of APs, N	10, 20, $\dots$, 70
Number of STAs, M	50, 100, 200
Transmission power levels, $\mathcal{P}_i$	0, 2, 5, $\dots$, 17, 20 dBm

3.4.1 Simulation Model

Assume that $\mathcal{W}$ is a square region that has dimension $400 \text{ m} \times 400 \text{ m}$ and that the APs and the STAs are uniformly and randomly deployed in $\mathcal{W}$. Each evaluation is conducted for 100 realizations of random distribution of the APs. It is assumed that all APs have the same configurable transmission power levels. The first-boundary APs and the second-boundary APs are determined from the relative positions among all the APs. In this simulation, the relative position from the received signal power strength is estimated using a spring model [42]. The simulation parameters are summarized in Table 3.2.

The path loss model is given by

$$L_{\text{fs}}(r) = 32.4 \text{ dBm} + 20 \log_{10}(r) \text{ dB} + 20 \log_{10}(f) \text{ dB},$$

$$L(r) = \begin{cases} L_{\text{fs}}(r) & (r \leq r_{\text{BP}}), \\ L_{\text{fs}}(r_{\text{BP}}) + 35 \log_{10}(r/r_{\text{BP}}) & (r > r_{\text{BP}}), \end{cases}$$

where r is the transmitter-receiver separation distance, f is the center frequency, and r_{BP} is the breakpoint distance [43]. In addition, the radio receiver generally experiences a shadowing effect, especially that which has the spatial correlation property. To confirm that the proposed TPC scheme works well in a practical environment, This study considers the effect of the

spatially correlated shadowing to investigate the robustness against fluctuations. As an example of the spatially correlated shadowing, this study assumes the shadowing with the exponential decay autocorrelation function, i.e., $\exp(-\ln 2 \cdot r/d_{\text{cor}})$, where d_{cor} is the decorrelation distance [44]. Note that such a spatial correlation property is appropriate, such as in the case where both a transmitter and a receiver are located at 1.5 m above the ground level [45]. The spatial correlated shadowing is generated by

$$L_{\text{cor}}(x, y, u, v) = \sigma_s \sqrt{\frac{2}{N_c}} \sum_{n=1}^{N_c} \cos[2\pi(f_{x,n}x + f_{y,n}y + f_{u,n}u + f_{v,n}v) + \theta_n], \quad (3.17)$$

where σ_s is the shadowing standard deviation, $[x, y]$ and $[u, v]$ indicate the positions of the transmitter and receiver, respectively, N_c is the number of sinusoids, and $\{\theta_n\}_{n=1}^{N_c}$ represents a set of uniformly distributed random phase variables in the range $[0, 2\pi)$ [45]. $[f_{x,n}, f_{y,n}]$ and $[f_{u,n}, f_{v,n}]$ are spatial frequencies that are generated by

$$f_{x,n} = f_n \cos(\phi_n), \quad f_{y,n} = f_n \sin(\phi_n), \quad (3.18)$$

$$f_n = \frac{\ln 2}{2\pi d_{\text{cor}}} \sqrt{\frac{1}{(1 - \beta_n)^2} - 1}, \quad (3.19)$$

where ϕ_n and β_n are i.i.d. uniformly distributed random variables over the range $[0, 1]$ and $[0, 2\pi)$, respectively. Note that there are the following conditions regarding the spatial frequencies and the phases:

$$\begin{aligned} [f_{u,n+N_c/2}, f_{v,n+N_c/2}] &= [f_{x,n}, f_{y,n}], \\ [f_{x,n+N_c/2}, f_{y,n+N_c/2}] &= [f_{u,n}, f_{v,n}], \\ \theta_{n+N_c/2} &= \theta_n, \end{aligned}$$

for $n = 1, 2, \dots, N_c/2$. The condition ensures the channel reciprocity of the shadowing model, i.e., $L_{\text{cor}}(x, y, u, v) = L_{\text{cor}}(u, v, x, y)$.

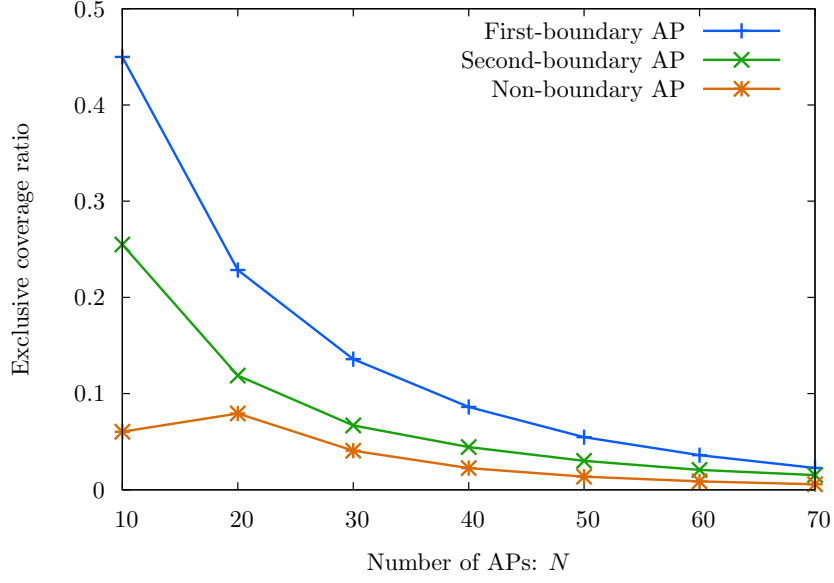


Figure 3.2: Exclusive coverage ratio for three boundary cases. ©2016 IEICE

3.4.2 Simulation Results

Ratio of Exclusive Coverage of Boundary APs

To confirm that a cell of an AP that belongs to the network's outer boundary includes much of the region covered by the AP alone compared to than of another AP that does not belong to the boundary. The area of a region that is exclusively covered by an AP is evaluated for each of the following types of AP: first-boundary APs, second-boundary APs, or non-boundary APs.

In addition, the *exclusive coverage ratio* is evaluated, which is defined as follows:

$$\text{ECR}_i := \left| \mathcal{S}_i(p_i) \setminus \bigcup_{j \neq i} \mathcal{S}_j(p_j) \right| / |\mathcal{S}_i(p_i)|. \quad (3.20)$$

This refers to the ratio of the area that is exclusively covered by AP $i \in \mathcal{N}$ to the area of cell $\mathcal{S}_i(p_i)$. We refer to APs that belong to neither the first-boundary nor the second-boundary as *non-boundary* APs. It is assumed that all APs operate at the maximum transmission power levels, i.e., $\mathbf{p} = \mathbf{p}_{\max}$.

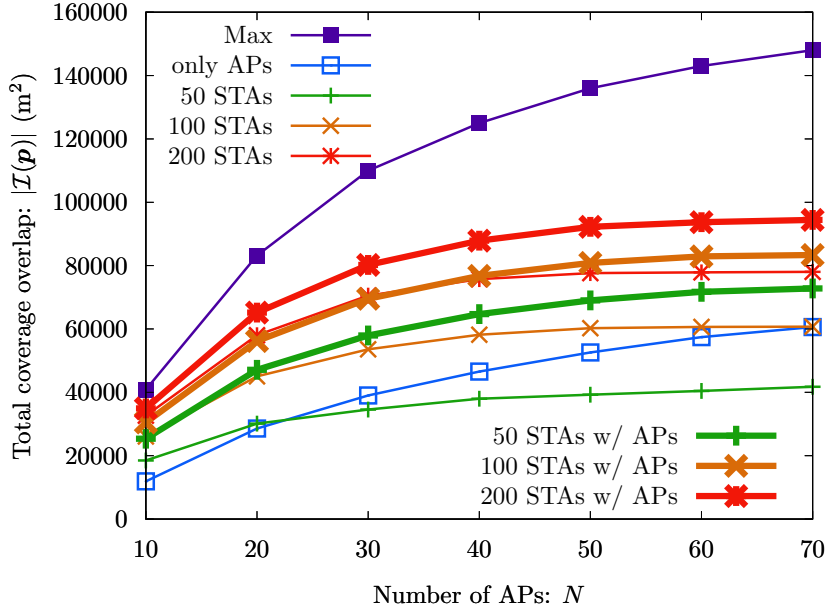


Figure 3.3: Total coverage overlap for each type of sensors. ©2016 IEICE

Fig. 3.2 shows the average ECRs for the first-boundary APs, the second-boundary APs, and non-boundary APs. The largest is the value of the first-boundary APs, followed in order by that of second-boundary APs and that of the non-boundary APs. This observation indicates that the targets for keeping transmission power levels at their maximum levels should be first-boundary APs and/or second-boundary APs rather than non-boundary APs.

Impact of Type of Sensors on TPC Performance

To investigate the difference in the types of sensors, the total overlap area $|\mathcal{I}(\mathbf{p})|$ and the area coverage hole $|\mathcal{H}(\mathbf{p})|$ after TPC are evaluated. For comparison, $|\mathcal{I}(\mathbf{p}_{\max})|$ and $|\mathcal{H}(\mathbf{p}_{\max})|$ are evaluated, which corresponds to the case in which all APs operate at the maximum transmission power level.

The sensors are classified into three types: using only APs, using only STAs, and using both APs and STAs. It is assumed that the number of STAs is 50, 100, or 200. Here, the boundary restriction is not considered.

Figs. 3.3 and 3.4 show the total coverage overlap and the area coverage hole for each type of sensor, respectively. We find that the proposed TPC

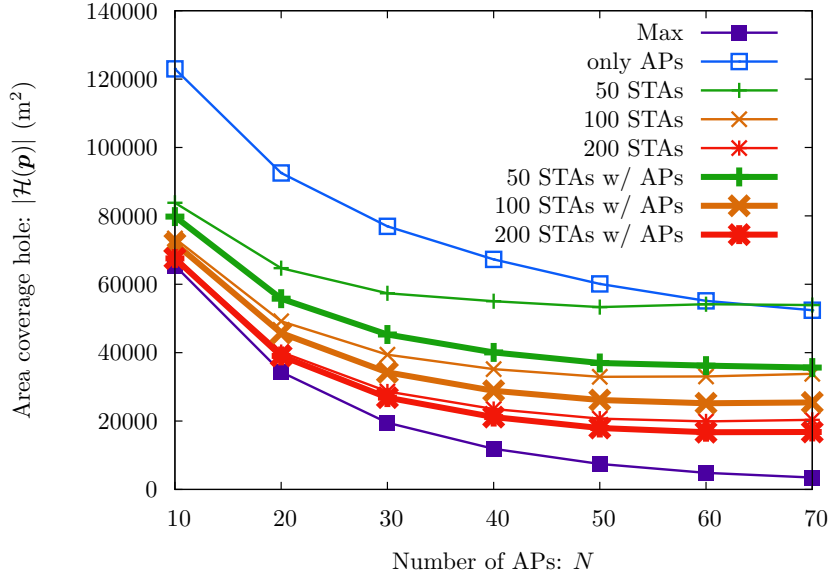


Figure 3.4: Area coverage hole for each type of sensors. ©2016 IEICE

mitigates the total overlap area, especially when the number of APs is large. With respect to the mitigation in the area coverage hole, we can see that the case using both APs and STAs is superior to the case involving the use of only STAs for each number of STAs, and that the case involving the use of many STAs is superior to the case involving the use of few STAs. Note that as the number of sensors increases, so too does the total overlap area, and the area coverage hole decreases. There is therefore a trade-off to be made between mitigating the total overlap area and eliminating the area coverage hole.

Effect of Boundary Restriction

The effect of the boundary restriction on the total overlap area $|\mathcal{I}(\mathbf{p})|$ and the area coverage hole $|\mathcal{H}(\mathbf{p})|$ are evaluated. As well as the previous subsection, each result includes the evaluation of $|\mathcal{I}(\mathbf{p}_{\max})|$ and $|\mathcal{H}(\mathbf{p}_{\max})|$.

The three types of boundary restriction are considered: the first-restriction, the second-restriction, and the *none*, where boundary APs are not considered. The two cases involving the sensors for TPC are considered, using 200 STAs and using only APs.

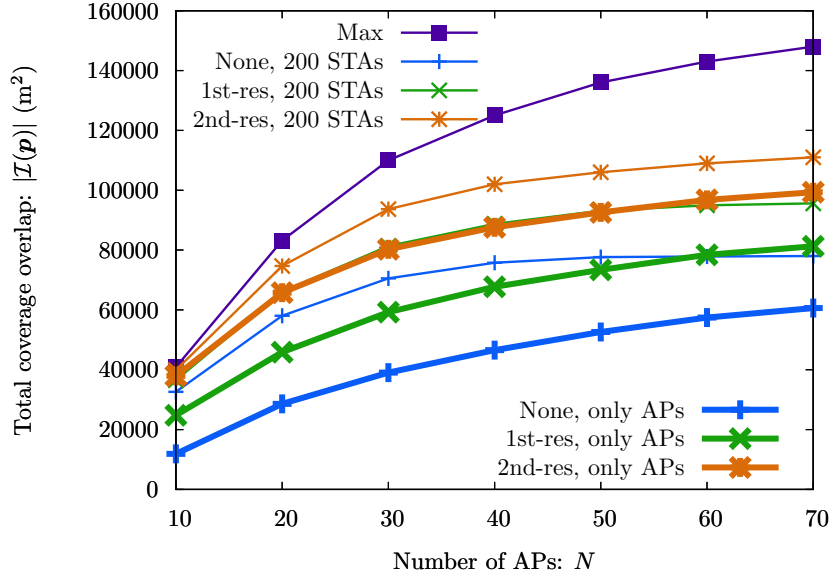


Figure 3.5: Total coverage overlap for each boundary restriction (“res” is abbreviation of “restriction”). ©2016 IEICE

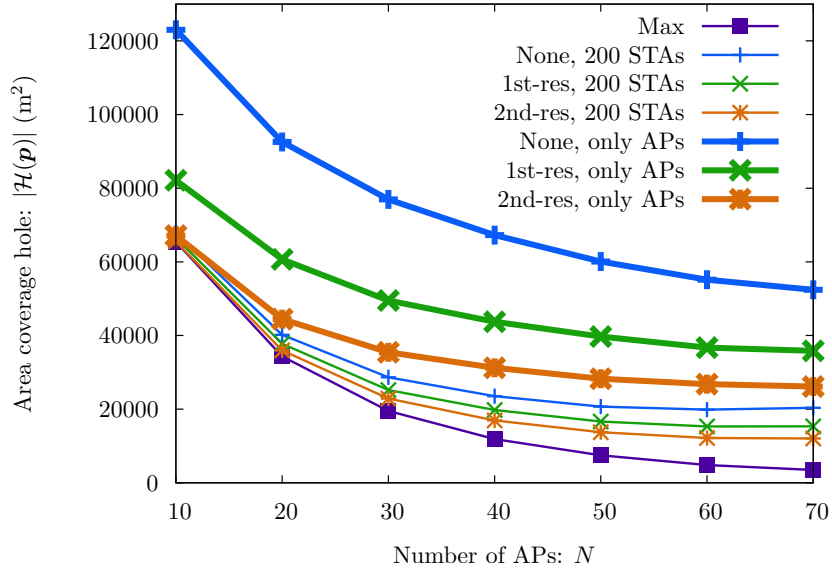


Figure 3.6: Area coverage hole for each boundary restriction (“res” is abbreviation of “restriction”). ©2016 IEICE

Figs. 3.5 and 3.6 respectively show the total coverage overlap and the area coverage hole for each boundary restriction case. In particular, Fig. 3.5

shows that the area coverage hole given by the second-restriction is smallest, followed in order that of the first-restriction, and none. On the other hand, note that the boundary restriction increases the total overlap area in exchange for a reduction in the area coverage hole. The proposed boundary restriction is still effective in terms of the reduction in the area coverage hole.

In conclusion, it is confirmed that the proposed TPC scheme works well under the effect of the spatially correlated shadowing.

3.5 Conclusion

This study proposed a TPC scheme that mitigates the spatial overlap among the coverage domains of APs. The proposed scheme considers the connectivity maintenance between APs and STAs. Considering that limiting the transmission power is effective for reducing the spatial overlap region, this study introduced the TPC using the STAs and/or APs as sensors that inform each AP about whether or not they exist within the cell of the AP. Also, the connectivity maintenance was guaranteed by keeping the transmission power levels of APs belonging to the network's outer boundary at their maximum levels. By performing simulations, it was shown that the total overlap area with the TPC is smaller than that without the TPC, and that as the number of sensors decreases, the area coverage hole increases. Besides, it was shown that the proposed boundary restriction is effective for reducing the area coverage hole.

Chapter 4

Spatial Co-channel Overlap Mitigation through Channel Assignment in WLANs

4.1 Introduction

4.1.1 Overview

In this chapter, decentralized channel assignment schemes are proposed for mitigating system-wide spatial overlap regions in WLANs. In WLANs, selecting channels with fewer contending STAs is more important rather than mitigating interference power on account of its MAC mechanism. The basic idea of the proposed schemes lies in the channel selection criterion, by which each AP selects a channel with smaller spatial overlaps with other APs. This chapter designs two channel selection games, which are based on naive overlap area and decomposed overlap area. Naive overlap-based assignment would perform the best overlap reduction if a sufficient number of STAs to detect overlaps are available; whereas decomposed overlap-based assignment does not necessarily require such STAs, while the performance would be degraded due to the shadowing effect. Both channel assignment games are proved to be potential games, so that unilateral improvement dynamics are guaranteed to converge to Nash equilibria. In addition, the

system-wide overlap area is analytically shown to be upper bounded by the negative potential functions, and thus local overlap reduction based on the decentralized channel assignment would lead to system-wide overlap reduction. The simulation results confirm that the proposed schemes perform better reductions in the system-wide overlap area compared to the conventional interference power-based scheme under the spatially correlated shadowing effect. The experimental results demonstrate that the channel assignment dynamics converge to stable equilibria even in a real environment, particularly when uncontrollable APs exist.

4.1.2 Motivations and Contributions

In densely deployed WLANs, unnecessary suppression of transmission can often occur due to noncooperation such as unmanaged frequency channel assignment or uncoordinated deployment of APs, resulting in inefficient use of wireless bandwidth [5]. In particular, without appropriate channel assignment, the performance and throughput are adversely affected due to channel contention over the same frequency. Hence, an appropriate channel assignment scheme is crucial for improving spectral efficiency [46]. To deal with the problem, WLAN operators should seek appropriate channels in terms of the spectral efficiency; however, it typically requires a manual site survey, which takes much effort and time. Moreover, a static assignment based on manual site survey is not flexible to accommodate environmental changes that occur after deployment, such as a permanent/temporal change in the radio environment caused by a new building/a mobile AP. Therefore, it is desirable that each AP surveys the environment and selects an appropriate channel accordingly in a distributed manner.

In an adaptive channel assignment, modeling and quantifying mutual interaction is important, such as an impact of an AP using a channel on the other APs using the channel. Game theory [22] provides powerful mathematical frameworks that formulate mutual interaction among multiple decision-makers, widely utilized for analyzing mutual interaction among multiple wireless transmitters [23, 47]. In particular, a potential game [25] that forms a class of non-cooperative games has been applied to a variety

of channel assignment problems [24, 28, 48–51]. When a game is proved to be a potential game, the game has the following desirable properties: the game always has at least one Nash equilibrium; and unilateral improvement dynamics in the game with finite strategy sets is guaranteed to converge to a Nash equilibrium in a finite number of steps [25]. A potential game theoretic approach provides us a decentralized and dynamic channel assignment scheme that always converges.

When we formulate game-theoretic model, designing an appropriate payoff function is important, which represents a preference ordering for determining the action to be taken. In most existing game-theoretic frameworks for assigning wireless channels, the payoff functions are based on interference powers from other transmitters [48–52]. However, selecting a channel with lower interference power is not necessarily critical for improving the system performance in WLANs due to the MAC mechanism, while such an approach is effective in interference-limited cellular networks. The MAC protocol of IEEE 802.11 WLAN is based on CSMA/CA [30], so that the main factor that degrades the system performance is the number of contending STAs rather than the strength of the interference powers. Specifically, in the interference power-based game, if an AP operates a channel at very high transmission power, other APs hardly select the channel even though the channel is used by few APs. Note that the interference power associated with nearby transmitters are often dominant in the sum of the interference powers because received signal power decreases exponentially with distance from transmitter.

This chapter designs the decentralized channel assignment in WLANs with taking into account the CSMA/CA mechanism. In this chapter, adaptive channel selection schemes are proposed to reduce the in-plane coverage overlap, which is formulated as a potential game. The reason for using the in-plane coverage overlap is that the overlap regions among coverage ranges of transmitters can reflect the area spectral efficiency such as in CSMA networks [53]. In addition, the size of coverage overlap among neighboring APs over the same channel is an effective criterion for quantifying the interaction among OBSSs and estimating the number of contending STAs because a large overlap region can result in few transmission opportunities

and frequent frame collisions for wireless transmitters and receivers in the region [54].

In this study, two payoff functions that reflect the interaction among OBSSs are designed (Fig. 4.2 shows the difference). The first payoff function consists of the area of the union of the overlap regions between itself and any neighboring APs, which is referred to the *naive overlap area*. The most similar approach can be found in [34], which discusses a time slot assignment for immobile sensors that is formulated as a potential game. The authors in [34] aimed to increase the exclusive coverage range of each sensors, while this study focuses on reducing the overlap region. The second payoff function consists of the sum of the overlap areas between itself and any neighboring APs, which is referred to the *decomposed overlap area*. The second payoff function is derived from the first payoff function by allowing the addition of the area of the same region. Moreover, it is analytically revealed that the system-wide overlap area is upper bounded by the negative potential functions, so that local overlap reduction based on the decentralized channel assignment would lead to system-wide overlap reduction.

The main difference between two schemes lies in the ease of estimating the payoff functions. Estimating the first payoff function requires a sufficient number of STAs and information exchange among APs, while estimating the second payoff function does not necessarily require them. The second payoff function can be estimated by assuming cells to be circular range, while the first payoff function cannot use such an estimation because the region to be detected is too complex to measure properly. In addition, the second scheme is applicable to the case in which there are some uncontrollable APs without information exchange. On the other hand, compared to the first scheme with a sufficient number of STAs, the performance of the second scheme based on the circular assumption is degraded due to the shadowing effect.

The contributions of this chapter are as follows:

- Two channel selection games are designed based on *naive overlap area* and *decomposed overlap area*, showing that both games are potential games.

- This study analytically reveals the relation between the system-wide overlap area and potential functions in the light of reducing coverage overlap.
- The computer simulations are conducted under the effect of the spatially correlated shadowing, while the related research [34] assumes the circular cell shape and does not discuss the feasibility nearly in a real environment.
- A testbed is implemented to demonstrate that the channel assignment dynamics surely converges in a real environment, particularly when there exist uncontrollable APs.

The rest of this chapter is organized as follows. Section 4.2 describes the in-plane framework to model mutual interference by the area of coverage overlap. Section 4.3 states the game theoretic framework to consider the mutual interaction among wireless transmitters. Section 4.4 introduces the algorithm of the decentralized channel assignment. Section 4.5 and Section 4.6 show the simulation results and the experimental results, respectively. Section 4.7 concludes this chapter.

4.2 System Model Based on In-Plane Overlap

This section describes the framework to formulate the problem of overlapping regions. Consider the overlap mitigation problem with two variables, namely, transmission power and frequency channel. Although this framework is presented based on a two-dimensional Euclidean plane, the framework can be easily extended to three-dimensional Euclidean space.

Let $\mathcal{N}$ be the index set of all APs under consideration. For each AP $i \in \mathcal{N}$, let $\mathcal{P}_i$ denote a finite set of configurable transmission power levels, and let $p_i \in \mathcal{P}_i$ denote the transmission power level. Similarly, for each AP $i \in \mathcal{N}$, let $\mathcal{C}_i$ denote a finite set of available channels and $c_i \in \mathcal{C}_i$ denote the channel. For $\mathcal{L} \subseteq \mathcal{N}$, let $\mathbf{p}_{\mathcal{L}}$ denote $(p_i)_{i \in \mathcal{L}}$ and $\mathbf{c}_{\mathcal{L}}$ denote $(c_i)_{i \in \mathcal{L}}$. Let $\mathcal{F}$ denote all available channels of managed APs, i.e., $\mathcal{F} := \bigcup_{i \in \mathcal{N}} \mathcal{C}_i$.

Let $\mathcal{N}_f$ denote the index set of all APs that operate channel $f \in \mathcal{F}$, i.e., $\mathcal{N}_f := \{i \in \mathcal{N} \mid c_i = f\}$.

Let $\mathcal{D} \subset \mathbb{R}^2$ denote the entire region under consideration. Each AP does not have to be aware of $\mathcal{D}$ itself as seen in the practical channel assignment discussed in Section 4.4.2. A *cell* $\mathcal{S}_i(p_i) \subset \mathcal{D}$ of AP $i \in \mathcal{N}$ is defined by the region where the received power is greater than a required power level T , i.e.,

$$\mathcal{S}_i(p_i) := \{z \in \mathcal{D} \mid G_{zi}p_i \geq T\}, \quad (4.1)$$

where G_{zi} is a link gain between AP $i \in \mathcal{N}$ and a receiver at $z \in \mathcal{D}$. Note that each cell $\mathcal{S}_i(p_i)$ of AP $i \in \mathcal{N}$ is assumed not to depend on its channel c_i . In addition, *joint coverage* $\mathcal{S}_{\mathcal{L}}(\mathbf{p}_{\mathcal{L}})$ is defined for $\mathcal{L} \subseteq \mathcal{N}$ as follows:

$$\mathcal{S}_{\mathcal{L}}(\mathbf{p}_{\mathcal{L}}) := \bigcup_{i \in \mathcal{L}} \mathcal{S}_i(p_i), \quad (4.2)$$

which represents the region that at least one AP in $\mathcal{L}$ cover. For simplicity, $\mathcal{S}_i(p_i)$ and $\mathcal{S}_{\mathcal{L}}(\mathbf{p}_{\mathcal{L}})$ are sometimes denoted by $\mathcal{S}_i$ and $\mathcal{S}_{\mathcal{L}}$, respectively.

As an evaluation criterion for system-wide performance, the area of the region included by more than two cells is important because as it increases, more wireless devices can experience channel contention and frame collisions [54]. We define it as *total overlap area* $O_{\text{total}}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}})$ as follows:

$$O_{\text{total}}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}}) := \sum_{f \in \mathcal{F}} \sum_{n \geq 2} O_{f,n}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}}), \quad (4.3)$$

$$O_{f,n}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}}) := \sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\} = n} \left| \left(\bigcap_{i \in \mathcal{L}} \mathcal{S}_i \right) \setminus \mathcal{S}_{\mathcal{N}_f \setminus \mathcal{L}} \right|, \quad (4.4)$$

where $|\cdot|$ represents the area of a region, $\#\{\cdot\}$ represents the number of elements, and $O_{f,n}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}})$ is the area covered by just n cells using channel $f \in \mathcal{F}$ as shown in Fig. 4.1. Consider total overlap area $O_{\text{total}}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}})$ as the objective function to be minimized. Note that the total overlap area $O_{\text{total}}(\mathbf{p}_{\mathcal{N}}, \mathbf{c}_{\mathcal{N}})$ is divided into the areas by means of the number of overlaps n . This is because representation (4.3) is useful for the proof of Theorem 4.3, which shows the relation between the total overlap area and potential functions.

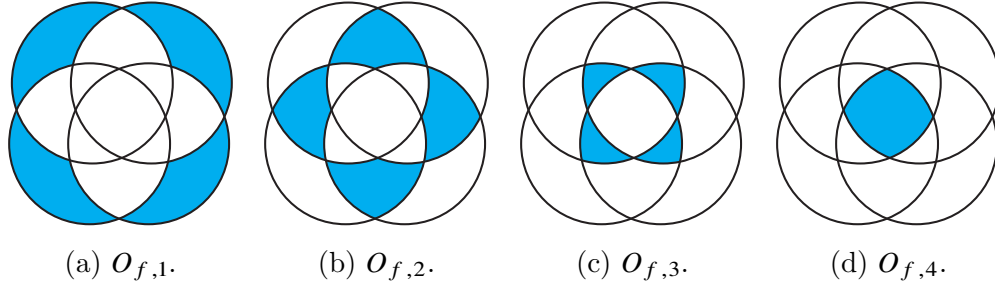


Figure 4.1: $O_{f,n}$ when there are four cells using channel f . ©2017 IEICE

The objective of this study is to design a distributed channel assignment algorithm to reduce total overlap area $O_{\text{total}}(\mathbf{p}_N, \mathbf{c}_N)$ when transmission power levels $\mathbf{p}_N$ are already determined. However, it should be pointed out that each AP has to know all the regions of cells $\{\mathcal{S}_i\}_{i \in N}$ to evaluate the effect of its channel update on the total overlap area, and obtaining such regions typically requires a manual site survey. In Section 4.3, it is proved that the total overlap area is upper bounded by another function, which can be decreased monotonously in a distributed manner. The formulation of this function leads to the decentralized channel selection procedure that indirectly reduces the total overlap area without manual site survey.

4.3 Channel Selection Game for Spatial Overlaps Mitigation

This section describes how to formulate channel assignment by game theory and constructs potential game-based decentralized channel assignment schemes. Furthermore, the relation between a potential function and the total overlap area is revealed.

4.3.1 Channel Selection Game Based on Naive Overlap Area

As smaller total overlap area leads to less channel contention and fewer frame collisions, The objective is to have APs select appropriate channels

$\mathbf{c}_N$ so that the total overlap area (4.3) is relatively small in a distributed manner.

Two decentralized channel assignment schemes are proposed to reduce the total overlap area, each of which has a different way to measure overlap regions, i.e., based on the naive overlap or the decomposed overlap. This section describes a naive overlap-based scheme, while the next section describes a decomposed overlap-based scheme.

The channel assignment problem is modeled as a strategic form game $G1 := (\mathcal{N}, (\mathcal{C}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$. The elements are as follows. The set of players $\mathcal{N}$ is the index set of APs. The strategy set $\mathcal{C}_i$ is the set of available channels for each AP $i \in \mathcal{N}$. Assume that each AP knows other APs' channels, for example, by detecting a beacon frame [30]. As a payoff function that incentivizes each AP to select its next channel, the following function is employed:

$$u_i(\mathbf{c}_N) := -\left| \mathcal{S}_i \cap \mathcal{S}_{\mathcal{N}_{c_i} \setminus \{i\}} \right|, \quad (4.5)$$

which represents the negative value of the area of the subset of $\mathcal{S}_i$ that is covered by cells of other managed APs, shown in Fig. 4.2(a).

Lemma 4.1. $G1$ has interaction potential

$$\Phi_{1\mathcal{L}}(\mathbf{c}_{\mathcal{L}}) = \begin{cases} (-1)^{\#\{\mathcal{L}\}-1} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| \mathbf{1}_{\{\exists f[\mathcal{L} \subseteq \mathcal{N}_f]\}}, & \#\{\mathcal{L}\} \geq 2; \\ 0, & \#\{\mathcal{L}\} = 0, 1, \end{cases} \quad (4.6)$$

where $\mathbf{1}_{\{condition\}}$ is an indicator function, which is 1 if the *condition* is true and is 0 otherwise.

Proof.

$$\begin{aligned} u_i(c_i, \mathbf{c}_{-i}) &= -\left| \bigcup_{j \in \mathcal{N}_{c_i} \setminus \{i\}} (\mathcal{S}_i \cap \mathcal{S}_j) \right| \\ &\stackrel{(a)}{=} -\sum_{n=1}^{\#\{\mathcal{N}_{c_i}\}-1} (-1)^{n-1} \sum_{\mathcal{L}_{-i} \subseteq \mathcal{N}_{c_i} \setminus \{i\} : \#\{\mathcal{L}_{-i}\}=n} \left| \bigcap_{j \in \mathcal{L}_{-i}} (\mathcal{S}_i \cap \mathcal{S}_j) \right| \\ &= \sum_{n=1}^{\#\{\mathcal{N}_{c_i}\}-1} (-1)^n \sum_{\mathcal{L}_{-i} \subseteq \mathcal{N}_{c_i} \setminus \{i\}} \left| \bigcap_{j \in \{i\} \cup \mathcal{L}_{-i}} \mathcal{S}_j \right| \mathbf{1}_{\{\#\{\mathcal{L}_{-i}\}=n\}} \end{aligned}$$

$$\begin{aligned}
 &\stackrel{(b)}{=} \sum_{n=1}^{\#\{N_{c_i}\}-1} (-1)^n \sum_{\mathcal{L} \subseteq N_{c_i}: i \in \mathcal{L}} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{\#\{\mathcal{L}\}=n+1\}} \\
 &= \sum_{n=1}^{\#\{N_{c_i}\}-1} (-1)^n \sum_{\mathcal{L} \subseteq N: i \in \mathcal{L}} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{\#\{\mathcal{L}\}=n+1\}} 1_{\{\mathcal{L} \subseteq N_{c_i}\}} \\
 &= \sum_{\mathcal{L} \subseteq N: i \in \mathcal{L}} \sum_{n=1}^{\#\{N_{c_i}\}-1} (-1)^n \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{n=\#\{\mathcal{L}\}-1\}} 1_{\{\mathcal{L} \subseteq N_{c_i}\}} \\
 &= \sum_{\mathcal{L} \subseteq N: i \in \mathcal{L}} (-1)^{\#\{\mathcal{L}\}-1} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{\exists f [\mathcal{L} \subseteq N_f]\}} \\
 &= \sum_{\mathcal{L} \subseteq N: i \in \mathcal{L}} \Phi 1_{\mathcal{L}}(\mathbf{c}_{\mathcal{L}}).
 \end{aligned}$$

(a) is derived from the inclusion-exclusion principle in combinatorics [55].

(b) $\mathcal{L} := \mathcal{L}_{-i} \cup \{i\}$. $\square$

Theorem 4.1. $G1$ is a potential game with potential function

$$V1(\mathbf{c}_N) = \sum_{f \in \mathcal{F}} \sum_{\mathcal{L} \subseteq N_f} (-1)^{\#\{\mathcal{L}\}-1} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right|. \quad (4.7)$$

Proof. According to Theorem 2.1 (in Section 2) and Lemma 4.1, $G1$ is a potential game. Substituting $\Phi 1_{\mathcal{L}}(\mathbf{c}_{\mathcal{L}})$ into (2.4), (4.7) is obtained. $\square$

In fact, channel selection game $G1$ is essentially the same as the game discussed in [34], in which each player maximizes its exclusive coverage region, i.e., $\tilde{u}1_i(\mathbf{c}_N) = |\mathcal{S}_i| + u1_i(\mathbf{c}_N)$, and has been proved to be a potential game with another formulation of potential function $V1(\mathbf{c}_N)$. Note that the formulation in [34] is not suitable for the discussion about coverage overlaps because there is no clear relationship between its potential function and the total overlap area. In contrast, the formulation of payoff (4.5) helps us to understand the relationship as to be shown in Theorem 4.3.

4.3.2 Channel Selection Game Based on Decomposed Overlap Area

In this section, another channel selection game is introduced, which constructs strategic form game $G2 := (N, (C_i)_{i \in N}, (u2_i)_{i \in N})$, where N and C_i

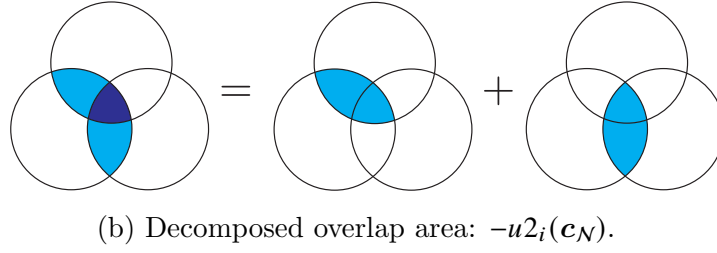
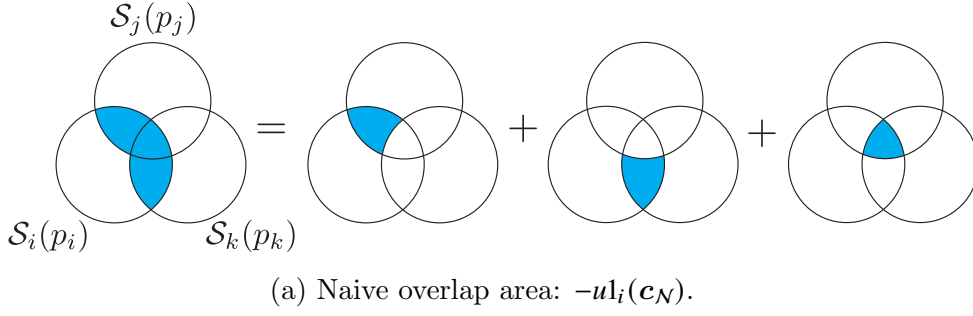


Figure 4.2: Relation between two payoff functions for AP $i \in \mathcal{N} = \{i, j, k\}$ ($c_i = c_j = c_k$). ©IEICE 2017

are the same as above. The payoff function $u2_i(\mathbf{c}_N)$ is given by

$$u2_i(\mathbf{c}_N) := - \sum_{j \in \mathcal{N}_{c_i} \setminus \{i\}} |\mathcal{S}_i \cap \mathcal{S}_j|. \quad (4.8)$$

The sign inversion of the payoff function is equal to the summation of the overlap areas between an AP and any other APs, shown in Fig. 4.2(b). Payoff function (4.8) is obtained by decomposing $u1_i(\mathbf{c}_N)$ allowing the addition of the area of the same region.

In this game, each AP has only to consider *decomposed* overlap area, which consists of the overlap area between only two APs' cells. Decomposed overlap area-based scheme is superior to the above scheme in terms of ease of estimating a payoff function as discussed in Section 4.4.2. Fig. 4.2 shows the relation between $u1_i(\mathbf{c}_N)$ and $u2_i(\mathbf{c}_N)$.

Theorem 4.2. $G2$ is a potential game with potential function

$$V2(\mathbf{c}_N) = - \sum_{f \in \mathcal{F}} \sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\}=2} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right|. \quad (4.9)$$

Proof. The payoff function can be written as

$$u_{2i}(\mathbf{c}_{\mathcal{N}}) = - \sum_{\mathcal{L} \subseteq \mathcal{N}: i \in \mathcal{L}} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{\#\{\mathcal{L}\}=2\}} 1_{\{c_i=c_j\}}. \quad (4.10)$$

This suggests that the interaction potential is given by

$$\Phi_{2\mathcal{L}}(\mathbf{c}_{\mathcal{L}}) = \begin{cases} - \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| 1_{\{\exists k [\mathcal{L} \subseteq \mathcal{N}_k]\}}, & \#\{\mathcal{L}\} = 2; \\ 0, & \#\{\mathcal{L}\} \neq 2. \end{cases} \quad (4.11)$$

According to Theorem 2.1, $G2$ is a potential game. Substituting $\Phi_{2\mathcal{L}}(\mathbf{c}_{\mathcal{L}})$ into (2.4), (4.9) is obtained. $\square$

Note that such a simple type of game, in which the interaction potential is zero except for $\#\{\mathcal{L}\} = 1, 2$, is called a bilateral symmetric interaction (BSI) game [26], and several channel assignment games are shown to be BSI games [24].

4.3.3 Discussion for the Case with Uncontrollable APs

In general, there are some APs whose channel is not adjustable in accordance with the proposed channel assignment. In this thesis, such APs is referred to as “uncontrollable APs” and represent an index set of uncontrollable APs by $\mathcal{N}' \subset \mathcal{N}$. The case in which there are some uncontrollable APs is regarded as a special case of a strategic form game $(\mathcal{N}, (\mathbf{C}_i)_{i \in \mathcal{N}}, (u_i)_{i \in \mathcal{N}})$, which satisfies $\mathbf{C}_i = \{c_i\}$, $\forall i \in \mathcal{N}'$. Therefore, by assuming that uncontrollable APs keep the present channel, a stable channel profile can be obtained by the channel assignment dynamics with $\mathcal{N} \setminus \mathcal{N}'$. Note that there would be a case in which uncontrollable APs cannot share the information that is necessary for channel assignment. However, the channel assignment scheme based on game $G2$ is available even in such a case as discussed in Section 4.4.2.

4.3.4 Relations Between Total Overlap Area and Potential Functions

To understand the improvement of the total overlap area by means of the a channel selection game, In this section, a relation between the total overlap

and the potential functions is revealed. As a matter of fact, the total overlap area is upper bounded by the negative potential functions.

Theorem 4.3. For every $\mathbf{c}_N$ and $\mathbf{p}_N$, $V1(\mathbf{c}_N)$, $V2(\mathbf{c}_N)$, and $O_{\text{total}}(\mathbf{c}_N)$ are related by

$$O_{\text{total}}(\mathbf{c}_N) \leq -V1(\mathbf{c}_N) \leq -V2(\mathbf{c}_N). \quad (4.12)$$

The equalities are attained if and only if there are no overlap areas among any three cells over the same channel, i.e., $O_{f,n}(\mathbf{c}_N) = 0, \forall f \in \mathcal{F}, \forall n \geq 3$.

Proof. $V1(\mathbf{c}_N)$ is rewritten by using $O_{f,n}$ as follows:

$$\begin{aligned} V1(\mathbf{c}_N) &= \sum_{f \in \mathcal{F}} \sum_{\mathcal{L} \subseteq \mathcal{N}_f} (-1)^{\#\{\mathcal{L}\}-1} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| = \sum_{f \in \mathcal{F}} \sum_{k \geq 2} \sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\}=k} (-1)^{k-1} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| \\ &= - \sum_{f \in \mathcal{F}} \sum_{k \geq 2} (-1)^k \sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\}=k} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right|. \end{aligned}$$

The third summation is deformed as

$$\sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\}=k} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| = \sum_{n \geq k} \binom{n}{k} O_{f,n}, \quad (4.13)$$

because the left-hand side includes n ($\geq k$) cells overlap area, $|\bigcap_{j \in \{j_1, \dots, j_n\}} \mathcal{S}_j|$, as many times as the number of subsets of $\{j_1, \dots, j_n\}$ that consist of k elements. We then obtain

$$\begin{aligned} V1(\mathbf{c}_N) &= - \sum_{f \in \mathcal{F}} \sum_{k \geq 2} (-1)^k \sum_{n \geq k} \binom{n}{k} O_{f,n} = - \sum_{f \in \mathcal{F}} \sum_{n \geq 2} \left(\sum_{k=2}^n \binom{n}{k} (-1)^k \right) O_{f,n} \\ &= - \sum_{f \in \mathcal{F}} \sum_{n \geq 2} (n-1) O_{f,n}. \end{aligned} \quad (4.14)$$

Rewriting $V2(\mathbf{c}_N)$ using (4.13), we obtain

$$V2(\mathbf{c}_N) = - \sum_{f \in \mathcal{F}} \sum_{\mathcal{L} \subseteq \mathcal{N}_f : \#\{\mathcal{L}\}=2} \left| \bigcap_{j \in \mathcal{L}} \mathcal{S}_j \right| = - \sum_{f \in \mathcal{F}} \sum_{n \geq 2} \binom{n}{2} O_{f,n}. \quad (4.15)$$

From (4.3), (4.14), and (4.15), we find that inequality (4.12) holds for any $\mathbf{c}_N \in (C_i)_{i \in N}$ because $1 \leq n-1 \leq \binom{n}{2}$ holds if $n \geq 2$. $\square$

Inequality (4.12) implies that the improvement of the potential functions, which is induced by the local improvement of a payoff function, can lead to the reduction in the total overlap area, especially when there are no overlaps among any three cells over the same channel. One way to achieve the condition, $O_{f,n} = 0, \forall f, \forall n \geq 3$, is TPC that reduces the size of cell $\mathcal{S}_i$ for each AP $i \in \mathcal{N}$, which is discussed in Chapter 3. Besides, it is effective to utilize as many channels as possible. If the condition, $O_{f,n} = 0, \forall f, \forall n \geq 3$, is satisfied, all an AP has to do is to seek a channel so that its payoff function increases.

4.4 Decentralized Channel Selection Algorithm

This section first describes how to seek a set of channels $\mathbf{c}_{\mathcal{N}}$ so that a potential function increases in a distributed manner. In addition, two schemes are introduced for estimating a value of a payoff function that is used in the channel selection.

4.4.1 Algorithm to Seek Better Channel

SAP [27, 28] is employed to achieve a Nash equilibrium at which the potential functions are large. If using SAP in a potential game, the potential function can be maximized with arbitrarily high possibility [27]. Let N denote $\#\{\mathcal{N}\}$, and let $c_i[t]$ denote c_i at time step t . Assume that each AP $i \in \mathcal{N}$ updates its channel in turn according to the order of indices in $\mathcal{N}$. At each time step t , each AP $i \in \mathcal{N}$ randomly selects next channel $c_i[t+1]$ according to the following distribution,

$$x_i(c_i | \mathbf{c}_{-i}[t]) = \frac{\exp[\beta u_i(c_i, \mathbf{c}_{-i}[t])]}{\sum_{c'_i \in C_i} \exp[\beta u_i(c'_i, \mathbf{c}_{-i}[t])]}, \quad (4.16)$$

$$\mathbf{c}_{-i}[t] := (c_1[t+1], \dots, c_{i-1}[t+1], c_{i+1}[t], \dots, c_N[t]),$$

where $\beta \geq 0$ is the exploration parameter. If β is as small as zero, each AP selects every strategy with nearly equal probability. In contrast, as β increases, each AP selects a strategy less stochastically, the dynamics are referred to as BRD also seen in Section 2.1.2.

The details of the procedure are given in Algorithm 4.1. Remarkably, β is linearly increased as the time step increases, i.e., $\beta = \beta_0(t+1)$ is used at time step t , where β_0 is the initial value of β . Such kind of time evolution of β can also be found in [56]. When β achieves a sufficiently large value, SAP approaches to BRD so that the dynamics converge to a Nash equilibrium [25].

Similar to TPC in chapter 3, this thesis does not consider the order of channel update because each AP in general is considered to change its channel asynchronously in a decentralized system.

Algorithm 4.1 Channel selection algorithm

```

1: initialization:
2:   set the initial channel  $c_i[0] \leftarrow f_i$  ( $f_i$  is selected from  $\mathcal{C}_i$  uniformly
   randomly) for each AP  $i \in \mathcal{N}$ , the initial channel profile as  $\mathbf{c}_{\mathcal{N}}[0] \leftarrow$ 
    $(c_i[0])_{i \in \mathcal{N}}$ , the iteration index  $t \leftarrow 0$ , and  $\beta \leftarrow \beta_0$ .
3: end initialization
4: while  $\mathbf{c}_{\mathcal{N}}[t]$  is not a Nash equilibrium do
5:   for AP  $i$  in 1 to  $N$  do
6:     choose the channel  $c_i[t+1]$  according to probability distribution
       (4.16).
7:   end for
8:   set the channel profile as  $\mathbf{c}_{\mathcal{N}}[t+1] \leftarrow (c_i[t+1])_{i \in \mathcal{N}}$ , the iteration
       index  $t \leftarrow t+1$ , and  $\beta \leftarrow \beta_0(t+1)$ .
9: end while

```

4.4.2 Calculation of Payoff Function

The key step for each AP in the algorithm is to find out a preference ordering represented by its payoff function. In this section, two methods for calculating a payoff function are described.

The first method is applicable for estimating both payoff functions, $u1_i(\mathbf{c}_{\mathcal{N}})$ and $u2_i(\mathbf{c}_{\mathcal{N}})$. Consider a discrete subset $\mathcal{D}_d$ of $\mathcal{D}$, such as a set of points at which STAs exist. For the sake of clarity, let $\mathcal{D}_d$ be referred to as the *locations of STAs*. Assume that each AP $i \in \mathcal{N}$ can recognize whether

or not each point $z \in \mathcal{D}_d$ is included in its cell $\mathcal{S}_i$. Assume that each AP $i \in \mathcal{N}$ shares the information of STAs in its cell with every other AP. Note that this assumption is not appropriate if there are some APs that cannot share such an information as discussed in Section 4.3.3.

To estimate a preference ordering of original payoff function $u1(\mathbf{c}_\mathcal{N})$ or $u2(\mathbf{c}_\mathcal{N})$, the number of STAs located in a region is used instead of the area of the region. Namely, the following payoff functions are employed:

$$\widehat{u1}_i(\mathbf{c}_\mathcal{N}) = -\#\{\{z \in \mathcal{D}_d \mid z \in \mathcal{S}_i \cap \mathcal{S}_{\mathcal{N}_{c_i} \setminus \{i\}}\}\}, \quad (4.17)$$

$$\widehat{u2}_i(\mathbf{c}_\mathcal{N}) = -\sum_{j \in \mathcal{N}_{c_i} \setminus \{i\}} \#\{\{z \in \mathcal{D}_d \mid z \in \mathcal{S}_i \cap \mathcal{S}_j\}\}, \quad (4.18)$$

by which each AP $i \in \mathcal{N}$ seeks a channel approximately according to the preference ordering determined by the original payoff functions. If the number of STAs $\#\{\mathcal{D}_d\}$ is sufficiently large and STAs are distributed uniformly randomly, each AP exactly estimates the magnitude relation among $\{u1_i(\mathbf{c}_\mathcal{N})\}_{c_i \in \mathcal{C}_i}$ or $\{u2_i(\mathbf{c}_\mathcal{N})\}_{c_i \in \mathcal{C}_i}$ from the point of view of Monte Carlo integration [41].

The second method is only applicable for payoff function $u2_i(\mathbf{c}_\mathcal{N})$. This method assumes that each cell $\mathcal{S}_i$ of AP $i \in \mathcal{N}$ has a circular range whose radius depends on its transmission power level p_i . On this assumption, $|\mathcal{S}_i \cap \mathcal{S}_j|$ is the area of the intersection of two circles, calculated with the cell radiuses of $\mathcal{S}_i$ and $\mathcal{S}_j$, and the distance between APs i and j [57]. Note that such an estimation is inappropriate for payoff function $u1_i(\mathbf{c}_\mathcal{N})$ due to the complexity of overlap areas among more than two cells. Although this scheme does not require STAs, compared to the previous scheme, the performance of this scheme based on the circular assumption is degraded due to the shadowing effect. The performance of this scheme and the influence of the approximation are verified through simulations in Section 4.5.

A cell radius and a distance between two APs are estimated as follows. Let $p_{i,\max}$ denote the maximum transmission power level of AP $i \in \mathcal{N}$. Let $r_i(p_i)$ (or simply r_i) denote the cell radius of $\mathcal{S}_i$ for each AP $i \in \mathcal{N}$, $r_{i,\max}$ denote the cell radius of $\mathcal{S}_i(p_{i,\max})$, and d_{ij} denote the distance between APs i and j . Each AP $i \in \mathcal{N}$ estimates its cell radius r_i from the relation between path loss and received signal power, i.e., $p_{i,\max}/r_{i,\max}^\alpha = p_i/r_i^\alpha$, where

α is path loss exponent. Required signal power T and received signal power $G_{ji}p_i$ are related through $G_{ji}p_i/r_i^\alpha = T/d_{ij}^\alpha$, so that each AP $i \in \mathcal{N}$ estimates the distance to AP j with G_{ji} , which is estimated by received signal power $G_{ij}p_j$ and transmission power level p_j . In addition, existing schemes for estimating a distance between nodes are available for determining the distance between two APs such as [58]. Note that, using this method, each AP can take into account uncontrollable APs for channel selection by obtaining their transmission power levels if possible, or over-estimating it otherwise.

Although this scheme does not require STAs, compared to the previous scheme, the performance of this scheme based on the circular assumption is degraded due to the shadowing effect. The performance of this scheme and the influence of the approximation are verified through simulations in Section 4.5.

4.5 Simulations

The following three points are revealed through performance evaluations of the proposed channel assignment schemes: 1) the comparison between two learning algorithms, i.e., SAP and BRD; 2) the superiority of the proposed channel assignment compared to the existing assignment in terms of the mitigation of the total overlap area; 3) the impact of the number of STAs on the performance.

4.5.1 Simulation Models

The following four points are revealed through performance evaluations of the proposed channel assignment schemes: 1) the comparison between two learning algorithms, i.e., SAP and BRD; 2) the superiority of the proposed channel assignment compared to the existing assignment in terms of the mitigation of the total overlap area; 3) the impact of the number of STAs on the performance; and 4) the impact of unmanaged APs.

4.5.2 Simulation Models

The key parameters are summarized in Table 4.1. Each AP is uniformly and randomly deployed in the region to be covered $\mathcal{D}$, which is the 300 m×300 m square region. Note that performance evaluations in many other papers, such as [12] and [24], employ this type of simple deployment model. In order to average the effect of deployment patterns, 100 realizations of a random deployment of APs are considered. Assume that all APs have the same sets of configurable transmission power levels and available channels. Transmission power levels are determined based on the transmission control scheme in Chapter 3, by which there are few overlaps among multiple cells while managed APs cover as much region in $\mathcal{D}$ as possible. Assume that STAs are also distributed uniformly and randomly in $\mathcal{D}$. Assume that each AP has information of the distance between itself and every other AP.

To discuss the feasibility nearly in a real environment, the spatially correlated shadowing with an exponential correlation model is taken into account in addition to path loss with path loss exponent 3, which is generated according to [45]. Assume that the shadowing standard deviation is 5 dB, and the correlation distance is 20 m [45].

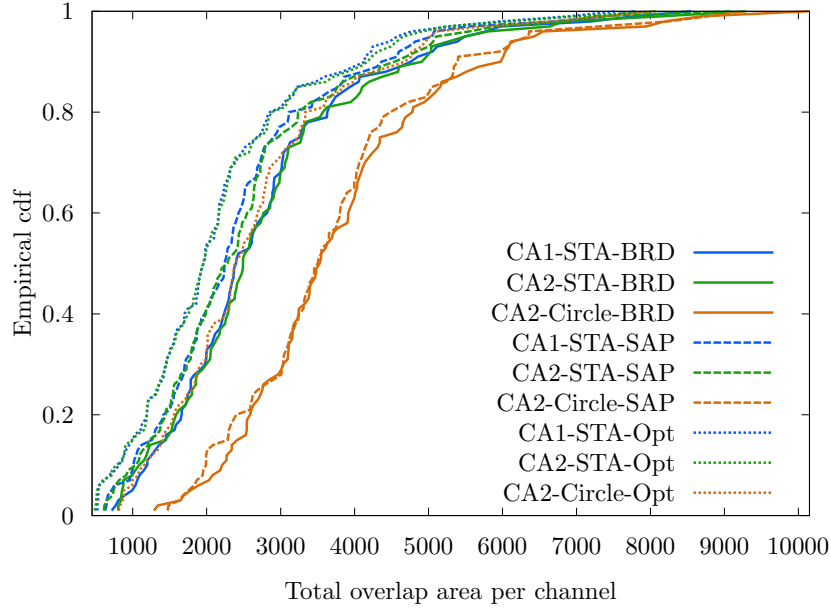
In Section 4.3, two payoff functions $u1_i(\mathbf{c}_N)$ and $u2_i(\mathbf{c}_N)$ have been introduced, and two approximation methods for calculating payoff functions in Section 4.4.2. For the ease of explanation, the following names are used to specify a channel selection to employ: CA1-STA represents the channel assignment based on payoff function $u1_i(\mathbf{c}_N)$ with estimating the payoff by using STAs (4.17); CA2-STA represents that based on payoff function $u2_i(\mathbf{c}_N)$ with estimating the payoffs by using STAs (4.18); and CA2-Circle represents that based on payoff $u2_i(\mathbf{c}_N)$ with estimating the payoffs by assuming each cell to be a circular range. Note that, as mentioned in Section 4.4.2, the approximation with a circular range is inappropriate for estimating payoff function $u1_i(\mathbf{c}_N)$.

4.5.3 Comparison Between SAP and BRD

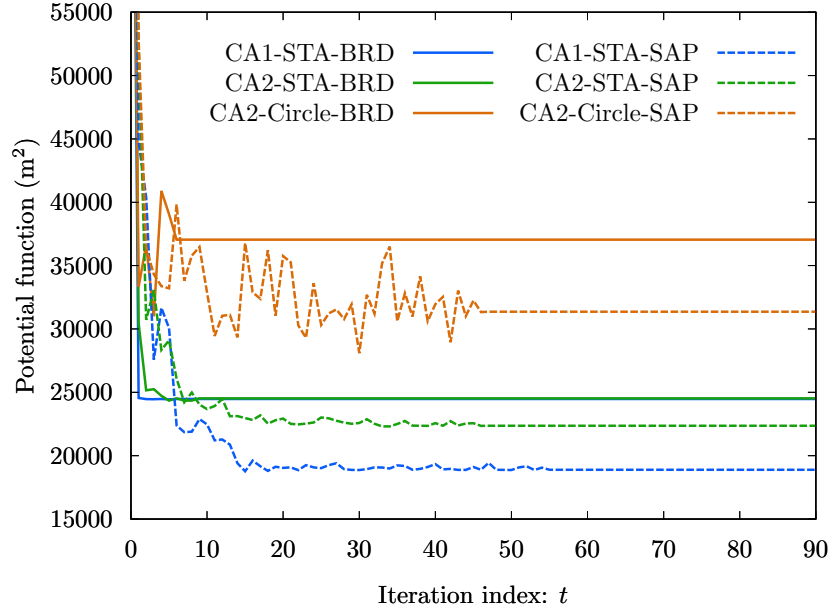
First, the performance comparison between two learning algorithms, i.e., SAP and BRD, are conducted in terms of mitigating the total overlap area.

Table 4.1: Parameters in simulations.

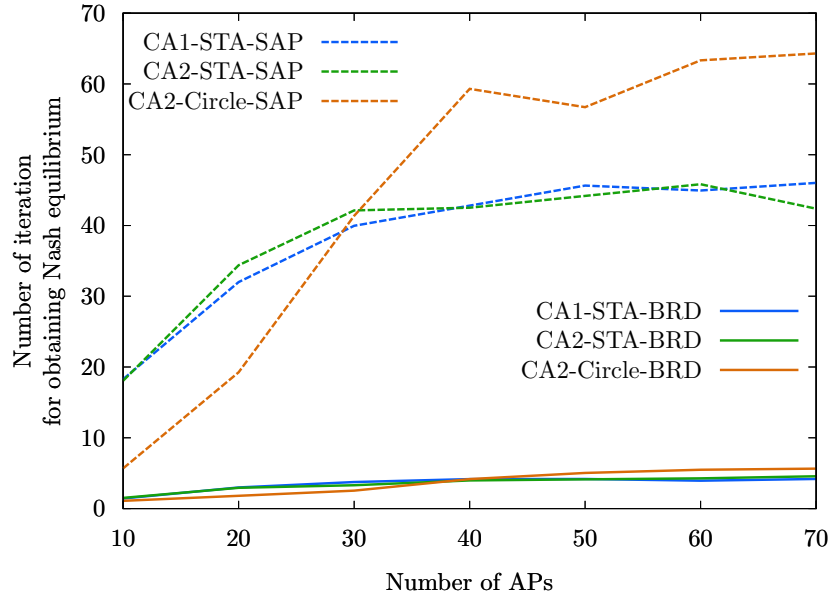
Parameter	Value
Region to be covered, $\mathcal{D}$	300 m $\times$ 300 m
Number of APs, N	10, 20, $\dots$, 70
Number of STAs, $\#\{\mathcal{D}_d\}$	900 (except 4.5.5)
Maximum cell radius, $r_{i,\max}$	200 m
Transmission power levels, p_i	0, 1, $\dots$, 20 dBm
Number of channels, $\#\{C_i\}$	8
Path loss exponent	3
Shadowing standard deviation	5 dB
Correlation distance	20 m

Figure 4.3: Empirical cdf of total overlap area per channel for 100 deployment patterns of APs ($N = 50$).

The initial values of β in SAP, i.e., β_0 of CA1-STA, CA2-STA, and CA2-Circle are determined through experimental trials, being set to be 0.05, 0.05, and 0.002, respectively. These values are empirically determined so that every channel assignment dynamics surely converge to a stable channel property.



(a) Transition of potential functions.



(b) Convergence time.

Figure 4.4: Convergence properties of BRD and SAP.

Fig. 4.3 shows the empirical cdf of the total overlap area per channel when the number of APs N is 50. Opt indicates an equilibrium with the

smallest total overlap area among 10000 Nash equilibria obtained by different initial channel profiles. Note that an obtained Nash equilibrium depends on initial channel profiles, and Opt is evaluated to show a kind of optimal solution instead of the solution of the centralized optimization. We can see that the value obtained through SAP is smaller than through BRD. Although SAP is superior to BRD, the performance of SAP is not comparable to the optimal solution. The difference between CA2-STA (or CA1-STA) and CA2-Circle results from the shadowing effect.

Next, the convergence properties of BRD and SAP is investigated. Fig. 4.4(a) shows that the transition of the potential function for each scheme. We can see that both learning algorithms converge, and convergence speed of SAP is slower than that of BRD for every scheme. The reason why potential functions sometimes increase even if BRD is employed is that each AP approximately calculates a payoff function according to Section 4.4.2, so that the potential function derived from the approximated payoff function decreases, while Fig. 4(a) displays the original potential function (4.7) or (4.9). Fig. 4.4(b) illustrates the number of iteration until each channel assignment dynamics converge, showing that SAP requires more convergence time than BRD as well as Fig. 4.4(a). It should be noted that the number of channel updates of each AP does not increase seriously even if the number of APs increases.

Note that these payoff functions have different order of magnitudes, so that if SAP is employed, a fair comparison among these schemes is almost impossible due to the difficulty of selecting each initial learning parameter β_0 without unfairness. Therefore, BRD is employed for comparison among different schemes in the following subsection.

4.5.4 Comparison Among Proposed Schemes and Conventional Schemes

In this section, the performance between the proposed scheme and other existing schemes are compared. As existing schemes, two common channel assignment schemes are employed, which are referred to *random assignment* (simply referred to as “RANDOM”) and *interference power-based assign-*

ment [59] (simply referred to as “IPA”), respectively. RANDOM is the scheme that assigns a uniform random channel to each AP. IPA is based on the strategic form game and employs the following payoff function [59]:

$$u3_i(\mathbf{c}_N) = -p_i \sum_{j \in \mathcal{N}_{c_i} \setminus \{i\}} G_{ij} p_j, \quad (4.19)$$

which consists of transmission power level p_i of AP i and the interference powers from the other APs that operate the same channel, $\{G_{ij} p_j\}_{j \in \mathcal{N}_{c_i} \setminus \{i\}}$. Game $G3 := (\mathcal{N}, (\mathcal{C}_i)_{i \in \mathcal{N}}, (u3_i)_{i \in \mathcal{N}})$ has been shown to be a potential game with the following potential function:

$$V3(\mathbf{c}_N) = -\frac{1}{2} \sum_{i \in \mathcal{N}} p_i \sum_{j \in \mathcal{N}_{c_i} \setminus \{i\}} G_{ij} p_j. \quad (4.20)$$

Note that the game in [59] is the typical formulation of various other interference signal power-based schemes [51, 52, 60–63], which also discuss this type of game.

Fig. 4.5 shows the total overlap area per channel. We can see that the values obtained by the proposed schemes are smaller than that of the compared schemes, so that the proposed schemes are effective for reduction in the total overlap area. Among CA1-STA, CA2-STA, and CA2-Circle, CA1-STA performs as small total overlap area as CA2-STA does, and CA2-STA (or CA1-STA) is superior to CA2-Circle. The superiority between CA2-STA and CA2-Circle is due to the shadowing effect as discussed in the next subsection.

4.5.5 Impact of Number of STAs

If either CA1-STA or CA2-STA is employed, the ability to reduce the total overlap area may depend on the number of STAs $\#\{\mathcal{D}_d\}$. In this section, the impact of the number of STAs on the performance is investigated. Note that in the case using CA1-STA or CA2-STA, each AP correctly selects a channel that maximizes the payoff function (4.5) or (4.8) when the number of STAs is sufficiently large as discussed in Section 4.4.2. In addition, the schemes are also compared to CA2-Circle. Note that the performance of CA2-Circle does not depend on the number of STAs. For a fair comparison,

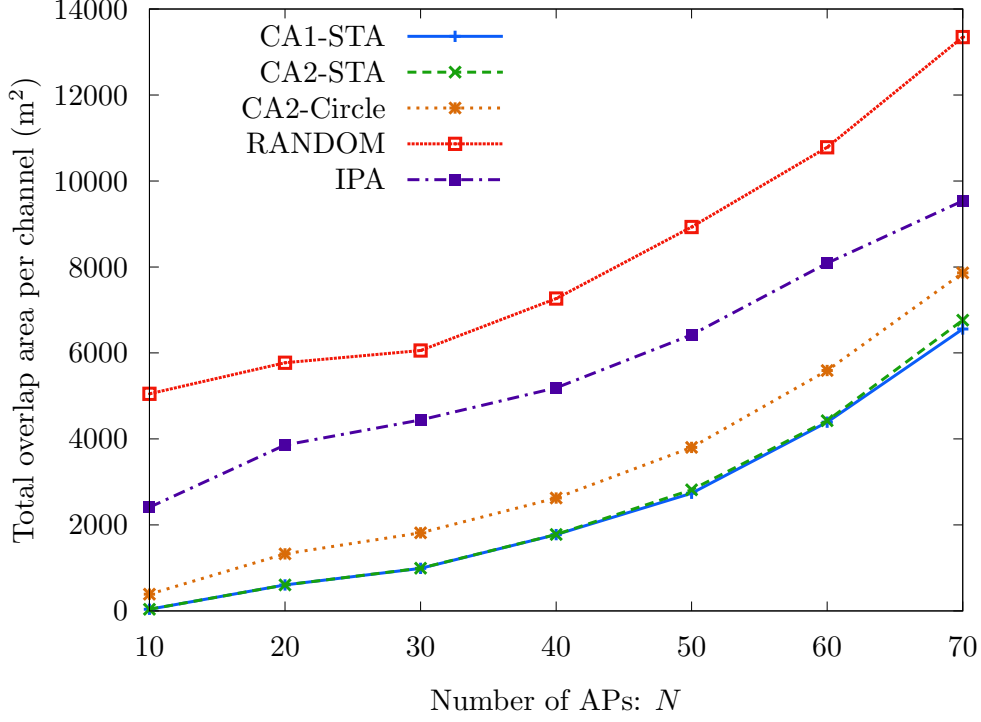


Figure 4.5: Total overlap area per channel with existing schemes.

the same transmission power levels p_N is used for each scheme, which is determined in the case $\#\{\mathcal{D}_d\} = 900$.

Fig. 4.6 shows the total overlap area per channel for each number of STAs. When the number of STAs is less than 200, we can see that the larger the number of STAs is, the smaller the total overlap area there is. This is because each AP cannot seek a channel that maximizes the payoff function exactly. When the number of STAs is more than 200, there is little change in the reduction in the total overlap area.

We can see that CA2-Circle performs as small total overlap area as CA2-STA with less than 100 STAs. Therefore, estimating the payoff function with the circular assumption is effective to reduce the total overlap area to some extent without STAs. On the other hand, when the number of STAs is more than 100, CA2-STA is superior to CA2-Circle. This is due to the shadowing effect, showing that CA2-STA estimates the original payoff function more exactly than CA2-Circle with a sufficient number of STAs.

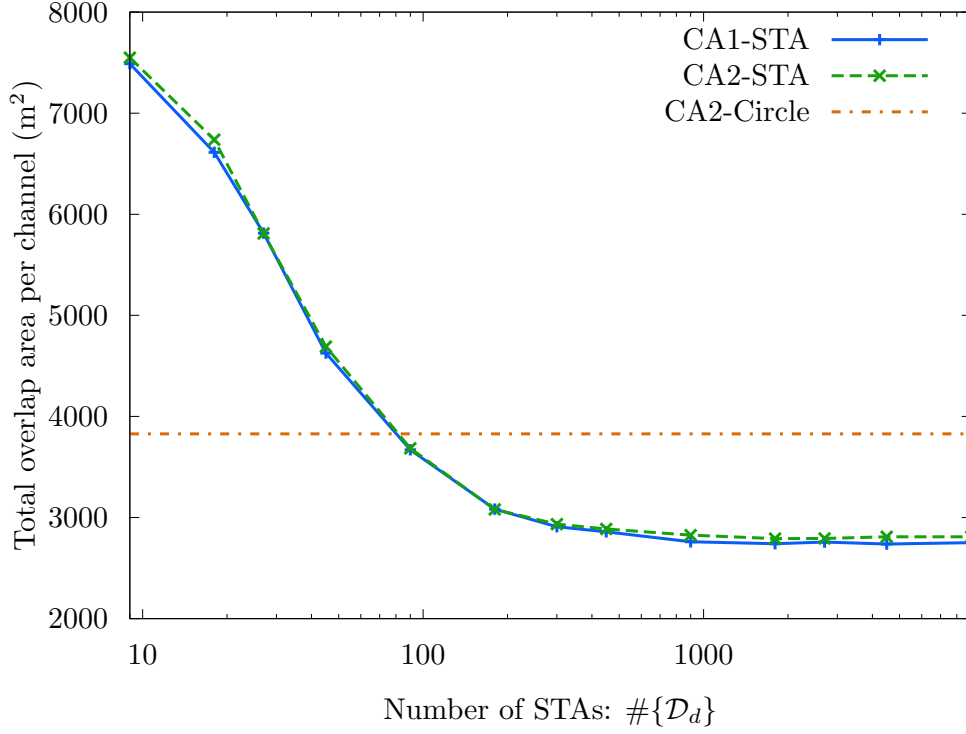


Figure 4.6: Number of STAs vs. total overlap area per channel ($N = 50$).

4.5.6 Comparison Among Proposed Schemes and Conventional Schemes with Unmanaged APs

In this section, the case in which there are uncontrollable APs is considered. Assume that there are 10 uncontrollable APs, which operate at the maximum transmission power level (i.e., 20 dBm). Assume that each uncontrollable AP operates a uniform random channel.

Fig. 4.7 shows the total overlap area per channel. When $N \leq 40$, the proposed schemes are superior to the existing schemes. In particular, CA1-STA performs the smallest total overlap area among all schemes. On the other hand, when the number of APs N is large, such as in the case $N = 70$, RANDOM shows better reduction in the total overlap area than the proposed schemes. The reason is as follows: Theorem 4.3 ensures that the proposed channel assignment schemes always reduce the total overlap area if there are no overlap areas among any three cells; thus if there are some overlap areas among more than two cells at all time steps in channel

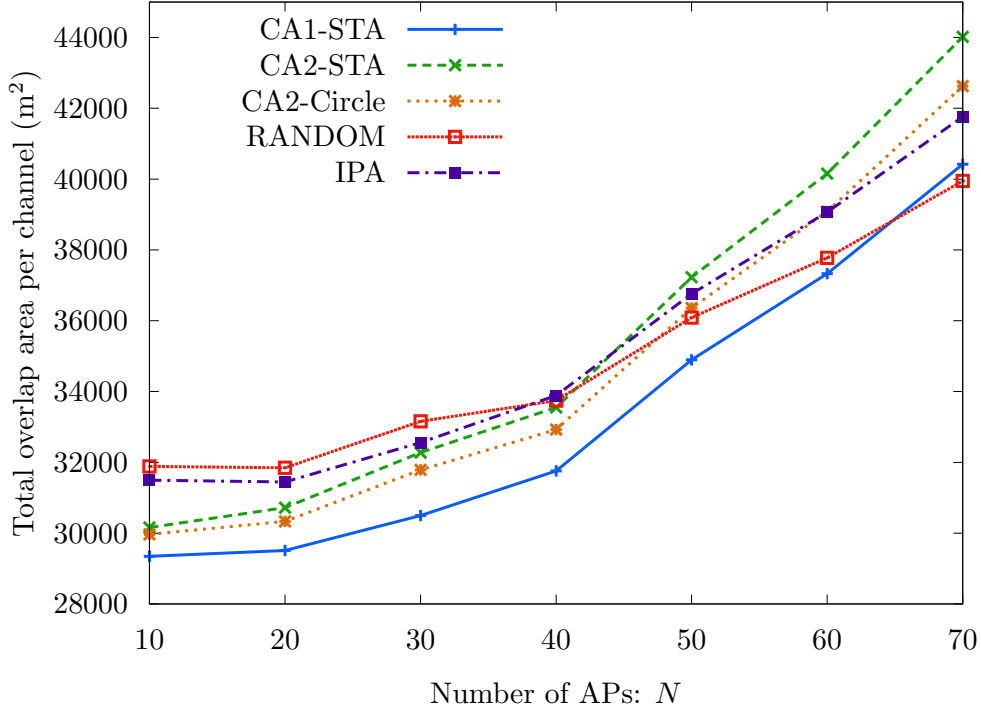


Figure 4.7: Total overlap area per channel with 10 unmanaged APs.

Table 4.2: Parameters in experiments.

Parameter	Value
Transmission power level, $\mathcal{P}_i, \forall i$	0, 3, 6, 9 dBm
Channels, $\mathcal{C}_i, \forall i$	1, 6, 11
Initial channel	1
Transmission power of STAs	10 dBm
Path loss exponent, α	3
Required RSSI, T	-75 dBm

assignment dynamics, the proposed schemes do not necessarily reduce the total overlap area. Such situations may often occur when many APs with extensive coverage ranges are simultaneously operated in a limited region, in which local improvement of overlaps can adversely affect the total overlap area. If in such situations, the proposed schemes would work well with increasing available channels of APs.

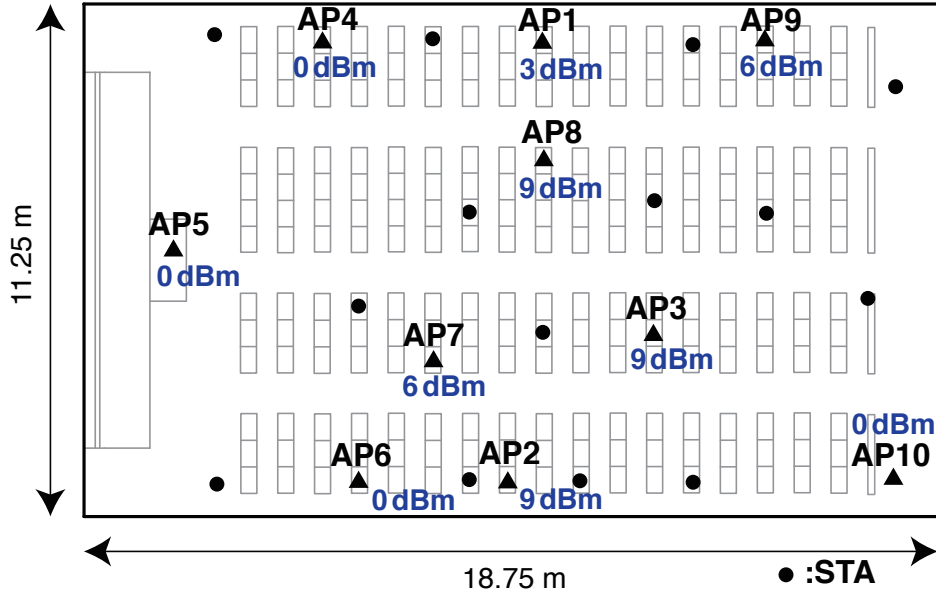


Figure 4.8: Geographic distribution of APs and STAs. ©2017 IEICE

4.6 Experimental Setups and Results

In practical operation, it is important that the channel assignment dynamics should converge. To confirm the feasibility and to show the convergence of the proposed channel assignment in a real environment, a testbed is built. In particular, some uncontrollable APs are taken into consideration in this experiment, which cannot share the necessary information with the APs under control.

The key parameters are shown in Table 4.2. The testbed consists of 10 APs and 14 STAs distributed in a rectangular region of dimension $11.25\text{ m} \times 18.75\text{ m}$ as shown in Fig. 4.8. Note that there are uncontrollable APs that mostly operate channel 1 in this region. The APs and STAs under control are implemented by Linux machines (Raspberry Pi 1 model B/B+) with a WLAN adapter (Buffalo WLI-UC-GNM2). Each managed AP $i \in \mathcal{N}$ is based on the IEEE 802.11g standard (this is not an essential condition), and is connected with the other managed APs via wired LAN.

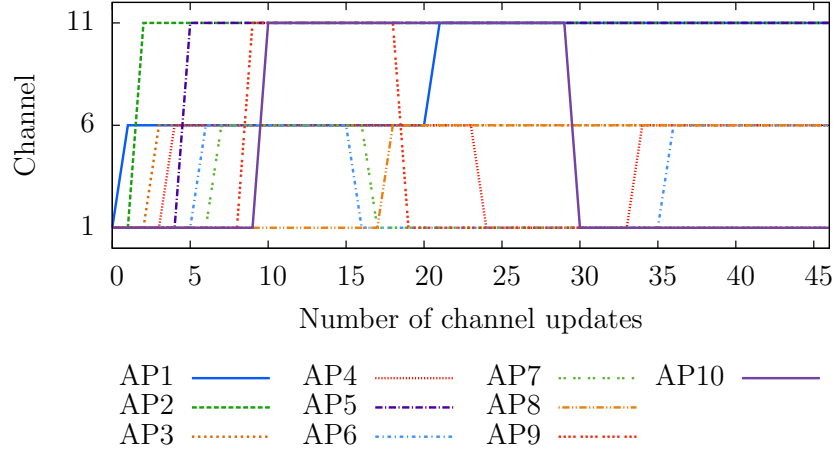
The detailed process of the experiment is as follows. First, the TPC proposed in chapter 3 is conducted, which is intended to verify the convergence

when the transmission power of APs varies; the resulting values are shown in Fig. 4.8. Note that the closed circles shown in Fig. 4.8 represent the locations of STAs, which are used as the sensors that detect coverage holes and overlaps in the TPC step. Since the purpose of this experiment is to confirm the convergence property, no special control is performed on the boundary APs. Next, the proposed channel assignment is conducted. In this process, CA2-Circle is used because it is applicable without the arrangement of the sufficient number of STAs, and BRD is employed to facilitate the fast convergence, which is also discussed in [64]. Through this experiment, each managed APs needs to share information with each other including STAs to be covered and the elements for calculating the proposed payoff function. To facilitate such an information sharing, a server to collect data is arranged in the same LAN, which is responsible for collecting data from all the APs and providing each AP with information about the other APs. Note that when transmission power levels of uncontrollable APs are not available, these values are assumed to be 13 dBm, which is more than the maximum transmission power level of managed APs (9 dBm).

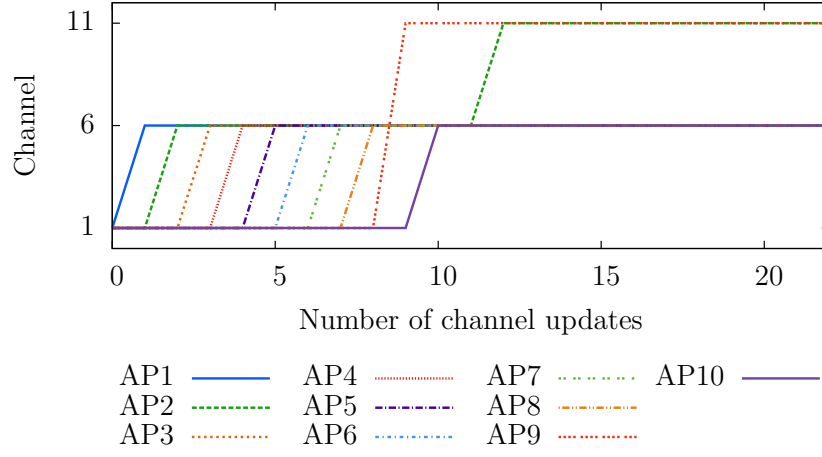
Fig. 4.9 illustrates the convergence properties of the channel transition for every AP $i \in \mathcal{N}$. In both the cases, we can see that channel assignment dynamics surely converges to a Nash equilibrium. This result thus confirms that the proposed scheme performs successfully in a real environment. The reason why managed APs $\mathcal{N}$ avoid channel 1 is that there are several uncontrollable APs that operate channel 1 in this region.

4.7 Conclusion

In this chapter, two decentralized channel assignment schemes are proposed based on in-plane overlap areas. The naive overlap-based scheme makes each AP reduce the union of the overlap regions between its cell and any other cells. The decomposed overlap-based scheme makes each AP reduce the sum of the overlap areas between its cell and any other cells. The main difference lies in the ease of estimating a payoff function. The naive overlap-based scheme requires a sufficient number of STAs and information exchange to detect the overlapping area, while the decomposed overlap-based scheme



(a) w/o uncontrollable APs.



(b) w/ uncontrollable APs.

Figure 4.9: Channel updates for every AP $i \in \mathcal{N}$. ©2017 IEICE

does not necessarily require them. In addition, the decomposed overlap-based scheme is applicable to the case in which there are some uncontrollable APs without information exchange. On the other hand, compared to the first scheme with a sufficient number of STAs, the performance of this scheme based on the circular assumption is degraded due to the shadowing effect.

Moreover, both channel assignment schemes are formulated as potential games, so that unilateral improvement dynamics are guaranteed to converge to a Nash equilibrium. In addition, it was analytically proved that

the system-wide overlap area is upper bounded by the negative potential functions, and showed that if the overlap areas among more than two cells are sufficiently small, local overlap reduction based on the decentralized channel assignment lead to system-wide overlap reduction. The simulation results confirmed that the proposed channel selection schemes are superior to the existing schemes in terms of reducing the system-wide overlap area. The experimental results demonstrated that the decomposed-overlap based assignment converge in a real environment even if there are some uncontrollable APs.

Chapter 5

SINR Distribution and Scheduling Gain Analysis of Uplink Channel-Adaptive Scheduling

5.1 Introduction

5.1.1 Overview

This chapter presents a stochastic geometry analysis of the SINR distribution and scheduling gain of normalized SNR-based scheduling in an uplink Poisson cellular network, in which the per-user truncated fractional TPC is performed. Because the effects of multi-user diversity depend on the number of candidate users to be scheduled, which is a random variable in a Poisson cellular network, the number distribution of candidate users is a major factor in analyzing the SINR distribution of user scheduling. However, the maximum transmit power constraint of users complicates the distribution of candidate users. This study provides the number distribution of candidate users in a general form, which is obtained by modeling the area of the existing range of candidate users using a beta distribution. Based on this result, this study successfully obtains the uplink SINR distribution under

channel-adaptive user scheduling, including cases in which edge users are both allowed and not allowed to transmit at the maximum transmit power. Numerical evaluations reveal that the scheduling gain varies depending on the SNR and the fraction of edge users.

5.1.2 Related Works: Commonalities and Differences

An uplink analysis fundamentally differs from a downlink analysis in that the locations of the transmitters are correlated and that per-user power control is performed [14]. Novlan *et al.* [13] derived the uplink coverage probability for a randomly chosen user (i.e., a typical user) under fractional power control by ignoring the correlation among active user locations, which simplifies the calculation but maintains the accuracy of the derived results. ElSawy *et al.* [14] presented a tractable framework for an uplink cellular network, in which they considered the channel inversion power control of users and ignored edge users, who do not have sufficient power to compensate completely for the exponential decay path loss owing to the maximum power constraint. These assumptions enabled the authors of [14] to drop the marginalization with respect to the contact distance and to derive tractable results. However, it should be emphasized that a channel-adaptive user scheduling was not considered in any of the aforementioned studies. In other words, the results includes only cases in which the transmitting user is selected uniformly randomly in each cell. In modern cellular systems, the transmitting user is not selected uniformly randomly but rather based on a specific channel-adaptive scheduling [19] such as the proportional fair scheduler [20].

The authors of [65, 66] derived the complementary cumulative distribution function (ccdf) of the SINR and the average data rate of a channel-adaptive user scheduling in a downlink cellular network. They assumed that the transmission of users in each cell follows the normalized signal-to-noise power ratio (SNR)-based scheduling [21], in which the scheduler in the cell selects the user having the largest instantaneous SNR normalized by the short-term average SNR. The authors ensured that a stochastic geometry analysis was possible by considering the largest order statistic [67] when

modeling the fading gain of the scheduled user. The analysis captures the topological randomness in a cellular network, which was not considered in other conventional analyses of channel-adaptive scheduling [21, 68–71].

In this study, the SINR cdf and the average data rate of a typical scheduled user are derived under the normalized SNR-based scheduling in an uplink Poisson cellular network with truncated fractional power control. As previously discussed, an uplink analysis essentially differs from a typical downlink analysis [11] in that per-user power control is performed. Thus, truncated fractional power control is considered as per-user power control. Simultaneously, the policy regarding edge users is considered in two ways: according to whether they are allowed to transmit at the maximum transmit power, as in [13, 72], or not allowed to transmit, as in [14]. Therefore, this study considers a more general TPC that includes those presented in [13] or [14]. In addition, this study considers the reduction of interference owing to the cells that include no transmitting user, whereas in a typical uplink analysis [13, 14] the locations of users are arranged such that each base station (BS) has at least one scheduled user.

5.1.3 Contributions

A noteworthy difference between uplink and downlink scheduling analyses is the number distribution of candidate users, which is the users that can potentially be assigned a resource block in each cell. In the analysis of user scheduling, the number of candidate users is a critical factor because the multi-user diversity gain increases along with the number of candidate users. Note that the number of candidate users is a random variable because of the inherent randomness of the positions of BSs and users in Poisson cellular networks. As discussed later in detail, the probability mass function (pmf) of the number of candidate users in an uplink network varies depending on the fraction of edge users, whereas the pmf in a downlink network is unique [65] given the BS and user densities. Therefore, to derive the SINR distribution in a general form, this study must develop a pmf of the number of candidate users for uplink networks that is applicable regardless of the fraction of edge users. In Section 5.3.2, this study first provides two pmfs

for two special cases: those in which all users in an entire cell are candidate users and those in which the users near the cell edges are not candidate users. The two pmfs are shown to be asymptotically equal to the exact number distributions of the candidate users. Then, in Section 5.3.2, the general pmf using beta distribution fitting is provided, which requires a relatively high calculation cost and is yet applicable regardless of the fraction of edge users.

The contributions of this study are as follows.

- For an uplink Poisson cellular network, the conditional SINR distribution of a typical scheduled user given the number of candidate users is derived. The conditional SINR distribution is a component of the complete SINR distribution, which is averaged over the pmf of the number of candidate users. In addition, this study considers two ways of handling edge users, that is, according to whether they are allowed to transmit at the maximum transmit power or are not allowed to transmit at all. It is also shown that the conditional SINR distribution is simplified by assuming a perfect channel inversion power control and by not allowing edge users to transmit. Furthermore, it is shown that the analytical expression is reduced to a closed-form expression for certain special cases.
- The pmf of the number of candidate users in each cell is provided in an uplink network, by which the marginalized SINR distribution under uplink user scheduling is derived. This study clarifies that the pmf of the number of candidate users depends on the BS density and achievable range, which is the maximum contact distance induced by the maximum power constraint, for a case in which edge users are not allowed to transmit. The pmf of the number of candidate users is derived in a general form using beta distribution fitting, including the asymptotic case in which the BS density is sufficiently large or small. Note that the number of candidate users is a critical factor, not only for multi-user diversity but also for other analyses that depend on the number of users, such as the probability that a randomly chosen user is assigned a resource block [73].
- The numerical evaluations of the derived analytical results confirm

that normalized SNR-based scheduling increases the coverage probability because of multi-user diversity gain. It is shown that the improvement in the SINR varies depending on the ratio of edge users and the SNR of a scheduled user. To investigate the degree of multi-user diversity, the scheduling gain is also evaluated, which is defined as the ratio of the average rate of a specific scheduling to that of random scheduling, and is thus the performance metric of the specific scheduling. The evaluation shows that the scheduling gain decreases as the ratio of edge users increases.

If a user scheduling is not considered (i.e., each BS selects a user regardless of instantaneous fading gain), the resulting performance metric is underestimated compared to the actual value. The generalized analyses given in this study will be useful for estimating the degree of multi-user diversity according to a given situation, and will help in effectively operating a user scheduler. In addition, the analytical results will help in providing insight into the design of cell deployment when considering the scheduling gain based on the number of accommodated users in each cell, which will be a building block for the guidelines of the cellular design.

5.2 System Model

The uplink cellular network to be analyzed consists of BSs, users, and schedulers. All of the following assumptions can be found in representative studies in which uplink cellular networks are analyzed [13, 14], except the assumptions that truncated fractional power control per user [14, 72] and channel-adaptive user scheduling [21, 65] are performed.

The locations of the BSs and users form independent PPPs in $\mathbb{R}^2$ with the respective intensities, λ_{BS} and λ_{UE} , as in [73, 74]. The PPP assumption is widely accepted as the baseline assumption for a cellular system analysis [9, 11]. Note that the performance gap between the PPP and actual distribution can be found in [11]. Each user is associated with the nearest BS, meaning that the cell of each BS comprises a Voronoi tessellation on a plane.

This thesis assumes that a single resource block exists in the frequency domain. Note that for the case of multiple resource blocks in the frequency domain, the analysis for each resource block reduces to an analysis with a single resource block by assuming independence among the resource blocks.

This thesis assumes that the desired and interference signals experience a path loss with a path loss exponent η and quasi-static Rayleigh fading (i.e., the channel gain is constant over a time slot and is exponentially distributed with a mean of 1).

Although the system model presented in this chapter for uplink cellular networks is based on many aspects of that presented in [14], two essential differences exist: this thesis considers the channel-adaptive user scheduling in which a transmitting user is selected according to the aforementioned manner, whereas a transmitting user is randomly chosen in [13, 14], and this thesis considers cells that include no transmitting user. By contrast, in [14], the locations of users are arranged such that each BS has at least one scheduled user. As a result, in this study the density of interfering users is reduced.

5.2.1 Transmission Power Control

This thesis assumes that each user adjusts its transmit power according to truncated fractional power control. In this system, each user transmits according to the following two rules.

As the first rule, **(P1)**, a user within $R_d := (P_M/\rho_o)^{1/\eta\epsilon}$ from the serving BS transmits at transmit power $r^{\eta\epsilon}\rho_o$, where P_M is the maximum transmit power, $\epsilon \in [0, 1]$ is a power control factor, r is a contact distance, and ρ_o is a constant. Note that R_d is the distance over which a radio signal transmitted at the maximum transmit power P_M from a user decays to the constant ρ_o on average. Note that the TPC in this study is a generalization of that given in [13, 14], in which uplink cellular networks were analyzed by means of stochastic geometry. The case in which $\epsilon = 1$, namely, when the factor relative to the contact distance r disappears from the product of transmit power $r^{\eta}\rho_o$ and distance attenuation $r^{-\eta}$ (i.e., *perfect channel inversion* is achieved), was analyzed in [14], and the case in which $P_M \rightarrow \infty$, namely,

when no maximum power constraint exists, was analyzed in [13].

The second rule is for the users outside the range of R_d (hereinafter referred to as *edge users* for simplicity) in each Voronoi cell. Note that the term “edge user” does not necessarily mean a user with poor communication quality in this context; this type of usage can also be found in [14]. How to treat edge users is considered in two ways: **(P2a)**, where an edge user is not allowed to transmit, and **(P2b)**, where an edge user transmits at the maximum transmit power. In previous studies, the rules (P2a) and (P2b) are used separately: (P2a) can be found in [14] and (P2b) in [13, 72, 75, 76]. Note that, although rule (P2a) does not ensure fairness among users, edge users transmitting at the maximum transmit power can significantly increase the interference in the system and thus degrade the network performance [14], which is the motivation to consider rule (P2a). This chapter starts by describing the case with (P1) and (P2a) in Section 5.3.1 and then extend it to the case with (P1) and (P2b) in Section 5.3.4. Note that considering the probability of no BS existing within R_d based on the definition of PPP [8], the fraction of edge users is given by $e^{-\pi\lambda_{BS}R_d^2}$, which is found in several parts of this chapter, including Sections 5.3.2 and 5.3.4.

5.2.2 Normalized SNR-Based Scheduler

In this system model, a scheduler selects the user to transmit in each time slot. Each BS is assumed to have knowledge of the instantaneous SNRs of the candidate users according to the channel estimation at the beginning of each time slot. Note that the SINR analysis with perfect channel state information (CSI) is discussed in Section 5.3, and then the SINR analysis with imperfect CSI is discussed in Section 5.4. This study considers the normalized SNR-based scheduler [21, 65], which selects the user with the largest instantaneous SNR normalized by the *short-term* average SNR in each time slot. Given the fading gain h_i , transmit power p_i , and distance to the serving BS (i.e., *contact distance*) r_i of user i , the normalized SNR of user i is obtained as follows.

$$\frac{SNR_i}{\mathbb{E}_{h_i}[SNR_i]} = \frac{h_i p_i r_i^{-\eta} / \sigma_i^2}{\mathbb{E}_{h_i}[h_i p_i r_i^{-\eta} / \sigma_i^2]} = h_i \quad (5.1)$$

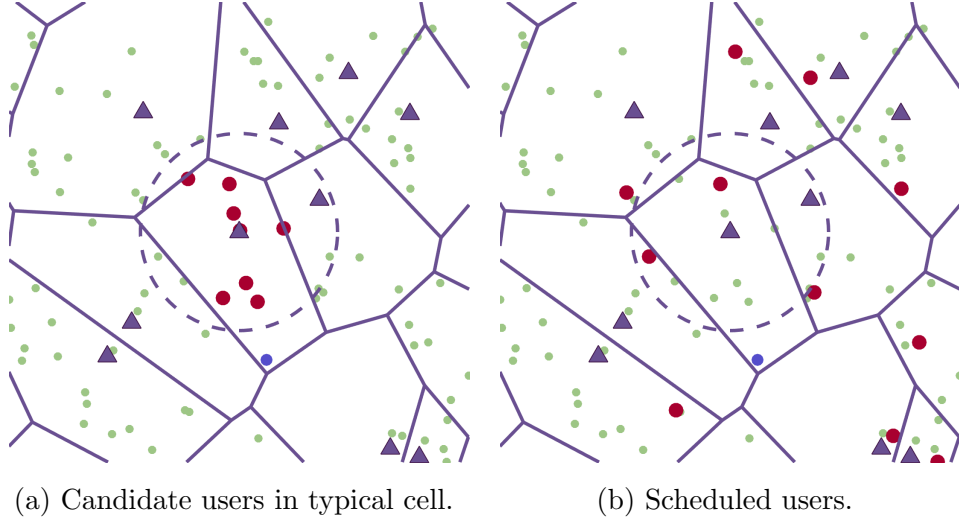


Figure 5.1: Red dots represent each type of user, the dashed circle represents the achievable range (see Section 5.3.2), purple triangles represent BSs, green dots represent users, and blue circles represent edge users in a typical cell. ©2019 IEEE

The short-term average SNR is the average value of the instantaneous SNR over a period during which the variation in the contact distance (as well as transmit power) is negligible. Note that if the data rate is proportional to the SNR [69], the normalized SNR-based scheduler is equivalent to the proportional fair scheduler [20].

As shown in the previous equation, this scheduler selects the user having the largest fading gain among all candidate users [65, 66], whereas the random scheduler selects a user regardless of the channel conditions. A user currently selected to transmit in each cell is referred to as a *scheduled user*. Fig. 5.1 presents the definitions of candidate users and scheduled users to clarify the difference between them. Note that the authors of [65] considered a downlink analysis with the same scheduler, whereas an uplink analysis with truncated fractional power control is addressed in the present study.

5.3 SINR ccdf and Average Data Rate for Perfect CSI and Single-User-Single-Resource-Block Case

This section describes the acquisition of the SINR ccdf and the average data rate for the uplink system. The SINR ccdf of a typical scheduled user is the probability that the user achieves a target value θ of the SINR when it is scheduled, which is defined as $\bar{F}_{SINR}(\theta) := \mathbb{P}(SINR > \theta)$.

In this section, as a basic scenario, it is assumed that the perfect CSI is available for schedulers and that at most one user is allowed to transmit in each resource block (or time slot). In this case, the scheduler always selects the user with the largest fading gain to be scheduled and does not select the other candidate users. The framework to handle the basic scenario in this section is extended to the case of assigning a single resource block to multiple users and the case of imperfect CSI in Section 5.4.

First, the SINR with truncated fractional power control is introduced. Without loss of generality, we can assume that a typical BS is located at the origin. The SINR relative to the typical scheduled user is denoted by:

$$SINR = \frac{\max_{i=1,2,\dots,n} h_i r^{\eta(\epsilon-1)} \rho_o}{\sigma^2 + I}, \quad (5.2)$$

where h_i is the fading gain of candidate user i exponentially distributed with a mean of 1, r is the contact distance of a typical scheduled user, and n represents the number of candidate users in the associated cell. The max operator reflects the fact that the scheduler selects the user with the largest fading gain. Note that the power control is assumed to be performed in advance of the scheduling. The parameter σ^2 denotes the noise power, and the value I is the aggregate interference power defined as:

$$I = \sum_{u \in \Phi_{su} \setminus \{u_o\}} g_u p_u \|u\|^{-\eta}, \quad (5.3)$$

where Φ_{su} is a point process formed by the locations of scheduled users, and u_o is a typical scheduled user. The parameters g_u and p_u represent the

fading gain and the transmit power relative to interfering user $u \in \Phi_{\text{su}} \setminus \{u_o\}$, respectively.

In normalized SNR-based scheduling, the fading gain of a typical scheduled user follows the distribution of the largest order statistic [67] for the given fading gains of the involved users in the corresponding cell [65]. The distribution is given by:

$$\mathbb{P}\left(\max_{i=1,2,\dots,n} h_i \leq x\right) = (1 - e^{-x})^n. \quad (5.4)$$

The aforementioned distribution also appears in the calculation of the selection combiner output [77]. However, unlike in selection combining, n is a random variable because of the inherent randomness of the positions of the BSs and users in Poisson cellular networks.

Now, the main results of this study are stated. Before deriving the SINR cdf in a complete form, we can give the general results by utilizing the fact that the multi-user diversity gain increases with the number of candidate users in the corresponding cell. Letting the number of candidate users be a random variable n , we obtain:

$$\begin{aligned} \bar{F}_{\text{SINR}}(\theta) &= \mathbb{E}_n[\mathbb{P}(\text{SINR} > \theta | n) | n > 0] \\ &= \sum_{n=1}^{\infty} \frac{f_n(n)}{1 - f_n(0)} \mathbb{P}(\text{SINR} > \theta | n), \end{aligned} \quad (5.5)$$

where $\mathbb{P}(\text{SINR} > \theta | n)$ denotes the SINR cdf conditional on n and $f_n(n)$ is the pmf of the number of candidate users in each cell. Note that we do not focus on the cells that include no candidate users because $\mathbb{P}(\text{SINR} | n = 0)$ is unreasonable, and thus we average over the distribution conditioned on $n > 0$. To simplify the notation of conditional expectation given $n > 0$, the notation $\mathbb{E}_{n>0}[\cdot] := \mathbb{E}_n[\cdot | n > 0]$ is used. First, the derivation of $\mathbb{P}(\text{SINR} > \theta | n)$ (see Lemma 5.1) is presented, as well as some simpler expressions in Section 5.3.1. Then the details of the number distribution of candidate users are discussed in Section 5.3.2.

5.3.1 Conditional SINR ccdf Given Number of Candidate Users

Before deriving the SINR ccdf, three approximations are made for analytical tractability. Assume that the number of candidate users n and the contact distance r are independent, the scheduled users form a PPP with intensity λ_{BS} , and the transmit powers of the scheduled users are independent. The first assumption was employed in [65], and the last two approximations were employed in [14], each of which showed that the approximations maintain the accuracy of the leading results. The validation of the approximations is also shown through a numerical evaluation described in Section 5.5. Note that the assumption that the PPP formed by all users (not scheduled users) is independent of the PPP formed by BSs, as given in Section 5.2, is not used in deriving the conditional SINR ccdf given the number of candidate users, but instead contributes to obtaining the pmf of the number of candidate users in each cell, as described in Section 5.3.2.

As the maximum contact distance is thought to be R_d , the contact distance follows the following truncated Rayleigh distribution:

$$f_r(r) = z_r^{-1} r e^{-\pi \lambda_{\text{BS}} r^2} \mathbf{1}_{\{0 \leq r \leq R_d\}}, \quad (5.6)$$

where z_r^{-1} is a normalizing constant and $\mathbf{1}_{\{condition\}}$ is the indicator function, which equals 1 if *condition* is true and zero otherwise. Note that the unrestricted case (i.e., $R_d \rightarrow \infty$) corresponds to a Rayleigh distribution, which is the standard assumption concerning the contact distance in a cellular analysis [8, 11]. By considering the distribution of a transformed variable $p = r^{\eta_\epsilon} \rho_o$, we can derive the distribution of the transmit powers of interfering users as:

$$f_p(p) = z_p^{-1} p^{\frac{2}{\eta_\epsilon} - 1} e^{-\pi \lambda_{\text{BS}} \left(\frac{p}{\rho_o}\right)^{\frac{2}{\eta_\epsilon}}} \mathbf{1}_{\{0 \leq p \leq P_M\}}, \quad (5.7)$$

where z_p^{-1} is a normalizing constant.

Lemma 5.1. Suppose n and r are independent, Φ_{su} is independent of the PPP formed by BSs, and the transmit powers of scheduled users are inde-

pendent. $\mathbb{P}(\text{SINR} > \theta | n)$ is given by:

$$\mathbb{P}(\text{SINR} > \theta | n) \quad (5.8)$$

$$= \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[\exp \left(-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o} - \frac{2\pi k\theta\lambda_{\text{BS}}r^{2-\eta\epsilon}}{(\eta-2)/(1-f_n(0))} \right. \right. \\ \left. \left. \mathbb{E}_p \left[p {}_2F_1 \left(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -\frac{k\theta p}{r^{\eta\epsilon}\rho_o} \right) \right] \right) \right]. \quad (5.9)$$

Proof. We have:

$$\begin{aligned} \mathbb{P}(\text{SINR} > \theta | n) &= \mathbb{E}_{r,I}[\mathbb{P}(\text{SINR} > \theta | n, r, I)] \\ &= \mathbb{E}_{r,I} \left[\mathbb{P} \left(\frac{\max_{i=1,2,\dots,n} h_i r^{\eta(\epsilon-1)} \rho_o}{\sigma^2 + I} > \theta \mid n, r, I \right) \right] \\ &= \mathbb{E}_{r,I} \left[\mathbb{P} \left(\max_{i=1,2,\dots,n} h_i > \frac{\theta(\sigma^2 + I)}{r^{\eta(\epsilon-1)} \rho_o} \mid n, r, I \right) \right] \\ &= \mathbb{E}_{r,I} \left[1 - \left(1 - \exp \left(-\frac{\theta(\sigma^2 + I)}{r^{\eta(\epsilon-1)} \rho_o} \right) \right)^n \right] \\ &= \mathbb{E}_{r,I} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \exp \left(-\frac{k\theta(\sigma^2 + I)}{r^{\eta(\epsilon-1)} \rho_o} \right) \right] \end{aligned} \quad (5.10)$$

$$\begin{aligned} &= \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[e^{-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o}} \mathbb{E}_I \left[e^{-\frac{k\theta I}{r^{\eta(\epsilon-1)}\rho_o}} \right] \right] \\ &= \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[e^{-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o}} \mathcal{L}_I \left(\frac{k\theta}{r^{\eta(\epsilon-1)}\rho_o} \right) \right]. \end{aligned} \quad (5.11)$$

Note that $\mathbb{P}(\text{SINR} > \theta | n, r)$ is given based on the expectation of the sum of the exponential functions of interference I in (5.10) because the distribution of the fading gain of the scheduled user (5.4) can be written as the sum of the exponential functions according to the binomial theorem. Although this property is true for the downlink analysis [65], the element regarding the Laplace transform is different because of the power control and the difference in the interference sources.

The remainder of the proof is given in Appendix 5.A. $\square$

Considering $p = r^{\eta\epsilon}\rho_o$, we can see that the average over p is equivalent to that over r . The conditional SINR distribution given that the number

of candidate users is fixed at one, i.e., $\mathbb{P}(\text{SINR} > \theta | n = 1)$, corresponds to the analysis given in [13], which does not consider channel-adaptive user scheduling but rather random scheduling.

For the interference-limited case (i.e., $\sigma^2 + I \simeq I$), the first exponential function in (5.8) can be ignored. When $\eta = 4$, the hypergeometric function reduces by $x {}_2F_1(1, 1/2; 3/2; -x) = \sqrt{x} \arctan \sqrt{x}$. The assumption of the previous two conditions yields a simpler expression:

$$\begin{aligned} \mathbb{P}(\text{SINR} > \theta | n) &= \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \cdot \\ &\quad \mathbb{E}_r \left[\exp \left(-\pi \lambda_{\text{BS}} (1 - f_n(0)) r^2 \mathbb{E}_p \left[\sqrt{\frac{k\theta p}{r^{4\epsilon} \rho_o}} \arctan \sqrt{\frac{k\theta p}{r^{4\epsilon} \rho_o}} \right] \right) \right]. \end{aligned} \quad (5.12)$$

Corollary 5.1. Suppose $\epsilon = 1$ (i.e., when perfect channel inversion is achieved), we can simplify the SINR cdf conditional on n as:

$$\begin{aligned} \mathbb{P}(\text{SINR} > \theta | n) &= \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \exp \left(-\frac{k\theta\sigma^2}{\rho_o} \right) \cdot \\ &\quad \exp \left(-\frac{2k\theta\gamma \left(2, \pi \lambda_{\text{BS}} R_d^2 \right) {}_2F_1(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -k\theta)}{(\eta - 2) \left(1 - e^{-\pi \lambda_{\text{BS}} R_d^2} \right) / (1 - f_n(0))} \right). \end{aligned} \quad (5.13)$$

Proof. See Appendix 5.B. □

Note that $\mathbb{P}(\text{SINR} > \theta | n = 1, \epsilon = 1)$ corresponds to the same analysis given in [14] except that the density of interfering users is reduced to $(1 - f_n(0))\lambda_{\text{BS}}$ because of the absence of users in certain cells. It should also be noted that for $\epsilon = 1$, we can drop the random variable r in the analysis, and thus we no longer require the assumption of independence between n and r , which is assumed in Lemma 5.1. Whereas the accuracy of these approximations was validated in [14] for the case without channel-adaptive scheduling, in Section 5.5 it is validated for a case in which channel-adaptive scheduling is employed.

Simpler expressions can be derived for certain special cases. For the interference-limited case, $\exp(-k\theta\sigma^2/\rho_o)$ can be ignored. When $\eta = 4$,

the part related to the hypergeometric function reduces to the closed-form expression, $\sqrt{k\theta} \arctan(\sqrt{k\theta})$. In the case of $P_M \rightarrow \infty$ (equivalently $R_d \rightarrow \infty$), $\gamma(2, \pi\lambda_{BS}R_d^2)$ reduces to 1 and $1 - e^{-\pi\lambda_{BS}R_d^2} \rightarrow 1$. The simplest form is obtained when the previous three conditions are simultaneously satisfied, which leads to

$$\mathbb{P}(\text{SINR} > \theta | n) = \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} e^{-(1-f_n(0))\sqrt{k\theta} \arctan \sqrt{k\theta}}. \quad (5.14)$$

Note that the previous expression is a closed form and depends only on a threshold θ . It should be also noted that allowing the number of candidate users n to be 1 with probability 1 corresponds to the results of typical uplink analyses [13, 14], and thus the results in this study are a natural extension of them to a case in which an active user is not randomly selected.

5.3.2 Number Distribution of Candidate Users

The derivation of the SINR ccdf is complete if we have the number distribution of candidate users in each cell, $f_n(n)$. In fact, the distribution depends on the existing range of a scheduled user. To discuss the existing range, the achievable region of the BS is introduced as the circle centered in a typical BS with radius R_d . The users outside the achievable range of the serving BS are not allowed to transmit frames owing to the maximum power constraint.

This section first provides the distribution for two asymptotic cases, where the achievable range relative to the typical BS includes the corresponding Voronoi cell, as shown in Fig. 5.2(a), with a high probability, and where the typical Voronoi cell includes the corresponding achievable range, as shown in Fig. 5.2(c), with a high probability. Next, a general distribution is given, which is more complicated than the former two distributions but is correct regardless of the manner in which a Voronoi cell and the corresponding achievable range overlap.

With respect to a typical BS, the existing range corresponds to the Voronoi cell, as shown in Fig. 5.2(a), with probability

$$g_1(\lambda_{BS}, R_d) = 1 - e^{-\pi\lambda_{BS}R_d^2}, \quad (5.15)$$

which is equivalent to the probability that at least one BS exists within R_d of a certain user. By contrast, the existing range corresponds to the achievable range, as shown in Fig. 5.2(c), with probability

$$g_2(\lambda_{BS}, R_d) = e^{-4\pi\lambda_{BS}R_d^2}, \quad (5.16)$$

which is equivalent to the probability that no cell edges exist within R_d from the BS, namely, the probability that no other BS exists within the circle centered at the typical BS with radius $2R_d$. Therefore, the case shown in Fig. 5.2(b) occurs with probability $1 - g_1 - g_2$.

Given area a of the corresponding existing range in a typical cell, the pmf of the number of involved users is given by:

$$f_{n|a}(n|a) = \frac{(\lambda_{UE}a)^n}{n!} e^{-\lambda_{UE}a}, \quad (5.17)$$

from the definition of PPP [8]. Therefore, if given the distribution $f_a(a)$ of area a of the existing range in a typical cell, we can obtain the number distribution of candidate users by

$$f_n(n) = \int_0^\infty f_{n|a}(n|a) f_a(a) da. \quad (5.18)$$

Asymptotic Cases

If $g_1(\lambda_{BS}, R_d) \simeq 1$, $f_a(a)$ corresponds to the distribution of the area of the typical Voronoi cell, and the corresponding distribution of the candidate users is given, as in [73], we can obtain:

$$f_n^{(1)}(n) = \frac{(\lambda_{UE}/c\lambda_{BS})^n}{cB(n+1, c-1)(\lambda_{UE}/c\lambda_{BS} + 1)^{n+c}}, \quad c = 3.5. \quad (5.19)$$

If $g_2(\lambda_{BS}, R_d) \simeq 1$, area a equals πR_d^2 with probability one, and therefore the number distribution of candidate users is given by:

$$f_n^{(2)}(n) = \frac{(\lambda_{UE}\pi R_d^2)^n}{n!} e^{-\lambda_{UE}\pi R_d^2}. \quad (5.20)$$

Substituting (5.8) and (5.19) or (5.20) into (5.5), we obtain (5.21) and the following theorem.

Theorem 5.1. The SINR ccdf $\bar{F}_{SINR}(\theta)$ of the normalized SNR-based scheduling in uplink cellular networks is given by the following equation, which is appropriate if $g_i(\lambda_{BS}, R_d) \simeq 1$ ($i = 1, 2$).

$$\bar{F}_{SINR}(\theta) = \sum_{n=1}^{\infty} \frac{f_n^{(i)}(n)}{1 - f_n^{(i)}(0)} \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[\exp \left(-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o} - \frac{2\pi k\theta\lambda_{BS}r^{2-\eta\epsilon}}{(\eta-2)/(1-f_n^{(i)}(0))} \mathbb{E}_p \left[p {}_2F_1 \left(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -\frac{k\theta p}{r^{\eta\epsilon}} \right) \right] \right) \right] \quad (5.21)$$

Corollary 5.2. Suppose that $\epsilon = 1$ (i.e., perfect channel inversion is performed). The SINR ccdf $\bar{F}_{SINR}(\theta)$ of the normalized SNR-based scheduling in uplink cellular networks is given by the following equation, which is appropriate if $g_i(\lambda_{BS}, R_d) \simeq 1$ ($i = 1, 2$).

$$\bar{F}_{SINR}(\theta) = \sum_{n=1}^{\infty} \frac{f_n^{(i)}(n)}{1 - f_n^{(i)}(0)} \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \exp \left(-\frac{k\theta\sigma^2}{\rho_o} - \frac{2k\theta\gamma \left(2, \pi\lambda_{BS}R_d^2 \right) {}_2F_1(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -k\theta)}{(\eta-2) \left(1 - e^{-\pi\lambda_{BS}R_d^2} \right) / (1 - f_n^{(i)}(0))} \right), \quad (5.22)$$

General Case

This section provides the pmf of n , which is always applicable regardless of λ_{BS} and R_d . To obtain the pmf of n , two facts regarding the area distribution $f_a(a)$ are taken into account. First, because of the restriction of the achievable range, it is necessary that area a of the existing range in a typical cell be distributed over $[0, \pi R_d^2]$. Second, an achievable range is included in the corresponding Voronoi cell with probability $g_2(\lambda_{BS}, R_d)$, and thus, $f_a(\pi R_d^2) = g_2(\lambda_{BS}, R_d)\delta(a - \pi R_d^2)$, where $\delta(a)$ is the Dirac delta function. In this sense, $g_2(\lambda_{BS}, R_d)$ can be interpreted as the degree to which the distribution is concentrated around $a = \pi R_d^2$.

Because of its flexibility and boundedness [72, 78], the beta distribution is used to model the distribution of the area of the existing range in a typical cell over $[0, \pi R_d^2]$. As the beta distribution is defined over $[0, 1]$, considering

the distribution of the normalized area $\hat{a} = a/\pi R_d^2$, we have a parametric model

$$f_{\hat{a}}(a) = (1 - g_2) \frac{a^{\alpha-1}(1-a)^{\beta-1}}{B(\alpha, \beta)} + g_2 \delta(a-1). \quad (5.23)$$

Parameters α and β are determined as the functions of λ_{BS} and R_d through the following two steps. First, the fitted parameters are obtained for certain values of λ_{BS} through Monte Carlo simulations, followed by the generalized representations of the parameters as functions of λ_{BS} and R_d through a piecewise linear approximation. Note that the derivation of (5.19) requires the distribution of the area of a typical Voronoi cell, which is also identified by parameter fitting through Monte Carlo simulations [79]. Fig. 5.3 shows the parameter estimates obtained by means of Monte Carlo simulations and the corresponding fitted curves, which are given by:

$$\log \alpha = \begin{cases} 1.3 \log(\lambda_{BS} R_d^2) + 9.72, & 5.36 \times 10^{-2} < \lambda_{BS} R_d^2; \\ 0.9, & \text{otherwise.} \end{cases} \quad (5.24)$$

$$\log \beta = \begin{cases} -0.96 \log(\lambda_{BS} R_d^2) - 7.74, & 6.7 \times 10^{-2} > \lambda_{BS} R_d^2; \\ -1.6, & \text{otherwise.} \end{cases} \quad (5.25)$$

Note that the parameters depend on λ_{BS} and R_d through $\lambda_{BS} R_d^2$, because the degree to which the distribution is concentrated around $a = \pi R_d^2$ is determined based on $g_2(\lambda_{BS}, R_d)$ and thus by $\lambda_{BS} R_d^2$.

Substituting (5.17) and (5.23) into (5.18), we obtain the following expression.

$$\begin{aligned} f_n^{(3)}(n) &= \int_0^1 \frac{(\lambda_{UE} \pi R_d^2 a)^n}{n!} e^{-\lambda_{UE} \pi R_d^2 a} f_{\hat{a}}(a) da \\ &= (1 - g_2) \frac{B(n + \alpha, \beta)}{B(\alpha, \beta)} \frac{(\lambda_{UE} \pi R_d^2)^n}{n!} \int_0^1 \frac{a^{n+\alpha-1}(1-a)^{\beta-1}}{B(n + \alpha, \beta)} e^{-\lambda_{UE} \pi R_d^2 a} da \\ &\quad + g_2 \frac{(\lambda_{UE} \pi R_d^2)^n}{n!} e^{-\lambda_{UE} \pi R_d^2} \\ &= (1 - g_2) \frac{B(n + \alpha, \beta)}{B(\alpha, \beta)} \frac{(\lambda_{UE} \pi R_d^2)^n}{n!} {}_1F_1(n + \alpha; n + \alpha + \beta; -\lambda_{UE} \pi R_d^2) \\ &\quad + g_2 \frac{(\lambda_{UE} \pi R_d^2)^n}{n!} e^{-\lambda_{UE} \pi R_d^2}. \end{aligned} \quad (5.26)$$

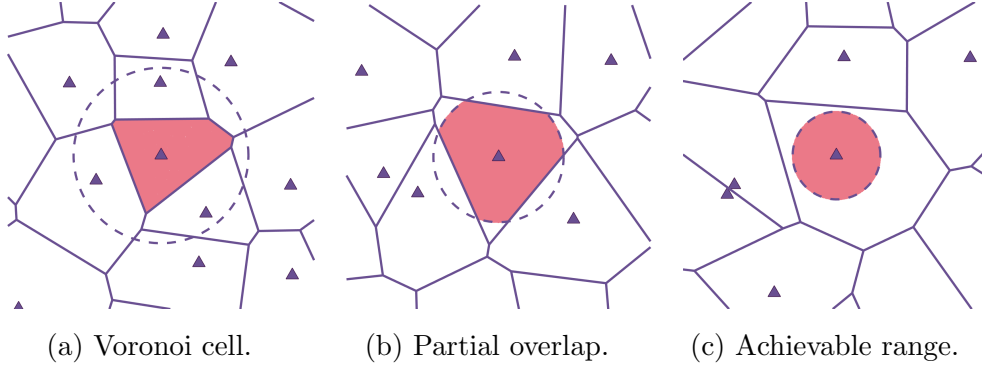


Figure 5.2: Existing range of scheduled user. The red region represents the existing range, the dashed circle represents the achievable range with radius R_d , and the purple triangles represent BSs. ©2019 IEEE

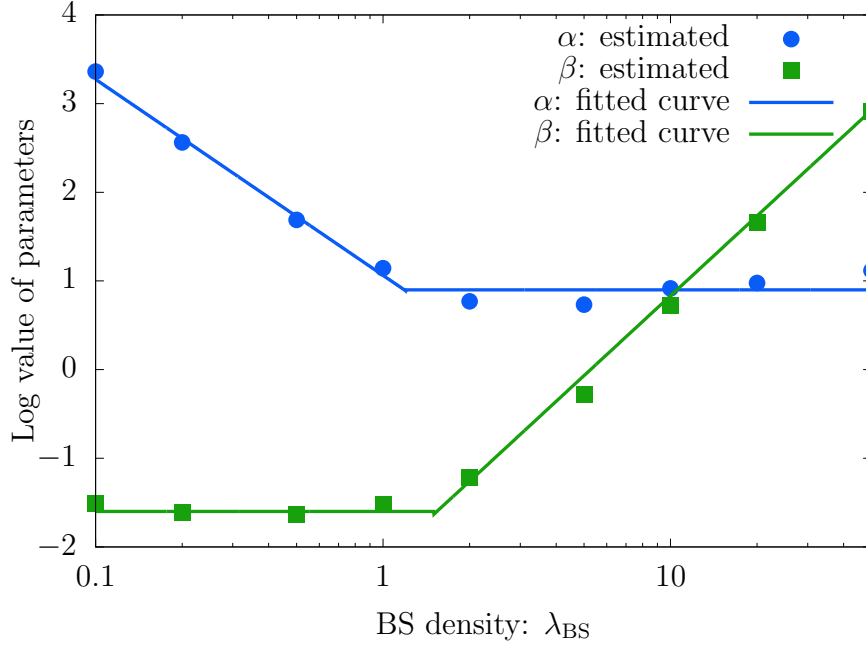


Figure 5.3: Parameters of a beta distribution. The points represent fitted parameters through Monte Carlo simulations, and the lines represent generalized representations of the parameters as functions of λ_{BS} ($\rho_o = -70$ dB). ©2019 IEEE

Therefore, we can derive the following theorem, which holds for any λ_{BS} and R_d .

Theorem 5.2. The SINR cdf $\bar{F}_{SINR}(\theta)$ of the normalized SNR-based scheduling in an uplink cellular network is given by letting $i = 3$ in (5.21).

Corollary 5.3. Suppose that $\epsilon = 1$ (i.e., perfect channel inversion is performed). The SINR cdf $\bar{F}_{SINR}(\theta)$ of the normalized SNR-based scheduling in an uplink cellular network is given by letting $i = 3$ in (5.22).

5.3.3 Average Data Rate

Using the SINR cdf, we can obtain the average data rate $\tau_s(\lambda_{BS}, \lambda_{UE}) := \mathbb{E}[\ln(1 + SINR)]$, and therefore, the scheduling gain [80] $G(\lambda_{BS}, \lambda_{UE}) := \tau_s(\lambda_{BS}, \lambda_{UE})/\tau_r(\lambda_{BS})$, where $\tau_r(\lambda_{BS})$ is the average data rate of the random scheduling, which is given as:

$$\tau_r(\lambda_{BS}) = \int_0^\infty \frac{e^{-\frac{x\sigma^2}{\rho_o}}}{x+1} \mathcal{L}_I\left(\frac{x}{\rho_o}\right) dx. \quad (5.27)$$

Note that these average data rates are not defined for cells in which no scheduled users exist. Also note that (5.27) differs from that presented in [14] in that this thesis considers BSs as having no users to serve.

Corollary 5.4. The average data rate $\tau_s(\lambda_{BS}, \lambda_{UE})$ of the normalized SNR-based scheduling is given by:

$$\mathbb{E}_{n>0} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[\int_0^\infty \frac{e^{-\frac{kx\sigma^2}{\rho_o r^{\eta(\epsilon-1)}}}}{x+1} \mathcal{L}_I\left(\frac{kx}{\rho_o r^{\eta(\epsilon-1)}}\right) dx \right] \right]. \quad (5.28)$$

In particular, letting $\sigma^2 = 0$, $P_M \rightarrow \infty$, $\eta = 4$, $\epsilon = 1$ yields a simpler form:

$$\mathbb{E}_{n>0} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \int_0^\infty \frac{e^{-(1-f_n^{(i)}(0))\sqrt{kx} \arctan(\sqrt{kx})}}{x+1} dx \right]. \quad (5.29)$$

Proof. See Appendix 5.C. □

5.3.4 Analysis with Edge Users

The aforementioned analyses were conducted by focusing on users within an achievable range, where the edge users are not allowed to transmit. We

now consider the extension of the aforementioned framework to the case in which edge users are permitted to transmit at the maximum transmit power P_M .

We introduce s_{in} supposed on $\{0,1\}$ as a variable indicating whether a typical scheduled user is located within an achievable range. As the proportion of edge users is given by $1 - g_1(\lambda_{\text{BS}}, R_d)$ in a Poisson cellular network, Here, $s_{\text{in}} = 1$ means the user is inside the achievable range, whereas $s_{\text{in}} = 0$ means the user is an edge user. we have $\mathbb{P}(s_{\text{in}} = 1) = g_1(\lambda_{\text{BS}}, R)$ and $\mathbb{P}(s_{\text{in}} = 0) = 1 - g_1(\lambda_{\text{BS}}, R_d)$.

The SINR ccdf conditional on $s_{\text{in}} = 1$ is the same as (5.11) except for the distribution of transmit power of an interfering user. Within the entire network, a fraction $1 - g_1(\lambda_{\text{BS}}, R)$ of users transmit according to the fractional power control, and a fraction $g_1(\lambda_{\text{BS}}, R)$ transmits at the maximum transmit power. Thus, the distribution of transmit power of an interfering user is given as:

$$f_{\hat{p}}(p) = g_1 z_p^{-1} p^{\frac{2}{\eta\epsilon}-1} e^{-\pi\lambda_{\text{BS}}\left(\frac{p}{\rho_o}\right)^{\frac{2}{\eta\epsilon}}} 1_{\{0 \leq p < P_M\}} + (1 - g_1) \delta(p - P_M) 1_{\{p=P_M\}}. \quad (5.30)$$

The SINR ccdf conditional on $s_{\text{in}} = 0$ is given by replacing $r^{\eta\epsilon}\rho_o$ with P_M in (5.11):

$$\begin{aligned} & \mathbb{P}(\text{SINR} > \theta \mid s_{\text{in}} = 0) \\ &= \mathbb{E}_{n>0} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_{\hat{r}} \left[\exp\left(-\frac{k\theta\sigma^2}{P_M \hat{r}^{-\eta}}\right) \mathcal{L}_I\left(\frac{k\theta}{P_M \hat{r}^{-\eta}}\right) \right] \right], \end{aligned} \quad (5.31)$$

where r' is a contact distance of an edge user, which follows the Rayleigh distribution truncated in (R_d, ∞) :

$$f_{\hat{r}}(r) = z_{\hat{r}}^{-1} r e^{-\pi\lambda_{\text{BS}} r^2} 1_{\{r > R_d\}}, \quad (5.32)$$

where $z_{\hat{r}}^{-1}$ is a normalizing constant.

Averaging out the random variable s_{in} yields the required SINR distri-

bution as follows:

$$\begin{aligned}
 \mathbb{P}(\text{SINR} > \theta) &= \sum_{i \in \{0,1\}} \mathbb{P}(\text{SINR} > \theta \mid s_{\text{in}} = i) \mathbb{P}(s_{\text{in}} = i) \\
 &= \mathbb{E}_{n>0} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \left\{ g_1 \mathbb{E}_r \left[e^{-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o}} \mathcal{L}_I \left(\frac{k\theta}{r^{\eta(\epsilon-1)}\rho_o} \right) \right] \right. \right. \\
 &\quad \left. \left. + (1 - g_1) \mathbb{E}_{\hat{r}} \left[e^{-\frac{k\theta\sigma^2}{P_M \hat{r}^{\eta}}} \mathcal{L}_I \left(\frac{k\theta}{P_M \hat{r}^{\eta}} \right) \right] \right\} \right] \quad (5.33)
 \end{aligned}$$

In this case, because every user can transmit, the number distribution of candidate users is given by $f_n^{(1)}(n)$, which is the number distribution of users in a typical Voronoi cell. Consequently, we have the following theorem.

Theorem 5.3. When edge users are allowed to transmit at the maximum transmit power, the SINR cdf $\bar{F}_{\text{SINR}}(\theta)$ of the normalized SNR-based scheduling in an uplink cellular network is given by as follows:

$$\begin{aligned}
 \mathbb{P}(\text{SINR} > \theta) &= \sum_{n=1}^{\infty} \frac{f_n^{(1)}(n)}{1 - f_n^{(1)}(0)} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \left\{ g_1 \mathbb{E}_r \left[e^{-\frac{k\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o}} \mathcal{L}_I \left(\frac{k\theta}{r^{\eta(\epsilon-1)}\rho_o} \right) \right] \right. \right. \\
 &\quad \left. \left. + (1 - g_1) \mathbb{E}_{\hat{r}} \left[e^{-\frac{k\theta\sigma^2}{P_M \hat{r}^{\eta}}} \mathcal{L}_I \left(\frac{k\theta}{P_M \hat{r}^{\eta}} \right) \right] \right\} \right]. \quad (5.34)
 \end{aligned}$$

5.4 Extension for Multiple User and Imperfect CSI

This section extends the aforementioned mentioned framework in two ways by considering the case in which multiple user are supported in a single resource block and the case in which perfect CSI is not available for schedulers. The two cases are related through the SINR analysis of a user with the i th largest fading gain in a cell.

5.4.1 Discussion on Multiple Users

Considering multiple orthogonal resource blocks in the frequency domain, we can consider multiple users to be scheduled in each time slot. In this

case, the SINR analysis in each resource block is reduced to the analysis under the single-user-single-resource-block assumption.

On the other hand, multiple users can also be supported in the same resource block by using space division multiple access [77] or non-orthogonal multiple access [81]. In that case, the normalized SNR-based scheduler selects a specified number of users to be scheduled in order of their fading gains.

This section gives mainly the conditional SINR cdf relative to the user with the i th largest fading gain in a cell given the number of candidate users n . After that, the derivation of the SINR cdf averaged over n and the average data rate are briefly explained because the corresponding processes are almost the same as in the single-user-single-resource block case.

Assume that the perfect CSI is available for schedulers in this subsection. Let $h_{(i,n)}$ be the i th largest of the fading gains $h_1, h_2, \dots, h_n$ of candidate users (i.e., $h_{(1,n)} \geq h_{(2,n)} \geq \dots \geq h_{(n,n)}$). The distribution of the i th largest fading gain $h_{(i,n)}$ is given by

$$\begin{aligned} \mathbb{P}(h_{(i,n)} \leq x) &= \sum_{j=n-i+1}^n \binom{n}{j} (1 - e^{-x})^j \cdot (e^{-x})^{n-j} \\ &= \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} (-1)^k e^{-(n+k-j)x}. \end{aligned} \quad (5.35)$$

Letting the SINR relative to the users with fading gain $h_{(i,n)}$ be denoted by $\text{SINR}_{(i,n)}$, we obtain

$$\begin{aligned} \mathbb{P}(\text{SINR}_{(i,n)} > \theta \mid n) &= \mathbb{E}_{r,I} \left[\mathbb{P} \left(\frac{h_{(i,n)} r^{\eta(\epsilon-1)} \rho_o}{\sigma^2 + I} > \theta \mid n, r, I \right) \right] \\ &= \mathbb{E}_{r,I} \left[\mathbb{P} \left(h_{(i,n)} > \frac{\theta(\sigma^2 + I)}{r^{\eta(\epsilon-1)} \rho_o} \mid n, r, I \right) \right] \\ &= \mathbb{E}_{r,I} \left[1 - \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} (-1)^k \exp \left(-\frac{(n+k-j)\theta(\sigma^2 + I)}{r^{\eta(\epsilon-1)} \rho_o} \right) \right] \end{aligned}$$

$$= 1 - \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} (-1)^k \mathbb{E}_r \left[e^{-\frac{(n+k-j)\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o}} \mathcal{L}_I \left(\frac{(n+k-j)\theta}{r^{\eta(\epsilon-1)}\rho_o} \right) \right]. \quad (5.36)$$

Noticing that the Laplace transform of I is given by (5.42) in the same manner as Appendix 5.A, we can obtain the analytical expression for $\mathbb{P}(\text{SINR}_{(i,n)} > \theta | n)$. Note that when applying the probability generation functional of PPP in the derivation of the Laplace transform of I , we need the density of interfering users, which is considered as $(1 - f_n(0))\lambda_{\text{BS}}$ in the previous section. However, if multiple users simultaneously transmit in a single resource block in each cell, the effective density of interfering users would be more than $(1 - f_n(0))\lambda_{\text{BS}}$ depending on a multiple access scheme. However, a detailed discussion on such an effective density is out of scope of this thesis, and hence a theoretical result is presented by letting the effective density of interfering users in a considered system be denoted by $\lambda_I^{(\text{eff})}$.

Lemma 5.2. Under the same assumptions as Lemma 5.1, the conditional SINR cdf $\mathbb{P}(\text{SINR}_{(i,n)} > \theta | n)$ relative to the user with the i th largest fading gain is given as follows:

$$\begin{aligned} \mathbb{P}(\text{SINR}_{(i,n)} > \theta | n) = 1 - \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} (-1)^k \cdot \\ \mathbb{E}_r \left[\exp \left(-\frac{(n+k-j)\theta\sigma^2}{r^{\eta(\epsilon-1)}\rho_o} - \frac{2\pi(n+k-j)\theta\lambda_I^{(\text{eff})}r^{2-\eta\epsilon}}{(\eta-2)} \right) \cdot \right. \\ \left. \mathbb{E}_p \left[p {}_2F_1 \left(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -\frac{(n+k-j)\theta p}{r^{\eta\epsilon}\rho_o} \right) \right] \right]. \quad (5.37) \end{aligned}$$

Similar to the derivation of (5.14), letting $\sigma^2 = 0$, $P_M \rightarrow \infty$, $\eta = 4$, $\epsilon = 1$, we have a simpler form as follows:

$$\begin{aligned} \mathbb{P}(\text{SINR}_{(i,n)} > \theta | n) = 1 - \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} (-1)^k \cdot \\ \exp \left(-\frac{\lambda_I^{(\text{eff})}}{\lambda_{\text{BS}}} \sqrt{(n+k-j)\theta} \arctan \sqrt{(n+k-j)\theta} \right). \quad (5.38) \end{aligned}$$

The only essential difference between (5.14) and (5.38) is that (5.38) includes one more finite summation than (5.14).

Averaging $\mathbb{P}(\text{SINR}_{(i,n)} > \theta | n)$ with respect to the number of candidate users n , we obtain the SINR ccdf $\mathbb{P}(\text{SINR}_{(i)} > \theta)$ relative to the user with the i th largest fading gain. Also, integrating $\mathbb{P}(\text{SINR}_{(i)} > e^t - 1)$ with respect to t from 0 to ∞ as in the single-user-single-resource-block case under the perfect CSI assumption, we obtain the average data rate $\tau_s(\lambda_{\text{BS}}, \lambda_{\text{UE}})$ as follows:

$$\tau_s(\lambda_{\text{BS}}, \lambda_{\text{UE}}) = \mathbb{E}_{n>0} \left[\sum_{i=1}^n p_{(i,n)}^{\text{sche}} \left(1 - \sum_{j=n-i+1}^n \binom{n}{j} \sum_{k=0}^j \binom{j}{k} \cdot \right. \right. \\ \left. \left. (-1)^k \mathbb{E}_r \left[\int_0^\infty \frac{e^{-\frac{(n+k-j)x\sigma^2}{r\eta(\epsilon-1)\rho_o}}}{x+1} \mathcal{L}_I \left(\frac{(n+k-j)x}{r\eta(\epsilon-1)\rho_o} \right) dx \right] \right] \right]. \quad (5.39)$$

The process of averaging for n and that of obtaining the average data rate are the same as in Section 5.3.2 and in Appendix 5.C, respectively.

5.4.2 Discussion on Imperfect CSI

Thus far this study has assumed that the perfect CSI is available for schedulers. However, the perfect CSI is not necessarily available in a practical system. In this section, the SINR distribution under the imperfect CSI assumption is considered.

Consider the case in which a scheduler tries to assign a resource block to the user who has the largest fading gain in actual, as in Section 5.3. Note that the case in which a scheduler tries to assign the same resource block to the user with the i th largest fading gain can be considered in the same manner as in the previous section. Under the imperfect CSI assumption, the scheduler observes the channel gains (equivalent to fading gains) of candidate users with noise. Let the fading gain of user i observed by the scheduler be denoted by $\tilde{h}_i$. In this system, a scheduler assigns a resource block to a user with fading gain $\max_{i=1,2,\dots,n} \tilde{h}_i$ in each time slot. Therefore,

a user with fading gain $h_{(1,n)} = \max_{i=1,2,\dots,n} h_i$ is not necessarily scheduled in general.

The probability that the scheduler assigns a resource block to the user with fading gain $h_{(i,n)}$ is denoted by $p_{(i,n)}^{\text{sche}}$, which depends on the observation model of fading gains. Note that under the perfect CSI assumption, $p_{(i,n)}^{\text{sche}} = 1$ for $i = 1$ and $p_{(i,n)}^{\text{sche}} = 0$ otherwise. Noticing that the SINR cdf for the user with fading gain $h_{(i,n)}$ is given in (5.37) or (5.38) (note that $\lambda_I^{(\text{eff})}$ is $(1 - f_n(0))\lambda_{\text{BS}}$ for the single-user-single-resource-block case), we obtain the SINR cdf under the imperfect CSI assumption as follows.

$$\mathbb{P}(\text{SINR} > \theta | n) = \sum_{i=1}^n p_{(i,n)}^{\text{sche}} \cdot \mathbb{P}(\text{SINR}_{(i,n)} > \theta | n). \quad (5.40)$$

We can derive the SINR cdf averaged over n and average data rate in the same way as the single-user-single-resource-block case under the perfect CSI assumption.

The performance degradation due to the imperfect CSI condition is determined by two factors: the probabilities of selecting users other than the user with the highest fading gain and the gap between the SINRs of the user actually selected and the user with highest fading gain. The results obtained in this study mainly contribute to the analysis of the latter factor.

Note that even if the observation model of fading gains is simple, the dependence of $h_{(1,n)}, h_{(2,n)}, \dots, h_{(n,n)}$ makes it difficult to write $p_{(i,n)}^{\text{sche}}$ ($i = 1, 2, \dots, n$) as a simple expression. However, the Monte Carlo estimation of these probabilities costs much less than the total evaluation of SINR distribution. The actual evaluation is found in Section 5.5.2.

5.5 Numerical Evaluations

5.5.1 Validation Through Simulations

First, the analytical results of SINR cdf will be validated through simulations. Unless otherwise specified, the parameters are set as: path loss exponent $\eta = 4$, noise power $\sigma^2 = -90$ dBm, maximum transmit power $P_{\text{M}} = 23$ dBm, BS density $\lambda_{\text{BS}} = 2$ BSs/km², power-related constant $\rho_o =$

Table 5.1: Parameters in the numerical evaluation (with default values indicated in bold).

Parameter	Value
Path loss exponent: η	4
Noise power: σ^2	0 mW, -90 dBm
Maximum transmit power: P_M	23 dBm
Power-related constant: ρ_o	-90, -70, -50 dBm
BS density: λ_{BS}	0.2, 2, 20 BSs/km ²
Average number of users per BS: $\lambda_{UE}/\lambda_{BS}$	4
Power control factor: ϵ	0, 0.25, 0.5, 0.75, 1

-70 dBm, power control factor $\epsilon = 1$, and average number of users per BS $\lambda_{UE}/\lambda_{BS} = 4$. Each simulation is repeated 10,000 times, and the corresponding empirical ccdf is shown.

Fig. 5.4 shows the SINR ccdfs for the cases of $\lambda_{BS} = 0.2, 2, 20$ BSs/km². In all cases, the figures also include three analytical results (5.22) for $i = 1, 2, 3$. Note that the achievable range R_d varies depending on ρ_o as $R_d = (P_M/\rho_o)^{1/\eta}$. We can see that for $i = 1, 2$, the analytical results averaged over $f_n^{(i)}(n)$ coincide with the simulation results when $g_i(\lambda_{BS}, R_d)$ is large. For example, $g_1 = 0.940$ for $\lambda_{BS} = 20$ BSs/km², $\rho_o = -70$ dBm and $g_2 = 0.894$ for $\lambda_{BS} = 0.2$ BSs/km², $\rho_o = -70$ dBm, which explains the good agreement between the simulation and analytical results averaged over $f_n^{(1)}(n)$ or $f_n^{(2)}(n)$. By contrast, neither of the two analytical results explains all simulation results simultaneously. It is remarkable that the analytical result using $f_n^{(3)}(n)$ accounts for the simulation results regardless of the BS density λ_{BS} and ρ_o .

Each figure also shows the multi-user diversity gain, which means that the SINR of the normalized SNR-based scheduling is superior to that of the random scheduling, particularly within a low SINR region. Note that some of the results show a subtle improvement in the SINR, which derives from the fact that an insufficient number of candidate users exist to obtain multi-user diversity gain.

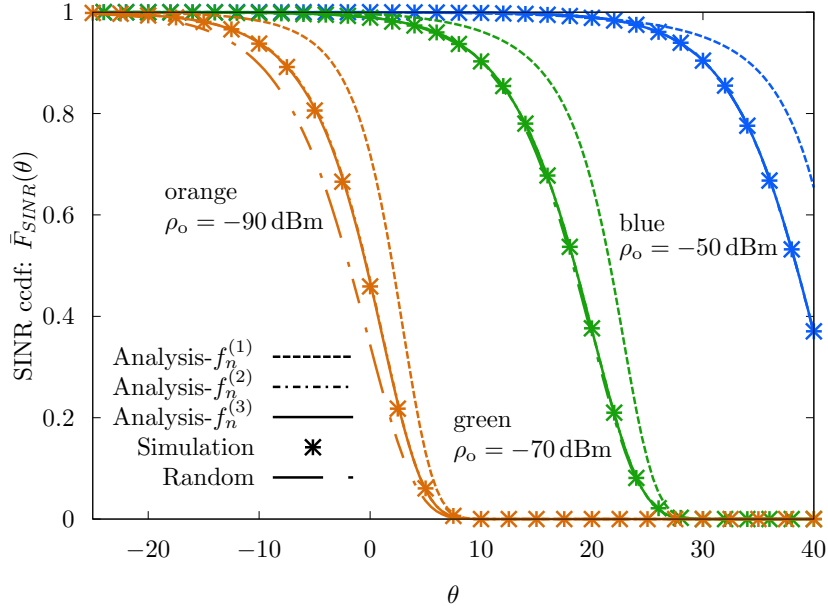
5.5.2 Validation Under Imperfect CSI Assumption

This section is devoted to the evaluation under the incomplete CSI assumption, which is discussed in Section 5.4.2, and the analytical result (5.40) is validated through a comparison with the Monte Carlo simulations. In this evaluation, $f_n^{(3)}(n)$ is used for the number distribution of candidate users, which shows a good agreement with simulation results for any λ_{BS} . To show the degradation of multi-user diversity clearly, the SINR ccdf is evaluated for the case of $\lambda_{\text{BS}} = 20 \text{ BSs/km}^2$. This is the case in which the gap between normalized SNR-based scheduling and random scheduling is clear, as shown in Fig. 5.4.

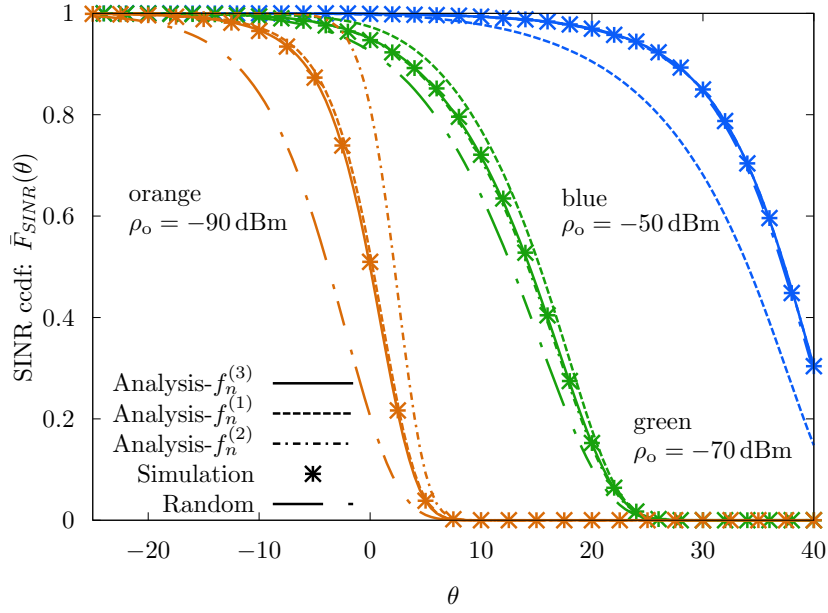
In this evaluation, $p_{(i,n)}^{\text{sche}}$ ($i = 1, 2, \dots, n$) is estimated under the assumption that the scheduler observes fading gains contaminated with additive i.i.d. Gaussian noise, which is used to evaluate (5.40). It is assumed that the observation model is a mapping from h_i to $\tilde{h}_i = |\sqrt{h_i} + z_i|^2$, where z_i is an i.i.d. complex Gaussian random variable [82] with zero mean and variance of $1/4$ ¹. The value of the variance is determined such that some, but not too many, errors occur with user selection (i.e., $p_{(1,n)}^{\text{sche}} \simeq 1/n$ and $p_{(1,n)}^{\text{sche}} \simeq 1$). Fig. 5.5 shows the estimated $p_{(i,n)}^{\text{sche}}$, $n = 2, 3, 4, 5$ for reference, which is obtained through 100,000-times simulations for each n .

Fig. 5.6 shows both the theoretical and simulation results under the imperfect CSI assumption, with the simulation results under the perfect CSI assumption given for reference. The results under the imperfect CSI assumption is, as a matter of course, inferior to the results under the perfect CSI assumption, and we can see that the theoretical results demonstrate the SINR degradation caused by the imperfect CSI.

¹The mapping is obtained in detail as follows. As discussed in [82], the noisy channel estimate of user i in the complex signal space is given as $\sqrt{h_i}e^{j\theta} + z_i$, where j is a imaginary unit, θ is a phase constant, and z_i is an i.i.d. circularly-symmetric complex Gaussian noise. Note that h_i is used to denote a channel power gain in this chapter. Therefore, the estimated channel power gain is given by $\tilde{h}_i = |\sqrt{h_i}e^{j\theta} + z_i|^2 = |\sqrt{h_i} + z_i e^{-j\theta}|^2 = |\sqrt{h_i} + z'_i|^2$, where $z'_i = z_i e^{-j\theta}$. Considering the circular symmetry of z_i , z'_i can be seen as an i.i.d. circularly-symmetric complex Gaussian random variable.



(a) $\lambda_{BS} = 0.2$ BSs/km².



(b) $\lambda_{BS} = 2$ BSs/km².

Figure 5.4: SINR cdfs $\bar{F}_{SINR}(\theta)$ obtained through a theoretical analysis and simulation. ©2019 IEEE

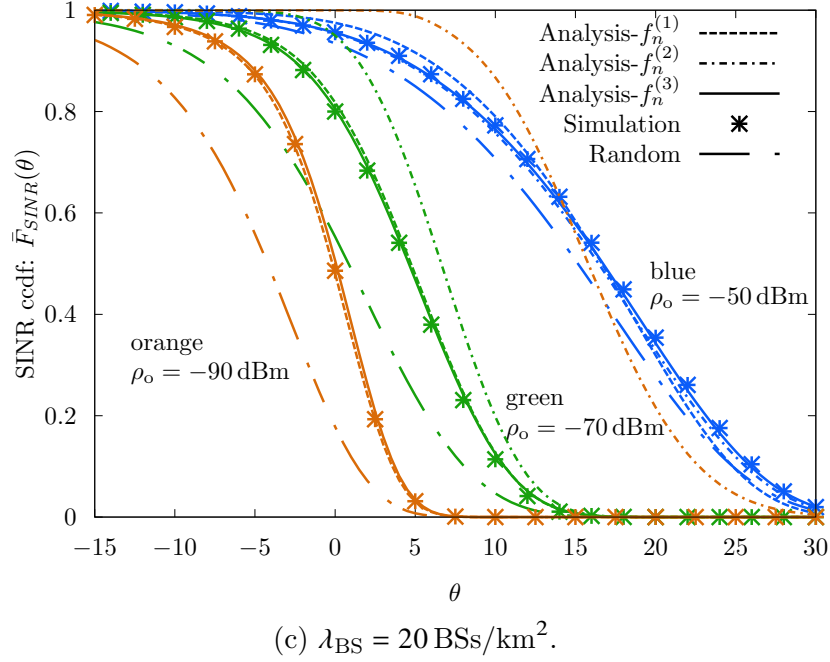


Figure 5.4: SINR cdfs $\bar{F}_{\text{SINR}}(\theta)$ obtained through a theoretical analysis and simulation. ©2019 IEEE

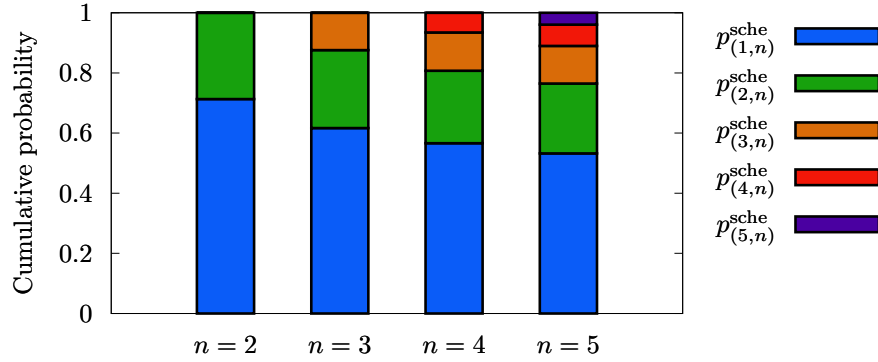


Figure 5.5: Results of Monte Carlo estimation of $(p_{(1,n)}^{\text{sche}}, p_{(2,n)}^{\text{sche}}, \dots, p_{(n,n)}^{\text{sche}})$, $n = 2, 3, 4, 5$, each of which is the probability that the user with the i th largest fading gain $h_{(i,n)}$ is scheduled. ©2019 IEEE

5.5.3 SINR Distribution for General Power Control Policy

Fig. 5.7 shows the SINR cdfs with edge users, who transmit at the maximum transmit power. We can also find that the SINR of the normalized

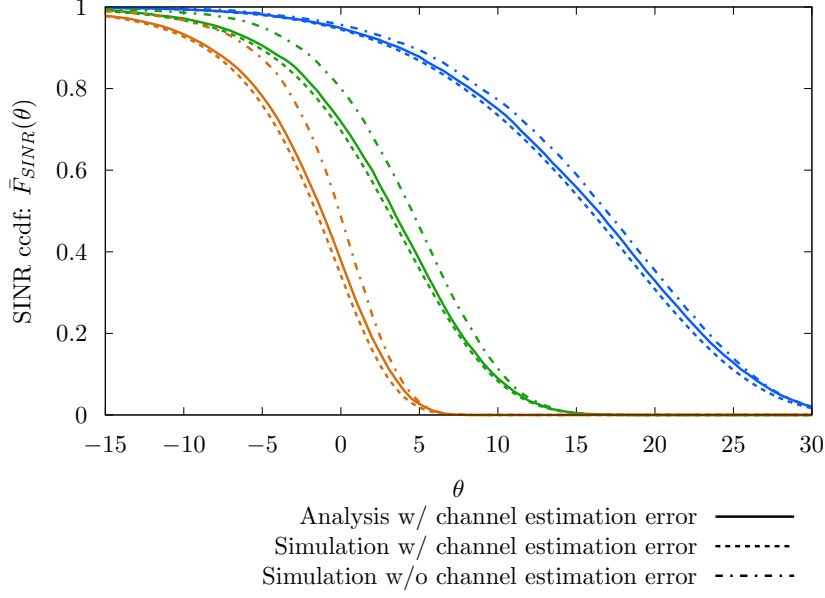


Figure 5.6: SINR cdfs $\bar{F}_{SINR}(\theta)$ obtained through a theoretical analysis and that of simulations under the imperfect CSI assumption for $\lambda_{BS} = 20$ BSs/km² (orange, green, and blue lines correspond to $\rho_o = -90, -70, -50$, respectively.) ©2019 IEEE

SNR-based scheduling is superior to that of the random scheduling. In addition, we can see that the SINR with edge users is inferior to that without edge users, particularly when ρ_o is large (i.e., the fraction of edge users $g_1(\lambda_{BS}, R_d)$ is large).

Fig. 5.8 shows the SINR cdfs as a function of the fractional power control factor ϵ . We can also find the multi-user diversity gain. Note that the value of the fraction of edge users $g_1(\lambda_{BS}, R_d)$ varies depending on the value of ϵ (i.e., $g_1(\lambda_{BS}, R_d) = 0, 0, 0, 4.7 \times 10^{-5}, 0.76$ for $\epsilon = 0, 0.25, 0.5, 0.75, 1$, respectively). We can see that the SINR cdf for $\epsilon = 1$ exhibits a special behavior as compared to the other cdfs. This result will contribute to determining the appropriate ϵ based on the system requirements.

5.5.4 Scheduling Gain Analysis

In this section, the theoretical scheduling gain $G(\lambda_{BS}, \lambda_{UE})$ is evaluated to investigate concrete numerical values and to review an example of how the

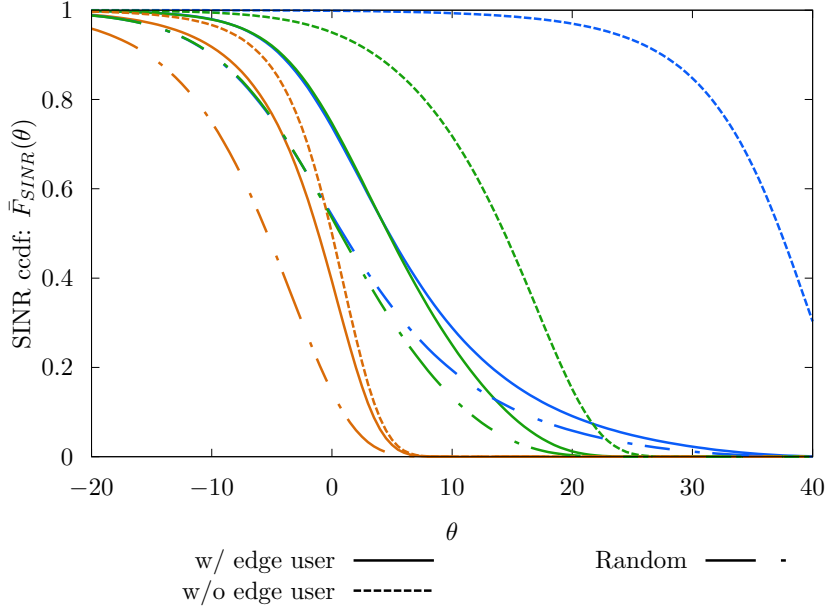


Figure 5.7: SINR cdfs when outage users are allowed and are not allowed to transmit (orange, green, and blue lines correspond to $\rho_o = -90, -70, -50$, respectively.) ©2019 IEEE

gain changes with parameters.

Fig. 5.9 shows the scheduling gains $G(\lambda_{BS}, \lambda_{UE})$ as the number of users per BS varies. Each figure shows that the scheduling gain grows along with the number of users per BS, which explains the multi-user diversity. We can see that as the value of ρ_o , which represents the required signal power for $\epsilon = 1$, decreases, the scheduling gain increases. Note that the function $\log x$ increases more sharply for a smaller argument. Therefore, a user with a low SNR tends to obtain more scheduling gain than a user with a high SNR.

Fig. 5.9(b) shows the scheduling gains when edge users are allowed to transmit at the maximum transmit power. Compared to Fig. 5.9(a) (i.e., a case in which edge users are not allowed to transmit), in this figure we can see that the scheduling gain increases for any ρ_o and λ_{BS} . This is because of the increase in the number of candidate users and in the number of users with low required signal powers. Note that when the edge users are not allowed to transmit, these users do not contribute to the scheduling gain

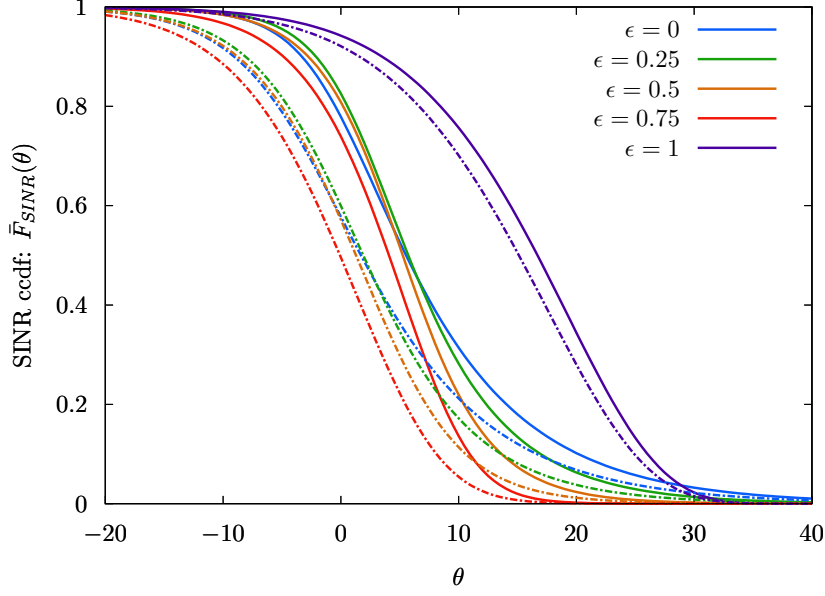


Figure 5.8: SINR cdfs when changing the value of ϵ (i.e., channel inversion is partially achieved) with $\sigma^2 = 0$ mW. The dashed lines represent the corresponding curves under random scheduling. ©2019 IEEE

because they are not considered to be scheduled and the derived data rate is the average data rate of the scheduled users.

Fig. 5.9(c) shows the scheduling gains for different values of ϵ . We can see that the scheduling gain varies depending on the value of ϵ . Therefore, we should consider the effect of the scheduling gain, in addition to the traditional consideration found in studies such as [13].

In all cases, we can also observe a performance gap between the random scheduling and the normalized SNR-based scheduling. It can be concluded that the analytical results derived from this study successfully capture the multi-user diversity.

5.6 Conclusion

This study presented a new framework for analyzing the SINR distribution of a typical scheduled user in an uplink cellular network. In particular, the SINR distribution with a normalized SNR-based scheduler was obtained

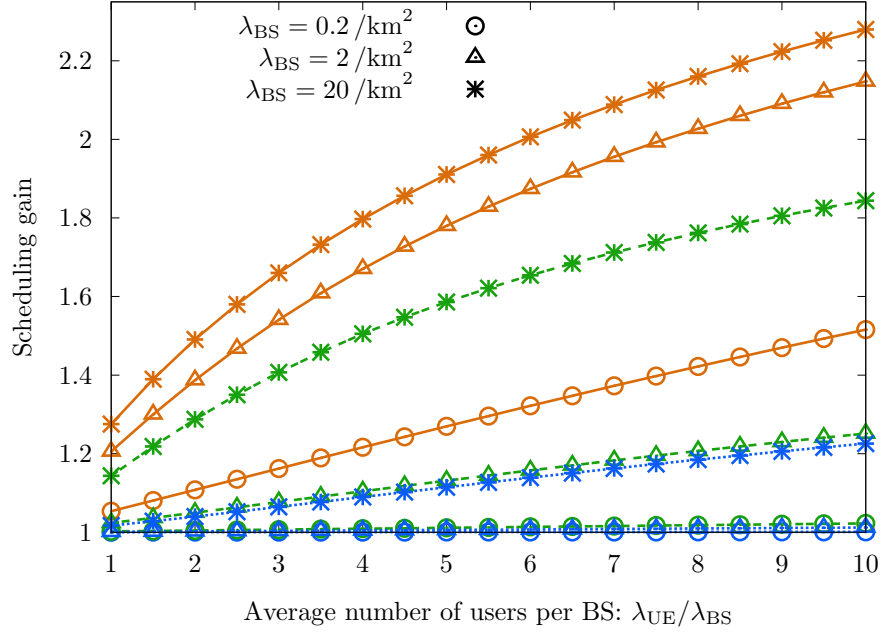
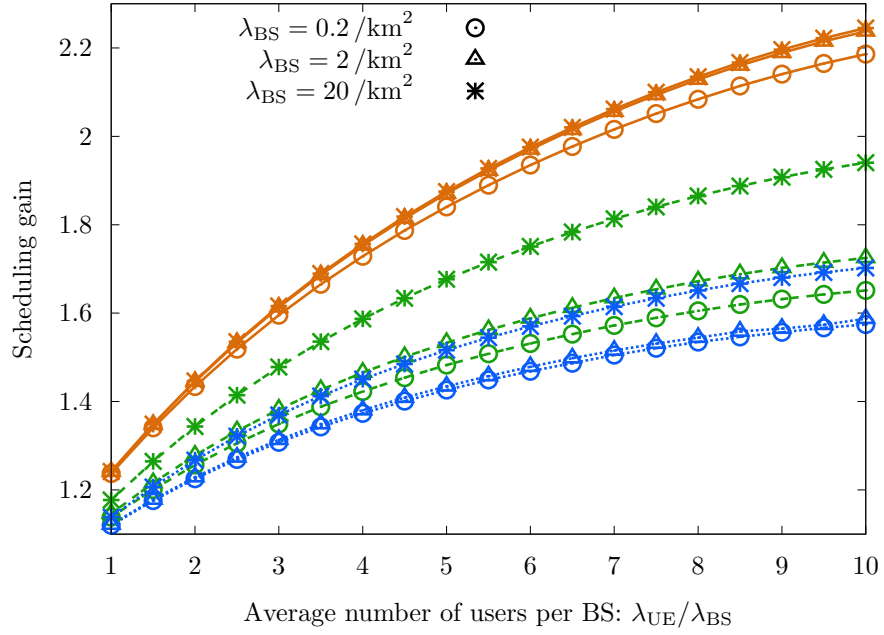
(a) $\epsilon = 1$, w/o edge user.(b) $\epsilon = 1$, w/ edge user.

Figure 5.9: Scheduling gain analyses (orange, green, and blue lines correspond to $\rho = -90^\circ, -70^\circ, -50^\circ$, respectively.) ©2019 IEEE

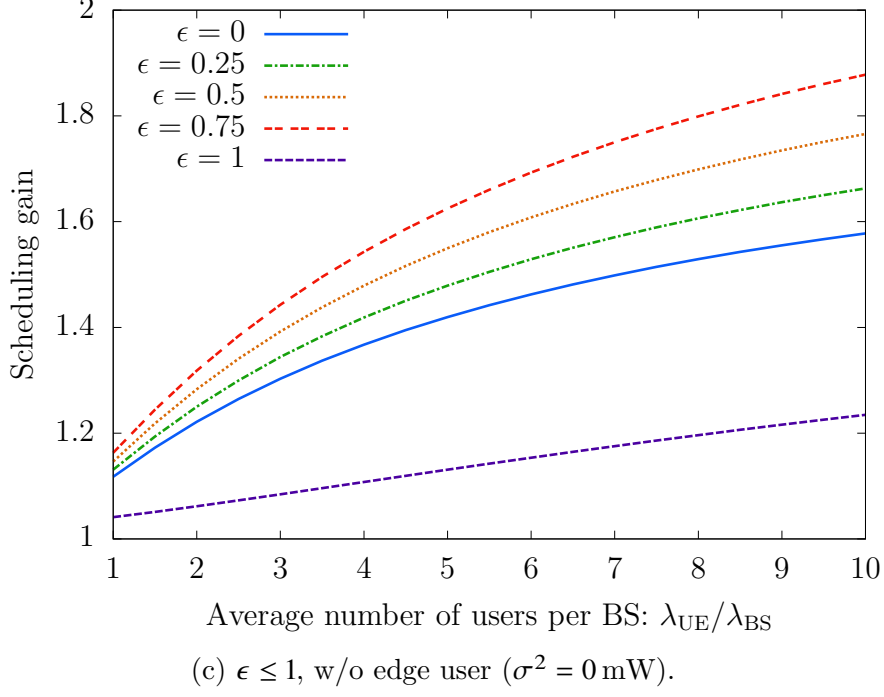


Figure 5.9: Scheduling gain analyses. ©2019 IEEE

using stochastic geometry. One of the main observations was that the multi-user diversity gain depends on the number of candidate users. Therefore, this study provided the averaged SINR distribution by considering the conditional SINR distribution given the number of candidate users and the number distribution of the candidate users in order. The number of candidate users in a typical cell was obtained in a general form by modeling the area of the existing range of candidate users with a beta distribution. The analytical SINR ccdfs were in good agreement with the simulation results regardless of the TPC policy.

Appendix 5.A Rest of Proof of Lemma 5.1

Considering that the scheduled users constitute a homogeneous PPP with intensity $(1 - f_n(0))\lambda_{BS}$, and that their transmit powers are independent random values, we obtain

$$\mathcal{L}_I(s) = \mathbb{E}[e^{-sI}]$$

$$\begin{aligned}
 &= \mathbb{E}_{\Phi_{\text{su}}, \{g_u\}, \{p_u\}} \left[e^{-s \sum_{u \in \Phi_{\text{su}} \setminus \{u_o\}} p_u g_u \|u\|^{-\eta}} \right] \\
 &= \mathbb{E}_{\Phi_{\text{su}}, \{g_u\}, \{p_u\}} \left[\prod_{u \in \Phi_{\text{su}}} e^{-s 1_{\{\|u\| > r\}} p_u g_u \|u\|^{-\eta}} \right] \\
 &= \mathbb{E}_{\Phi_{\text{su}}} \left[\prod_{u \in \Phi_{\text{su}}} \mathbb{E}_{g,p} \left[e^{-s 1_{\{\|u\| > r\}} p g \|u\|^{-\eta}} \right] \right] \tag{5.41}
 \end{aligned}$$

$$\begin{aligned}
 &\stackrel{(a)}{=} \exp \left(-c \int_0^\infty \mathbb{E}_p \left[1 - \mathbb{E}_g \left[e^{-s 1_{\{x > r\}} p g x^{-\eta}} \right] \right] x \, dx \right) \\
 &= \exp \left(-c \cdot \mathbb{E}_p \left[\int_r^\infty \left(1 - \mathbb{E}_g \left[e^{-s p g x^{-\eta}} \right] \right) x \, dx \right] \right) \\
 &= \exp \left(-c \cdot \mathbb{E}_p \left[\int_r^\infty \left(1 - \frac{1}{1 + s p x^{-\eta}} \right) x \, dx \right] \right) \\
 &= \exp \left(-\frac{c s r^{2-\eta}}{\eta - 2} \mathbb{E}_p \left[p {}_2F_1 \left(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -s p r^{-\eta} \right) \right] \right), \tag{5.42}
 \end{aligned}$$

where $c := 2\pi(1 - f_n(0))\lambda_{\text{BS}}$, and (a) follows from the probability generation functional of PPP [8]. Substituting $s = k\theta/r^{\eta(\epsilon-1)}\rho_o$ into $\mathcal{L}_I(s)$, we obtain the result of the lemma.

Appendix 5.B Proof of Corollary 5.1

Substituting $\epsilon = 1$ into (5.11) yields

$$\mathbb{P}(\text{SINR} > \theta \mid n) = \sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[e^{-\frac{k\theta\sigma^2}{\rho_o}} \mathcal{L}_I \left(\frac{k\theta}{\rho_o} \right) \right]. \tag{5.43}$$

Note that $\mathcal{L}_I(s)$ depends on r , which is found in (5.41). Notice that we can remove u_o from the summation by $1_{\{p_u \|u\|^{-\eta} < \rho_o\}}$ or equivalently $1_{\{\|u\| > (p_u/\rho_o)^{1/\eta}\}}$ instead of $1_{\{\|u\| > r\}}$. Then, we can obtain the Laplace transform of I , which is independent of r :

$$\begin{aligned}
 \mathcal{L}_I(s) &= \mathbb{E}_{\Phi_{\text{su}}, \{g_u\}, \{p_u\}} \left[\prod_{u \in \Phi_{\text{su}}} e^{-s 1_{\{\|u\| > (p_u/\rho_o)^{1/\eta}\}} p_u g_u \|u\|^{-\eta}} \right] \\
 &= \mathbb{E}_{\Phi_{\text{su}}} \left[\prod_{u \in \Phi_{\text{su}}} \mathbb{E}_{g,p} \left[e^{-s 1_{\{\|u\| > (p/\rho_o)^{1/\eta}\}} p g \|u\|^{-\eta}} \right] \right]
 \end{aligned}$$

$$\begin{aligned}
&= \exp \left(-c \cdot \mathbb{E}_p \left[\int_{(p/\rho_o)^{1/\eta}}^{\infty} \left(1 - \frac{1}{1 + spx^{-\eta}} \right) x \, dx \right] \right) \\
&\stackrel{(a)}{=} \exp \left(-cs^{2/\eta} \mathbb{E}_p [p^{2/\eta}] \int_{(sp_o)^{-1/\eta}}^{\infty} \frac{y}{y^\eta + 1} \, dy \right). \tag{5.44}
\end{aligned}$$

Here (a) is followed by $y = x/(sp)^{1/\eta}$. Such an approach can be found in [14]. In addition, $\mathbb{E}_p[p^{2/\eta}]$ was obtained in [14] as:

$$\mathbb{E}_p[p^{2/\eta}] = \frac{\rho_o^{2/\eta} \gamma \left(2, \pi \lambda_{BS} R_d^2 \right)}{\pi \lambda_{BS} \left(1 - e^{-\pi \lambda_{BS} R_d^2} \right)}, \tag{5.45}$$

which is averaged over the distribution of the transmit power (5.7) with $\epsilon = 1$. Substituting $s = k\theta/\rho_o$ into (5.44) yields

$$\begin{aligned}
\mathcal{L}_I \left(\frac{k\theta}{\rho_o} \right) &= \exp \left(- \frac{2(k\theta)^{2/\eta} \gamma \left(2, \pi \lambda_{BS} R_d^2 \right) \int_{(k\theta)^{-1/\eta}}^{\infty} \frac{y}{y^\eta + 1} \, dy}{\left(1 - e^{-\pi \lambda_{BS} R_d^2} \right) / (1 - f_n(0))} \right) \\
&= \exp \left(- \frac{2k\theta \gamma \left(2, \pi \lambda_{BS} R_d^2 \right) {}_2F_1 \left(1, 1 - \frac{2}{\eta}; 2 - \frac{2}{\eta}; -k\theta \right)}{(\eta - 2) \left(1 - e^{-\pi \lambda_{BS} R_d^2} \right) / (1 - f_n(0))} \right). \tag{5.46}
\end{aligned}$$

Finally, substituting (5.46) into (5.43) and averaging with respect to r yield (5.13).

Appendix 5.C Proof of Corollary 5.4

We have

$$\begin{aligned}
\tau_s(\lambda_{BS}, \lambda_{UE}) &= \int_0^\infty \mathbb{P}(\ln(1 + SINR) > t) \, dt \\
&= \int_0^\infty \mathbb{P}(SINR > e^t - 1) \, dt = \int_0^\infty \bar{F}_{SINR}(e^t - 1) \, dt \\
&= \int_0^\infty \frac{\bar{F}_{SINR}(x)}{x + 1} \, dx \\
&= \mathbb{E}_{n>0} \left[\sum_{k=1}^n \binom{n}{k} (-1)^{k+1} \mathbb{E}_r \left[\int_0^\infty \frac{e^{-\frac{kx\sigma^2}{\rho_o r^\eta(\epsilon-1)}}}{x + 1} \mathcal{L}_I \left(\frac{kx}{\rho_o r^\eta(\epsilon-1)} \right) \, dx \right] \right]. \tag{5.47}
\end{aligned}$$

The simplification is given by considering (5.14).

Chapter 6

Conclusions

This thesis presented the modeling and analysis of resource allocation in wireless communication. This thesis discuss this subject with two topic, decentralized resource allocation in WLANs and uplink channel-adaptive user scheduling. Chapters 3, 4, and 5 are devoted to the TPC in WLANs, the decentralized channel selection in WLANs, and the analysis of uplink channel-adaptive user scheduling, respectively.

In Chapter 3, this thesis proposed the TPC scheme that mitigates the spatial overlap among the coverage domains of APs by limiting the transmission power levels of the APs. The features of the proposed TPC scheme are summarized in two points. First, STAs and/or APs are used as sensors that inform each AP about whether or not they exist within the cell of the AP. Second, the connectivity maintenance is guaranteed by keeping transmission power levels of the APs belonging to the network's outer boundary at their maximum levels. Simulation results showed that the proposed TPC reduced total overlap area, that the area coverage hole decreases along with the number of sensors, and that the proposed boundary restriction is effective for reducing the area coverage hole. Through this work, this thesis revealed a trade-off between coverage overlap and area coverage hole, i.e., the boundary restriction reduces the area coverage hole by also increasing the overlap area.

In Chapter 4, this thesis proposed two decentralized channel assignment schemes based on in-plane overlap areas; the naive overlap-based scheme

and the decomposed overlap-based scheme. The common idea is that each AP has its payoff function based on in-plane overlap areas and is assumed to act selfishly, i.e., the system considered is modeled by a non-cooperative game. Both channel assignment schemes were formulated as potential games, so that unilateral improvement dynamics are guaranteed to converge to a Nash equilibrium. In addition, this thesis analytically proved that the system-wide overlap area is upper bounded by the negative potential functions, and showed that if the overlap areas among more than two cells are sufficiently small, local overlap reduction based on the decentralized channel assignment leads to system-wide overlap reduction. The decomposed overlap-based scheme is superior to the naive overlap-based scheme in terms of the ease of calculating payoff functions; while, the first one is inferior to the latter one in terms of the performance for overlap mitigation. Although, the performance gap between two schemes is negligible using the TPC in Chapter 3. Experimental results demonstrated that the decomposed-overlap based assignment converges in a real environment even if there are some uncontrollable APs.

In Chapter 5, this thesis presented a new framework for analyzing the SINR distribution of a typical scheduled user in an uplink cellular network. In particular, the SINR distribution with a normalized SNR-based scheduler was obtained using stochastic geometry. Since the multi-user diversity gain depends on the number of candidate users, this study provided the averaged SINR distribution by considering the conditional SINR distribution given the number of candidate users and the number distribution of the candidate users in order. Numerical evaluations showed that the analytical results were in good agreement with the simulation results and highlighted the gap of the SINR ccdf between random scheduling and normalized SNR-based scheduling. It was observed that the resulting scheduling gain varies depending on the TPC policy and the number of accommodated users in each cell. In this sense, the given analytical framework provides a unified design method for estimating multi-user diversity for uplink cellular networks, enabling a performance evaluation that avoids underestimation that occurs when channel-adaptive user scheduling is not considered.

Finally, I would like to conclude this thesis. These studies are elemental

technologies, and there are other possible axes that improve current communication systems. Nevertheless, they are undoubtedly important factors, and will have a potential that continues to affect future generations including beyond IEEE 802.11be and 5G. Transmission power control and channel assignment in WLANs are still important regardless of generation because they are fundamental solution for problem of few transmission opportunities. The trend of growing hotspots is the evidence of importance. Also, recent diversified developments of wireless communications require general understanding of performances in wireless communications because it is difficult to evaluate all possibilities by simulations or experiments. The analytical results including the SINR performance in uplink cellular networks will be a building block for the guidelines of the cellular design. Based on these viewpoints, I believe that these studies will accelerate future wireless communication developments.

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Publication List

Journal Papers

1. S. Kamiya, K. Nagashima, K. Yamamoto, T. Nishio, M. Morikura, and T. Sugihara, “Self-organization of coverage of densely deployed WLANs considering outermost APs without generating coverage holes,” *IEICE Trans. Commun.*, vol.E99-B, no.9, pp.1980–1988, Sep. 2016.
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5. W. Deng, S. Kamiya, K. Yamamoto, T. Nishio, and M. Morikura, “Thompson sampling-based channel selection through density estimation aided by stochastic geometry,” accepted for *IEEE Access*.
6. K. Nakashima, S. Kamiya, K. Ohtsu, K. Yamamoto, T. Nishio, and M. Morikura, “Deep reinforcement learning-based channel allocation

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International Conference Papers

1. S. Kamiya, K. Nagashima, K. Yamamoto, T. Nishio, M. Morikura, and T. Sugihara, “Joint range adjustment and channel assignment for overlap mitigation in dense WLANs,” in *Proc. IEEE Int. Symp. Personal, Indoor and Mobile Radio Commun. (PIMRC)*, pp.2164–2169, Hong Kong, Sep. 2015.
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Technical Reports and Local Conference Papers

1. S. Kamiya, K. Nagashima, K. Yamamoto, T. Nishio, M. Morikura, and T. Sugihara, “Transmission power control for overlap mitigation in densely deployed WLANs,” in *Proc. IEICE Society Conf.*, B-5-100, Sendai, Japan, Sep. 10, 2015 (in Japanese).
2. K. Nagashima, S. Kamiya, K. Yamamoto, T. Nishio, M. Morikura, and T. Sugihara, “Proposal of transmission power control focusing on coverage boundary,” in *Proc. IEICE Society Conf.*, B-5-99, Sendai, Japan, Sep. 10, 2015 (in Japanese).

3. S. Kamiya, K. Nagashima, K. Yamamoto, T. Nishio, M. Morikura, and T. Sugihara, "Potential game analysis of wireless resource allocation for overlap mitigation in WLANs," *IEICE Technical Report*, RCS2015-270, pp.157–162, Dec. 2015 (in Japanese).
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13. S. Kamiya, K. Yamamoto, T. Nishio, and M. Morikura, “Stochastic geometry analysis of normalized-SNR based scheduling in uplink cellular networks,” in *Proc. IEICE Society Conf.*, B-11-3, Tokyo, Japan, Sep. 2017 (in Japanese).
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15. S. Kamiya, K. Yamamoto, T. Nishio, and M. Morikura, “Stochastic geometry analysis of user scheduling in uplink cellular networks under maximum transmit power constraint,” in *Proc. IEICE General Conf.*, B-5-54, Tokyo, Japan, Mar. 2018 (in Japanese).
16. S. Kamiya, K. Yamamoto, S.-L. Kim, T. Nishio, and M. Morikura, “Scheduling gain analysis of normalized SNR-based scheduling in uplink cellular networks,” in *Proc. IEICE Society Conf.*, B-5-65, Kanazawa, Japan, Sep. 2018 (in Japanese).
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19. S. Kamiya, K. Yamamoto, T. Nishio, and M. Morikura, “Stochastic geometry analysis of user scheduling with channel estimation error in uplink cellular networks,” in *Proc. IEICE Society Conf.*, B-5-5, Toyonaka, Japan, Sep. 2019 (in Japanese).

Awards

1. IEEE Wireless Communications Letter Exemplary Reviewer in 2017.
2. TELECOM System Technology Award for Students in 2017.
3. IEEE Wireless Communications Letter Exemplary Reviewer in 2019.
4. Outstanding Paper Award for Young C&C Researchers in 2019.
5. IEEE Kansai Section Student Award in 2019.