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Resource Allocation for Multiple Access and Broadcast Channels under Quality of Service Requirements Based on Strategy Proof Pricing

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Zusammenfassung

Aufgrund der hohen Nachfrage nach Datenrate und wegen der Knappheit an Ressourcen in Funknetzen ist die effiziente Allokation von Leistung ein wichtiges Thema in den heutigen Mehrnutzer-Kommunikationssystemen. Die Spieltheorie bietet Methoden, um egoistische und soziale Konfliktsituationen zu analysieren.

Das vorgeschlagene System befasst sich mit der Erfüllung der auf Signal-zu-Rausch-und-Interferenz-Verhältnis (SINR) basierenden Quality-of-Service (QoS)-Anforderungen aller Nutzer mittels effizienter Leistungsallokation, anstatt die Übertragungsrate zu maximieren. Es wird ein Framework entworfen, um die Leistungsallokation mittels universellen Pricing-Mechanismen umzusetzen. In der Dissertation werden zentralisierte und verteilte Leistungsallokationsalgorithmen unter Verwendung verschiedener Pricing-Ansätze diskutiert.

Die Nutzer in Funksystemen handeln rational im spieltheoretischen Sinne, indem sie ihre eigenen Nutzenfunktionen maximieren. Die mobilen Endgeräte, die dasselbe Spektrum nutzen, haben den Anreiz durch bewusste Fehlinterpretation ihrer privaten Informationen das eigene Ergebnis zu verbessern. Daher ist es wichtig, die Funktionalität des Systems zu überwachen und durch Optimierung des Pricings und Priorisierungsgewichte zu beeinflussen.

Für den zentralisierten Ressourcenallokationsansatz werden der allgemeine Mehrfachzugriffskanal (Multiple Access Channel, MAC) und der Broadcastkanal (BC) mit linearen bzw. nichtlinearen Empfängern untersucht. Die Preise, die resultierenden Kostenterme und die optimale Leistungsallokation, mit der die QoS-Anforderungen in der zulässigen Ratenregion erfüllt werden, werden in geschlossener Form hergeleitet. Lineare und nichtlineare Pricing-Ansätze werden separat diskutiert. Das unendlich oft wiederholte Spiel wird vorgeschlagen, um Spieler vom Betrügen durch Übermittlung falscher Kanalinformationen abzuhalten.

Für die verteilten Ressourcenvergabe wird das nichtkooperative Spiel in Normalform verwendet und formuliert. Die Nutzer wählen ihre Sendeleistung zur Maximierung ihrer eigenen Nutzenfunktion. Individuelle Preise werden eingeführt und so angepasst, dass die QoS-Anforderungen mit der Leistungsallokation im eindeutigen Nash-Gleichgewicht erfüllt werden. Verschiedene Arten des Nutzerverhaltens werden bezüglich der Täuschung ihrer Nutzenfunktion analysiert, und ein Strategy-Proof-Mechanismus mit Strafen wird entwickelt.

Die Ergebnisse für den MAC sind anwendbar auf heterogene Netzwerke, wobei zwei neuartige Ansätze zur Kompensation bereitgestellt werden, die den hybriden Zugang zu Femtozell-Netzwerken motivieren. Mithilfe des Stackelberg-Spiels wird gezeigt, dass die vorgeschlagenen Ansätze in einer Win-Win-Situation resultieren.

Abstract

The efficient allocation of power is a major concern in today's wireless communications systems. Due to the high demand in data rate and the scarcity of wireless resources such as power, the multi-user communication systems like the multiple access channel (MAC) and broadcast channel (BC) have become highly competitive environments for the users as well as the system itself. Theory of microeconomics and game theory provide the good analytical manner for the selfish and social welfare conflict problems.

Instead of maximizing the system sum rate, our proposed system deals with fulfilling the utility (rate) requirement of all the users with efficient power allocation. The users formulate the signal to interference-plus-noise ratio (SINR) based quality-of-service (QoS) requirements. We propose the framework to allocate the power to each user with universal pricing mechanisms. The prices act as the control signal and are assumed to be some virtual currency in the wireless system. They can influence the physical layer operating points to meet the desired utility requirements. Centralized and distributed power allocation frameworks are discussed separately in the thesis with different pricing schemes.

In wireless systems we have users that are rational in the game theoretic sense of making decisions consistently in pursuit of their own individual objectives. Each user's objective is to maximize the expected value of its own payoff measured on a certain utility scale. Selfishness or self-interest is an important implication of rationality. Therefore, the mobiles which share the same spectrum have incentives to misinterpret their private information in order to obtain more utility. They might behave selfishly and show also malicious behavior by creating increased interference for other mobiles. Therefore, it is important to supervise and influence the operation of the system by pricing and priority (weights) optimization.

In the centralized resource allocation, we study the general MAC and BC (with linear and nonlinear receiver) with three types of agents: the regulator, the system optimizer and the mobile users. The regulator ensures the QoS requirements of all users by clever pricing and prevents cheating. The simple system optimizer solves a certain system utility maximization problem to allocate the power with the given prices and weights (priorities). The linear and nonlinear pricing mechanisms are analyzed, respectively. It is shown that linear pricing is a universal pricing only if successive interference cancellation (SIC) for uplink transmission or dirty paper coding (DPC) for downlink transmission is applied at the base station (BS). For MAC without SIC, nonlinear pricing which is logarithmic in power and linear in prices is a universal pricing scheme. The prices, the resulting cost terms, the optimal power allocation to achieve the QoS requirement of each user in the feasible rate region are derived in closed

form solutions for MAC with and without SIC using linear and nonlinear pricing frameworks, respectively.

The users are willing to maximize their achievable rate and minimize their cost on power by falsely reporting their channel state information (CSI). By predicting the best cheating strategy of the malicious users, the regulator is able to detect the misbehavior and punish the cheaters. The infinite repeated game (RG) is proposed as a counter mechanism with the trigger strategy using the trigger price. We show that by anticipating the total payoff of the proposed RG, the users have no incentive to cheat and therefore our framework is strategy-proof.

In the distributed resource allocation, each user allocates its own power by optimizing the individual utility function. The noncooperative game among the users is formulated. The individual prices are introduced to the utility function of each user to shift the Nash equilibrium (NE) power allocation to the desired point. We show that by implicit control of the proposed prices, the best response (BR) power allocation of each user converges rapidly. The Shannon rate-based QoS requirement of each user is achieved with minimum power at the unique NE point. We analyse different behavior types of the users, especially the malicious behavior of misrepresenting the user utility function. The resulting NE power allocation and achievable rates of all users are derived when malicious behavior exists. The strategy-proof mechanism is designed using the punishment prices when the types of the malicious users are detected. The algorithm of the strategy-proof noncooperative game is proposed. We illustrate the convergence of the BR dynamic and the Price of Malice (PoM) by numerical simulations.

The uplink transmission within the single cell of heterogeneous networks is exactly the same model as MAC. Therefore, the results of the pricing-based power allocation for MAC can be implemented into heterogeneous networks. Femtocells deployed in the Macrocell network provide better indoor coverage to the user equipments (UEs) with low power consumption and maintenance cost. The industrial vendors show great interest in the access mode, called the hybrid access, in which the macrocell UEs (MUEs) can be served by the nearby Femtocell Access Point (FAP). By adopting hybrid access in the femtocell, the system energy efficiency is improved due to the short distance between the FAP and MUEs while at the same time, the QoS requirements are better guaranteed. However, both the Macrocell base station (MBS) and the FAP are rational and selfish, who maximize their own utilities. The framework to successively apply the hybrid access in femtocell and fulfill the QoS requirement of each UE is important.

We propose two novel compensation frameworks to motivate the hybrid access of femtocells. To save the energy consumption, the MBS is willing to motivate the FAP for hybrid access with compensation. The Stackelberg game is formulated where the MBS serves as the leader and the FAP serves as the follower. The MBS maximizes its utility by choosing the compensation prices. The FAP optimizes its utility by selecting the number of MUEs in hybrid access. By choosing the proper compensation price, the optimal number of MUEs served by the FAP to maximize the utility of the MBS coincides with that to maximize the utility of the

FAP. Numerous simulation results are conducted, showing that the proposed compensation frameworks result in a win-win solution.

In this thesis, based on game theory, mechanism design and pricing framework, efficient power allocation are proposed to guarantee the QoS requirements of all users in the wireless networks. The results are applicable in the multi-user systems such as heterogeneous networks. Both centralized and distributed allocation schemes are analyzed which are suitable for different communication scenarios.

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Nomenclature

List of Notations

$\boldsymbol{a}$	Vectors are denoted by boldface lowercase letters
$\boldsymbol{A}$	Matrices are denoted by boldface capital letters
$\mathcal{F}$	Sets are denoted by calligraphic font
$(\cdot)^T$	Transpose
$\boldsymbol{I}$	Identity matrix
$\lfloor \cdot \rceil$	Round function
$\mathbb{C}$	Complex number set
$\mathbb{N}$	Natural number set
N_0	One-side power spectral density of noise
$\mathbb{R}$	Real number set
$\mathbb{R}^+$	Nonnegative real number set
$\mathbb{Z}$	Integer number set
$*$	Convolution operation
p_i	Power allocation of user i for MAC
p_{-i}	Transmit power of all other users except user i
α_i	Channel state information of user i
r_i	Achievable rate of user i
$\underline{u}_i$	QoS requirement of user i
u_i	Utility function of user i
w_i	Weighting factor of user i
β_i	Price of power for user i
$\mathcal{G}(\mathcal{K}, \mathcal{S}, \mathcal{U})$	Game in normal form
$u(\boldsymbol{p}, \boldsymbol{w})$	Utility of weighted sum SINR
$\tilde{u}(\boldsymbol{p}, \boldsymbol{w}, \boldsymbol{\beta})$	System utility function for centralized power allocation
p_i^{maax}	Single user power constraint
β_i^M	Punishment price for malicious users
p_i^{BR}	Best response power allocation of user i
p_i^{NE}	Nash equilibrium power allocation of user i
π	SIC decoding order
q_i	Power allocation of user i for BC
κ	Compensation price
$\hat{\alpha}_i$	Reported channel state information of user i

$\hat{u}_i$	Short-term user utility of user i
$\bar{u}_i$	Long-term user utility of user i in the repeated game
β_i^{tr}	Trigger pricing parameter
V_i	Private type of user behavior
U_M	Utility of the macrocell base station
U_F	Utility of the femtocell access point
c_K	Compensation function
δ_i	Discount factor in discounting repeated game
λ	Load factor, $\lambda > 1$
η	Equivalent revenue per unit of energy saving
K_F^*	Optimal number of accepted MUEs in the hybrid access
$\hat{K}_F^*$	Approximation of optimal number of accepted MUEs in the hybrid access

List of Symbols

MAC	Multiple access channel
BC	Broadcast channel
QoS	Quality of service
BS	Base station
SIC	Successive interference cancelation
IC	Interference cancelation
CSI	Channel state information
SINR	Signal to interference plus noise ratio
DPC	Dirty paper coding
TDMA	Time-division multiple-access
CDMA	Code-division multiple-access
FDMA	Frequency-division multiple-access
SDMA	Space-division multiple-access
BR	Best response
BRD	Best response dynamic
NE	Nash equilibrium
RG	Repeated game
SMP	System maximization problem
FAP	Femtocell access point
MBS	Macrocell base station
UE	User equipment
MUE	Macrocell user equipment
FUE	Femrocell user equipment
UMP	Utility maximization problem
AWGN	Additive white Gaussian noise
EE	Energy efficicy
PoM	Price of Malice
MMSE	Minimum mean square error
RAN	Radio access networks
CQI	Channel quality indicator
DoF	Degrees of Freedom
MIMO	Multiple input multiple output

Contents

1 Introduction

1.1 Motivation

Wireless communication has undergone significant development over the past years, e.g. by the introduction of new physical layer technologies, marketing of new application layer services and entry of players who were not traditionally considered an operator participating in the market. To tame such an ever-changing market of wireless systems, it is pivotal to ensure that wireless resources are allocated in a socially optimal manner.

Research results show that nowadays about 0.2% of the global CO_2 emissions are due to mobile telecommunication networks, and this percentage is expected to increase. The fundamental concern of radio resource management is the physical layer transmit power allocation. In a wireless system, each user's objective may be maximizing the expected value of its own payoff measured on a certain utility scale, while the system regulator aims at minimizing the system total resource consumption. This makes the users and the system regulator conflicting entities. Game theory is suitable for analyzing this kind of problems. Each user is endowed with intelligence in a game theoretic sense of knowing the rules about the underlying game.

Since the self-interested users act selfishly, the outcome of the game may not be the best operating point. How to allocate communications resource fairly and more efficiently in order to not only minimize the energy consumption of the whole system, but also achieve the quality-of-service (QoS) requirement of each user is the main issue discussed in this thesis. The signal-to-interference plus noise ratio (SINR) based Shannon rate is set to be the criterion of the QoS requirement.

Today's wireless communications and networking practices are tightly coupled with economic considerations [1]. In particular, pricing on the system resources such as power is a useful tool to lead the resource allocation result to the socially optimal point. The prices are assumed to be some virtual currency in the wireless system and can influence the physical layer operating points to meet the desired utility requirements. However, the mobiles which share the same spectrum have incentives to misinterpret their private information in order to obtain more utility. They might behave selfishly and show also malicious behavior by creating increased interference to other mobiles. A pricing mechanism is said to be strategy-proof if with properly designed pricing, the user behavior is guided to a more robust and efficient point. Pricing is typically motivated because it is beneficial to the wireless system regulator and it encourages better resource allocation and more reliable user behavior. Comparing with the real monetary charges on the higher layer, pricing on the physical layer refers more to the control signal [2].

We basically distinguish two models for the user-centric resource allocation of the multi-user wireless systems.

- The first model deploys a central controller which supervises and influences the operation of the system by pricing and priority (weights) optimization. The central controller is referred to as the regulator. The regulator acquires all necessary information of the whole system. It is responsible of detecting and preventing the user misbehavior.
- The second model allocates the power based on the distributed manner. The noncooperative game is played among the multiple users. Each user allocates its own power by maximizing its utility function. The individual prices are introduced into the user utility function to motivate a more efficient distributed resource allocation and better user behavior.

The multiple access channel (MAC) is a typical multi-user transmission system. Due to the uplink-downlink duality, the broadcast channel (BC) is also considered. Firstly, the MAC instantiating in different scenarios is investigated. In the traditional setting, multiple transmitters send at the same time and frequency to one base station (BS). The BS is interested in all data and applies the optimal receive strategy, e.g., the minimum mean square error (MMSE) estimator receiver plus successive interference cancellation (SIC) [3]. Another case occurs in the passive infrastructure sharing if one BS is shared by several operators with different radio access networks (RANs). In this case, we assume that SIC is not applied and complete interference from all other mobile stations is present in the single user decoder. In order to guarantee the QoS requirements of all the users in the wireless system, linear and nonlinear pricing mechanisms are investigated, respectively. Different types of user behavior are analyzed in detail. A variety of games are proposed to prevent user misbehavior with the carefully tailored prices. We show that by clever pricing, the users in the system have no incentive to cheat and therefore our framework is strategy-proof.

With the explosion of 4G, the indoor wireless data traffic is increasing rapidly. Many mobile operators have launched femtocell service, including Vodafone, SFR, AT&T, Sprint Nextel, Verizon and Mobile TeleSystems. The Femtocell Access Points (FAPs), also known as home BSs, are small and low power devices to provide high-quality indoor coverage. These FAPs are connected to the operators' macrocell networks via backhaul DSL, optical fibre or other connections [4]. By adopting femtocells, the expensive spectrum is better utilized. Different from other wireless access equipments, the macrocell BS (MBS) is able to get all the information about the femtocells inside its range by the backhaul connection. The MBS is responsible to allocate the wireless resource in the femtocell in order to manage the interference between the femto and macrocells.

Within the single cell of macrocell or femtocell, the uplink transmission is exactly the same model as MAC. In order to ensure the rate requirement of each user equipment (UE), the power allocation analyzed in MAC can be implemented in the setting of heterogeneous networks. Currently, there are three access control mechanisms: open access, closed access [5] and hybrid access. From an energy aware point of view, by selecting the nearby macrocell UEs (MUEs) under the range of service of the femtocell, hybrid access shows the most potential and is of high interest to the industry operators.

The MBS and the FAPs are considered to be simple and selfish devices, who maximize their own interest. In order to gain in the energy saving of the whole two-tier macro-femtocell system, the MBS is willing to compensate the FAP for accepting some nearby MUEs. Pricing is introduced in the compensation function to motivate the hybrid access. The MBS can indirectly control the two-tier system by adapting the compensation prices in the compensation function.

1.2 Multiple Access and Broadcast Channel

The thesis mainly discusses the user-centric resource allocation in the general multiple access and broadcast channels under the QoS requirement of each user. In this section, the mathematical model of the multiple access and broadcast channels are described.

1.2.1 Multiple Access Channel

The uplink transmission with multiple transmitters and single receiver is referred to as MAC. A common example of MAC is a couple of mobiles communicating with a BS. The general MAC with K transmitters is depicted in Fig. 1.1. The K transmitters wish to communicate to the BS over the common channel. They send signal $x_i, i \in 1, \cdots, K$ to the BS simultaneously. Both the transmitters and the receiver BS are equipped with single antenna. The transmission power of the transmitter i is p_i with single user power constraint p_{max}, i,e., $0 < p_i \leq p_{max}$. The transmitters in the MAC compete not only with the received noise, but also the interference from each other [6].

The quasi-static block flat-fading channels are statistically independent of each other and remain constant for a sufficient long time period. The channel coefficient from the transmitter i to the BS is denoted as h_i.

The received complex signal in the equivalent base-band representation for the BS in MAC is given by

$$y = \sum_{i=1}^{K} h_i x_i + n, \tag{1.1}$$

where $n \sim \mathcal{CN}(0, \sigma_n^2)$ is the additive white Gaussian noise (AWGN) with zero-mean and variance of σ^2. The channel gain from the transmitter i to the BS is $\alpha_i = |h_i|^2$. All x_i and n are statistically independent. The data signal x_i is created by a Gaussian codebook with zero-mean and variance $p_i \geq 0$.

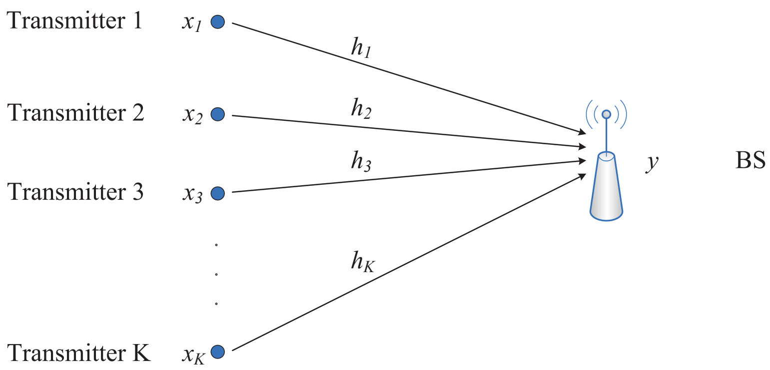

Figure 1.1: General multiple access channel

Let $S \subseteq \{1, 2, \ldots, K\}$. Let S^c denote the complement of S. Denote $R(S) = \sum_{i \in S} R_i$ and $x(S) = \{x_i : i \in S\}$. Then the capacity region of the K-user MAC is derived as follows [6].

1.1 Definition. The capacity region of the K-user MAC is the closure of the convex hull of the rate vectors satisfying

$$R(S) \leq I(x(S); y \mid x(S^c)) \qquad \text{for all} \qquad S \subseteq \{1, 2, \ldots, K\}. \tag{1.2}$$

The BS receives the superposition of all signals from the K transmitters. If the BS treats the interference from all the other transmitters as noise, then the achievable rate r_i of transmitter i at the BS without successive interference cancelation[1] (SIC) is

$$\begin{aligned} r_i &= I(x_i; y) \\ &= \log\left(1 + \frac{\alpha_i p_i}{1 + \sum_{k \neq i} \alpha_k p_k}\right), \end{aligned} \tag{1.3}$$

where the noise power is normalized to be 1.

1.2 Definition. *Successive Interference Cancelation (SIC)* decodes the signals in an arbitrary order and subtracts the re-encoded signal, which effectively increases the SINR. It is iteratively repeated for K transmitters.

[1] SIC is explained in Sec. 1.2.3

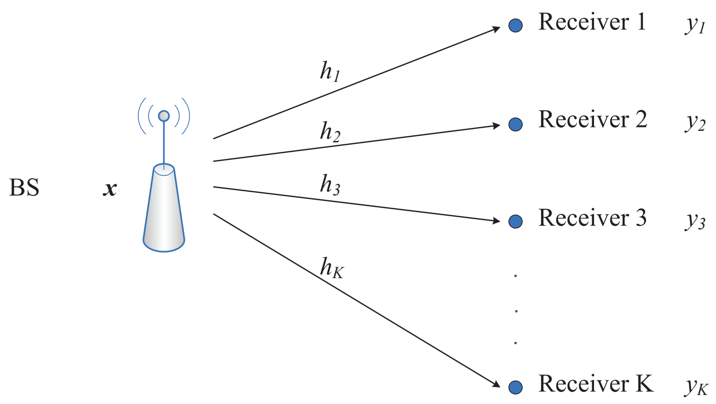

Figure 1.2: General broadcast channel

1.2.2 Broadcast Channel

If there are single input and multiple outputs for the channel, it is referred to as the BC. Typically, the mathematical model of the BC is to describe the simultaneous communication of information from single source to several receivers [6].

Fig. 1.2.2 shows the standard representation of the BC. The received complex signal in the equivalent base-band representation at each receiver i for BC is

$$y_i = h_i \sum_{k=1}^{K} x_i + n. \tag{1.4}$$

If there is no dirty paper coding[2] (DPC), the achievable rate r_i achieved at the receiver i is

$$\begin{aligned} r_i &= I(x; y_i) \\ &= \log\left(1 + \frac{\alpha_i p_i}{1 + \alpha_i \sum_{k \neq i} p_k}\right). \end{aligned} \tag{1.5}$$

[2]DPC will be discussed in Sec. 1.2.3.

1.2.3 Successive Interference Cancelation and Dirty Paper Coding

The growing need for QoS enhancements along with the dense user deployment in the wireless systems contradict mainly to capacity limitations. Interference plays a crucial role in such limitations. Interference cancelation (IC) is an interesting alternative to the interference avoidance [7]. The SIC, where the signals are decoded at the receiver successively, is first suggested in [6]. By adopting SIC, the signal of one user is removed in the following decoding process if it is already decoded. Thus, it is more efficient when comparing with conventional reception, where the interference from all the other users are treated as noise.

The achievable rate r_i of transmitter i in the general MAC when SIC is adopted with the decoding order $\pi = [K \to \cdots \to 1]$ is then

$$\begin{aligned} r_i &= I(x_i; y \mid x_1, \ldots, x_{i-1}) \\ &= \log\left(1 + \frac{\alpha_i p_i}{1 + \sum_{k<i} \alpha_k p_k}\right). \end{aligned} \tag{1.6}$$

DPC is an efficient transmission technique when some interference is known to the transmitter. It requires channel state information (CSI) of all users. As long as the full knowledge of the i.i.d interference is given to the encoder, the capacity of a channel with additive Gaussian noise and power constrained input is not affected [8]. In the downlink BC, the transmitter precodes the data in order to cancel the interference. If DPC is adopted with the precoding order π in the BC , the achievable rate r_i of receiver $i, i = [1, \ldots, K]$ is

$$r_i = \log\left(1 + \frac{\alpha_i p_i}{1 + \alpha_i \sum_{k<i} p_k}\right). \tag{1.7}$$

1.2.4 Uplink-Downlink Duality

Given a set of powers, the uplink performance of the kth user is only a function of the receive filter of user k. In the downlink, however, the SINR of each user is a function of all transmit signals of the users. Thus, the problem is seemingly more complex. However, there is in fact an uplink-downlink duality to achieve the same SINR for the users under the same sum power [9].

For the transmission with single antenna at both the transmitters and receivers, the SINR for user i of the uplink transmission with normalized noise is given by

$$SINR_i := \frac{\alpha_i p_i}{1 + \sum_{j \neq i} \alpha_j p_j}, \tag{1.8}$$

where p_i is the power allocated to user i.

Now consider the downlink channel that is naturally 'dual' to the given uplink channel. The SINR for user i of the downlink transmission with normalized noise is given by

$$SINR_i := \frac{\alpha_i p_i}{1 + \alpha_i \sum_{j \neq i} p_j}. \tag{1.9}$$

The relationship between the performance of the downlink transmission and its dual uplink is that to achieve the same SINR for the users in both links, the *total transmit power* is the same for the MAC and BC systems.

Denote $\boldsymbol{p} := [p_1, \ldots, p_K]$ as the power allocation for the uplink transmission and $\boldsymbol{q} := [q_1, \ldots, q_K]$ as the power for the dual downlink transmission, respectively. Then to achieve the same SINR, the power is solved by

$$\boldsymbol{p} = (\boldsymbol{D_a} - \boldsymbol{A}^t)^{-1} \cdot \mathbf{1}, \tag{1.10}$$

$$\boldsymbol{q} = (\boldsymbol{D_b} - \boldsymbol{A})^{-1} \cdot \mathbf{1}, \tag{1.11}$$

where $D_a := \mathrm{diag}(\frac{1}{a_1}, \ldots, \frac{1}{a_K})$, $D_b := \mathrm{diag}(\frac{1}{b_1}, \ldots, \frac{1}{b_K})$ and $\mathbf{1}$ is the column vector of all 1's. $\boldsymbol{A}$ is a $K \times K$ matrix with index of $\boldsymbol{\alpha}$, i.e.,

$$\boldsymbol{A}^t = \begin{bmatrix} \alpha_1 & \ldots & \alpha_k & \ldots & \alpha_K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \alpha_1 & \ldots & \alpha_k & \ldots & \alpha_K \end{bmatrix}. \tag{1.12}$$

Since the SINR requirement is the same for both the uplink and its dual downlink,

$$\begin{aligned} a_i &:= \frac{SINR_i}{(1 + SINR_i)\alpha_i}, \qquad b_i := \frac{SINR_i}{(1 + SINR_i)\alpha_i}, \\ \boldsymbol{a} &= \boldsymbol{b}. \end{aligned} \tag{1.13}$$

Therefore, the total transmit power for both links is

$$\begin{aligned} \sum_{i=1}^{K} p_i &= \mathbf{1}^t (D_a - \boldsymbol{A}^t)^{-1} \mathbf{1} = \mathbf{1}^t \left[(D_a - \boldsymbol{A}^t)^{-1} \right]^t \mathbf{1} \\ &= \mathbf{1}^t (D_a - \boldsymbol{A})^{-1} \mathbf{1} = \sum_{i=1}^{K} q_i. \end{aligned} \tag{1.14}$$

The duality holds that under the same sum transmit power, the MAC and its dual BC can achieve the same SINR. The individual powers p_i and q_i are not the same in both links to achieve the same SINR. The results in (1.10) and (1.11) are utilized to calculate the power allocation under SINR-based QoS requirement in this thesis.

1.3 User-Centric Resource Allocation

We aim to investigate an user-centric interference management perspective of resource allocation strategies. User-centric refers to that each user k in the system has a QoS requirement $\underline{u}_k$, or more specifically the Shannon rate requirement to be guaranteed by the wireless system. The user-centric resource allocation problem is to allocate the power efficiently under different criterions while guaranteeing the QoS requirement of each user. These criterions include minimum power, energy efficiency (EE), social welfare and so on, which will be discussed in detail in Chapter 3-6.

In a wireless system, consider K transmitters with source messages are transmitting with power[3] $\boldsymbol{p} = [p_1, \cdots, p_K]^T$, and at least K sinks are interested in their messages. Consider a general utility function

$$u(\boldsymbol{p}, \boldsymbol{\omega}) = \sum_{k=1}^{K} \omega_k g_k \left(\frac{p_k}{I_k(\boldsymbol{p})} \right), \tag{1.15}$$

where ω_k is the weight for user k, $\boldsymbol{\omega} = [\omega_1, \cdots, \omega_K]$ and ω_k is usually between zero and one, $\sum \omega_k = 1$.

The QoS requirement of each user k is fulfilled if the following condition is satisfied.

$$g_k \left(\frac{p_k}{I_k(\boldsymbol{p})} \right) \geq \underline{u}_k, \tag{1.16}$$

where $g_k \left(\frac{p_k}{I_k(\boldsymbol{p})} \right)$ is a general SINR-based utility function.

$I_k(\boldsymbol{p})$ is from the set of simple linear interference (plus noise) functions $\mathcal{I}(\boldsymbol{p})$.

1.3 Definition. *Interference functions*: $\mathcal{I}(\boldsymbol{p})$: $\mathbb{R}_+^{K+1} \mapsto \mathbb{R}_+$ is an interference function for all $\boldsymbol{p} \geq 0$ if the following properties are satisfied [10].

- Positivity: $\mathcal{I}(\boldsymbol{p}) > 0$
- Monotonicity: $\mathcal{I}(\boldsymbol{p}) \geq \mathcal{I}(\boldsymbol{p'})$ if $\boldsymbol{p} \geq \boldsymbol{p'}$
- Scalability: $\alpha\mathcal{I}(\boldsymbol{p}) > \mathcal{I}(\alpha\boldsymbol{p})$ for all $\alpha > 1$.

The vector inequality $\boldsymbol{p} > \boldsymbol{p'}$ is a strict inequality in all components. The property of positivity is implied by the nonzero background receiver noise. The property of scalability shows that if all powers are scaled up uniformly, the resulting interference is smaller than scaling up the existing interference function directly. In other words, the SINR of scaling up all the powers simultaneously is better than the original SINR [10].

One general expression of an interference function is

$$I_k(\boldsymbol{p}) = \boldsymbol{a}^T \cdot \boldsymbol{p} + \sigma_n^2, \tag{1.17}$$

[3] The sources as well as sinks could be collocated resulting in MAC or BC.

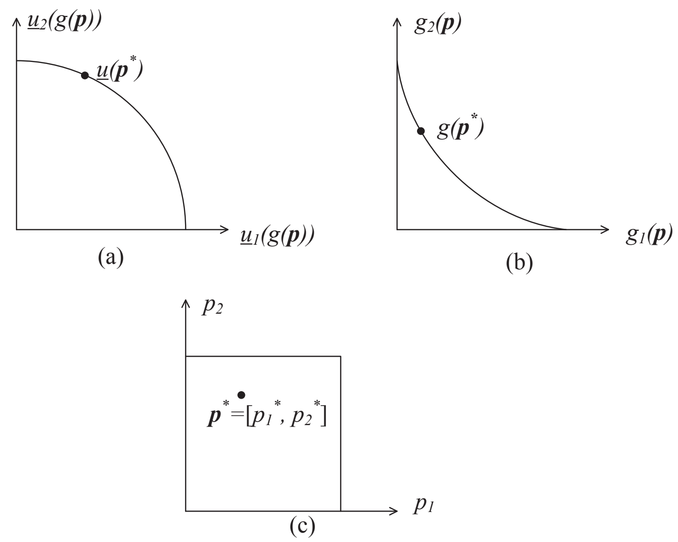

Figure 1.3: Illustration of a set of resources $\boldsymbol{p}$ and the QoS set $\underline{\boldsymbol{u}}$ for the case of 2 users in a wireless system. (a) QoS region after the transformation of the SINR region via the utility function mapping $\underline{u}(p) = \underline{u}(g(\boldsymbol{p}))$; (b) SINR region corresponding to the set of powers, with the transformation $g = g(\boldsymbol{p})$; (c) Set of power resources for 2 users. In this case the set of powers are permitted by the power constraints for the 2 users.

where the vector $\boldsymbol{a}$ depends on the concrete system scenario and contains the effective channel coefficients, e.g., by adopting SIC, some a_i are zero. σ_n^2 is the additive noise power.

The general interference function possesses the properties of positivity, scalability and monotonicity with respect to the power allocation and strict monotonicity with respect to the noise component [11]. We assume $g_k \in Conc$.

1.4 Definition. [12] $Conc$ is the family of all strictly monotonic increasing, continuous functions g, such that $g(x)$ is concave.

In the whole thesis, the Shannon rate is referred to as criterion of the QoS requirement if without specification. Then (1.16) becomes

$$r_k(\boldsymbol{\alpha}, \boldsymbol{p}) = g_k\left(\frac{p_k}{I_k(\boldsymbol{p})}\right) \quad (1.18)$$

$$r_k(\boldsymbol{\alpha}, \boldsymbol{p}) \geq \underline{u}_k, \quad (1.19)$$

where $r_k(\boldsymbol{\alpha}, \boldsymbol{p})$ is the achieved rate of user k as a function of the power allocation $\boldsymbol{p}$ and CSI $\boldsymbol{\alpha}$.

Fig. 1.3 shows an example of wireless communication for a 2-user resource allocation problem under QoS requirement. Each user has an SINR-based QoS requirement to be guaranteed by the wireless system, which is shown in (a) as the QoS region. The corresponding SINR region to achieve the QoS as a function of the set of powers is shown in (b). (c) shows the region of power resource such that the QoS requirements are fulfilled in (a). The user-centric resource allocation we are dealing with is to find the efficient power allocation in (c) such that the QoS requirements in (a) can be achieved.

The dense deployment of the wireless equipments and the scarcity of the wireless resources, such as power, frequency, etc., make the resource allocation an important problem [13]. The conflicts are not only among the users who wish to transmit with higher data rate and therefore create more interference to others, but also between the users and the system. Since the users may have incentives to manipulate their private information, such as CSI or user preferences, in order to maximize their own utility, the system regulator is responsible to detect and prevent the user misbehavior. Otherwise the QoS requirements of each user cannot be guaranteed.

Microeconomic theory [14, 15] provides an efficient manner to analyze this kind of conflict problem. The alternative approach based on economic models has been introduced to resource allocation problem in wireless systems [16, 17, 18, 19]. Each user in the system is assume to be *rational*, who only cares about its own utility.

Each user in the system plays the role as a decision maker in the market. Game theory studies the interaction among rational decision makers. In the book *The Theory of Games and Economic Behavior* [20], von Neumann and Morgenstern introduced game theory. One could study the strategic interactions of multiple agents from different directions, such as sociology, psychology, biology, etc. Game theory emphasizes the mathematical modeling on the conflict problem of the rational agents. These economic agents are referred to as 'players' in game theory. Each player aims at maximizing its own utility function by choosing a particular combination of strategies. Selfishness or self-interest is an important implication of rationality in traditional models.

Game theory has been deeply developed and widely applied to many aspects such as economics, politics and engineering in the last decades. Indeed, most economic behavior can be viewed as special cases of game theory. We will discuss game theory in detail in Sec. 1.3.1.

In wireless systems we have agents that are rational in the game theoretic sense of making decisions consistently in pursuit of their own individual objectives. In particular, each agent is strategic, i.e. takes into account its knowledge or expectation of the behaviour of other agents and is capable of carrying out the required computations. For example the users would like to maximize their individual rate and therefore cause more interference to others. In multiuser wireless communications, resource allocation is a challenging topic in studying the conflict problems between the wireless resources and the demands of users. Such resources include the time slots, frequency bands, orthogonal codes or spaces, power, etc. From an economic theoretic point of view, these resources can be regarded as valuable goods that are allocated by the BS to the multiple users centrally or among the users distributively. Time division multiple access (TDMA), frequency division multiple access (FDMA), code division multiple access

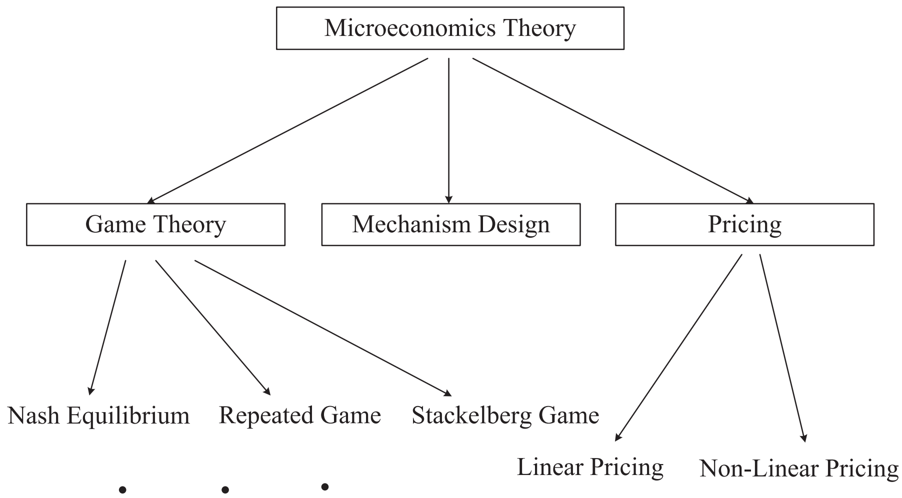

Figure 1.4: Distinctions in microeconomics related to user centric resource allocation in wireless communications.

(CDMA) and space division multiple access (SDMA) are commonly used resource allocation methods. In our work, we focus on the power allocation where the system organizer has to intelligently conjure a mechanism to design a game such that the individual user's QoS requirement is satisfied and the system efficiency is achieved.

In our system the users have the possibility to manipulate the system objective by falsely reporting their private types such as CSI and/or individual preference for utilities. We shall utilize tools from microeconomics such as mechanism design, pricing and game theory and analyze this problem from an information theoretic point of view to obtain resource allocation strategies for wireless systems. These resource allocation strategies shall possess the properties of non-manipulability of the system, system spectral efficiency and non-dictatorial behaviour for all users in the system.

Fig. 1.4 shows the branches in microeconomics theory that are related to the resource allocation for the user centric interference management in wireless communications. The centralized and decentralized implementation of these strategies or outcome rules are studied in terms of complexity, feedback overhead, and performance. The tools from game theory, mechanism design and pricing are analyzed in Sec. 1.3.1, Sec. 1.3.2 and Sec. 1.3.3, respectively.

1.3.1 Game Theory

In this section, the basic knowledge about game theory is introduced, especially those applied in our study of the user-centric resource allocation for wireless communications. Game theory is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers [19]. Game theory is widely used in economics, political science, psychology, logic and biology. Nowadays, game theory is applied to a broader range of studies such as in engineering. It provides a powerful manner to analyze interactions between self-interested users and to predict their strategies [21, 22, 23].

There are three basic elements to describe a game $\mathcal{G}(\mathcal{K}, \mathcal{S}, \mathcal{U})$ in strategic (or normal) form: the set of players $i \in \mathcal{K}$. $\mathcal{K}$ is the finite set $\{1, 2, \ldots, K\}$; The strategy space S_i of each user i, $\mathcal{S} = S_1 \times S_2 \cdots \times S_K$ is the set of strategy profiles; and player i's von Neumann-Morgenstern utility $u_i(\boldsymbol{s})$ for each strategy profile $\boldsymbol{s} = \{s_1, \ldots, s_K\}$. For example, the most familiar interpretations of strategies in economics may be the choices of prices or output levels [23].

The structure of the game is common knowledge among the players. All players participating in the game are assumed to be fully aware of the game structure of the strategic form. The players are supposed to be *rational* that they know that their opponents know this, and are aware that their opponents know that they know, and so on ad infinitum. Strategic form of finite games are usually depicted as matrices. A *pure strategy* provides a complete definition of how a player will play a game. A *mixed strategy* is a probability distribution over pure strategies. Mixed strategies are not considered in this thesis, because mixed strategies correspond to time-sharing which requires coordination overhead [24].

1.5 Definition. [23] Pure strategy s_i is *dominated for player* i if there exists $s_i' \in S_i$ such that

$$u_i(s_i', s_{-i}) \geq u_i(s_i, s_{-i}) \qquad for \quad all \qquad s_{-i} \in S_{-i}, \tag{1.20}$$

and the inequality is strict for at least one s_{-i}.

The strategy s_i is *strictly dominated* if the inequality (1.20) holds with strong inequality. A set of dominating strategies is not guaranteed to exist.

1.3.1.1 Nash Equilibrium

In game theory, the concept of Nash equilibrium (NE) [25, 26] takes a very important role. NE is a profile of strategies of a noncooperative game such that the strategy of each player is an optimal response to other players' strategies. The formal definition of NE is as follows.

1.6 Definition. A strategy profile $s^* \in \mathcal{S}$ is an *NE* if, for all players i, $i \in [1, \ldots, K]$,

$$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*) \qquad for \quad all \qquad s_i \in S_i. \tag{1.21}$$

At the NE, no unilateral deviation in strategy by any single player is profitable for that player.

When the inequality above holds strictly for all players and all feasible alternative strategies, then the equilibrium is classified as a strict NE. If instead, for some player, there is exact equality between s_i^* and some other strategy in the set $\mathcal{S}$, then the equilibrium is classified as a weak NE. By definition [27], a strict NE is necessarily a pure-strategy equilibrium such that each user has a unique best response (BR) to his rivals's strategies. The BR of player i is the strategy or set of strategies from $\mathcal{S}_i$ that maximizes player i's utility function against the strategies of other players.

The NE is a stable state when each player in the game chooses his BR to the strategies of other players. Therefore the NE is achieved by playing the BR dynamic (BRD), i.e., a series of BRs [28]. Strict NE is more compelling and robust to various small changes in the nature of the game. However, strict NE needs not exist. Conditions for the existence and uniqueness of a pure strategy NE are proposed in [29].

A game can have either a pure-strategy or a mixed NE (in the latter a pure strategy is chosen stochastically with a fixed probability). All players choose the strategy which is the BR to the anticipated action of their opponents. In a noncooperative game, the NE holds the property that all players can predict it, predict that their opponents can predict it and so on.

J. Nash in his work [25] shows the existence of a NE: Every finite strategic-form game has a mixed strategy equilibrium. A pure-strategy equilibrium is an equilibrium in degenerate mixed strategies. However, the NE point may not be efficient. That is why pricing is introduced to indirectly influence the outcome of the game to the desired efficient point.

1.3.1.2 Repeated Game

In the previous part, the game in static form is discussed, where the players choose their actions simultaneously. However, many applications of game theory have an important *dynamic* structure. Such dynamic situations can be represented by using the concept of *extensive form* games. The extensive form allows explicit representation of the order in which players move, and what acquired by each player when making each strategy.

The following information should be contained when defining the extensive form of a game:

- the set of players
- the order of moves
- the players' payoffs as a function of the moves that were made
- what the players' choices are when they move
- what each player knows when he makes his choices
- the probability distributions over any exogenous events.

Repeated game (RG) is the best understood class of dynamic games [23, 19, 30, 31]. The RG consists of certain number of repetitions of some stage game and the player's long-term overall payoff is a weighted average of the payoffs in each stage. The RG leads to different equilibrium outcomes to that of the stage game which is played only once. Because the players are able to condition their strategies on the past actions of their opponents.

The RG can be divided into two classes: infinite RG and finite RG, depending on the horizon played in the game is infinite or finite. The outcome of the finite RG is determined by backward-induction because finite horizon of the game is played. If the terminal horizon of the game is not a common knowledge to players, the infinite RG is a suitable measure of describing a game. It is found that the optimal method of playing an RG is to cooperate and play a socially optimum strategy. One essential part of infinite RG is to punish players who deviate from this cooperative strategy.

There are several alternative utility functions to describe a infinite RG.

- Discounting RG: Players discount future utilities by the discount factor δ_i, $0 < \delta_i < 1$. Player i's total payoff is

$$\bar{u}_i = (1 - \delta_i) \sum_{t=0}^{\infty} \delta_i^t g_i(s^t), \tag{1.22}$$

  where $\delta_i^t g_i(s^t)$ is the payoff of each stage game. t denotes the number of rounds in the RG.

- Limit of means RG: If the players are completely patient, corresponding to the limit $\delta_i = 1$, the time-average criterion can be implemented. Player i's total payoff is

$$\bar{u}_i = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T} g_i(s^t). \tag{1.23}$$

The players in the RG choose their strategy by anticipating the long-term total payoff as shown in (1.22) or (1.23). The game designer can punish those players when they perform actions not leading to the social optimal outcome. Then by predicting the overall payoff of the infinite RG, no user will have incentives to misbehave.

1.3.1.3 Stackelberg Game

The Stackelberg game is a strategic game named after the German economist Heinrich Freiherr von Stackelberg [32]. The players of the Stackelberg game are a leader and a follower competing on quantity. The leader chooses her strategy s_1 first and the follower chooses his own strategy s_2 after observing s_1.

The leader should predict that the follower will choose the best response $s_2(s_1)$ to whatever s_1 she chooses. The follower's strategy is to solve $s_2^* = \max_{s_2} u_2(s_1, s_2(s_1))$. Before choosing her own strategy, the leader predicts s_2^* first and then solves $s_1^* = \max_{s_1} u_1(s_1, s_2^*)$. Comparing to the possibly existing NEs where the strategies are the same as if the players move simultaneously, the 'Stackelberg equilibrium' is the unique credible outcome [23]. 'Backward induction' is applied to obtain this Stackelberg equilibrium. The idea is to firstly solve the BR of the last mover and then compute backward of the BR for the player before, and so on [33, 34].

1.3.2 Mechanism Design

Mechanism Design is a branch of the study in game theory. It can be thought as the reverse game theory and is rather unique in economics to have an engineering perspective. From the game theoretic point of view, the objective of each user is to maximize the expected value of its own payoff measured on certain utility. Each rational user is endowed with intelligence in a game theoretic sense of knowing the rule about the underlying game. Since each player in the game is strategic by taking into account the strategy of other players, announcing one's true private type or preference to the system regulator may not be the best strategy of players. That is why the theory of mechanism design comes into play.

In order to allocate the resources in a socially optimal manner, the system regulator has the pivotal role to envisage and extract the true value of the user preferences and/or private types. The preferences or private types of users include CSI, location, data traffic, QoS and other private information. Mechanism design concerns the settings for the problem of aggregating the announced preferences of multiple users in a collective or social decision. Assume that all the players act rationally, mechanism design attempts to implement the desired goals in a strategic setting. The goals of the proposed mechanism is normally viewed as *social choice*.

1.7 Definition. *Social Choice* is an aggregate or sum of individual preferences of different users into a single combined social welfare decision.

Mechanism design theory uses the framework of non-cooperative games with incomplete information and seeks to investigate how the privately held preferences or types can be elicited from the users. Furthermore it investigates the extent to which the information elicitation problem constrains the way in which social decisions can respond to individual preferences. The main focus of mechanism design is to design institutions or outcome rules (protocols) that satisfy certain desired objectives, assuming that the individual users, interacting through the institution will act strategically and may hold private information that is relevant to the decision at hand [23].

1.8 Definition. In mechanism design, a process is *Incentive Compatible* if all participants fare best when they truthfully reveal any private information asked for by the mechanism.

1.9 Definition. In game theory, an asymmetric game where players have private information is said to be *Strategy Proof* if none of the players has an incentive to lie about or hide their private information from the other players.

Strategy proofness is also known as *dominant strategy incentive compatibility*. For the user-centric resource allocation we studied in wireless communications, incentive compatibility and strategy proofness are very important. Due to the interference coupling, the wireless system is able to guarantee the QoS requirement only when each user reveals its true information to the system.

1.3.3 Pricing in Wireless Communications

As stated in Sec. 1.3.1, the outcome of a game such as the NE, may not be efficient, some measure should be implemented to lead the outcome of the game to the desired point. Pricing is a useful tool to design such a framework. Traditionally, engineers design the physical layer algorithm in wireless communications without considering how the communication services or the wireless resources are priced. However, due to the scarcity of wireless resources and the exploded demand of data transmission in the competitive market, technology and pricing are highly related with each other. In particular, pricing affects the way how communication services are used and the resources are consumed. Modern networking technologies provide possibilities for producers and consumers to exchange economic signals on fast time scale [35]. Pricing can be viewed as a mechanism designed by the system regulator to motivate the users to utilize the network efficiently. As a result, the robustness and stability of the wireless system is enhanced with the mechanism of pricing. The strategies that the users choose according to the pricing mechanism can also feed back some signal to the system regulator about their user preferences, which helps the system regulator allocate the wireless resource and make sure that the system is incentive compatible.

A well designed pricing mechanism is responsible to collect the correct information about the users. With these information, the system regulator can allocate the resources amongst the users indirectly to meet the desired operating point.

One simple model for pricing a single link can be formulated as follows [35]. Let P denote the problem of maximizing the total user benefit, i.e.,

$$P: \qquad \max_{x_1,\cdots,x_N} \sum_{i=1}^{N} u_i(x_i) \quad s.t. \sum_{i=1}^{N} x_i \leq C, \tag{1.24}$$

where C is the capacity of the link. Each of the N customers is allocated x_i bits per second with the utility function u_i.

If each u_i is a concave increasing function, then there exists a price $\bar{\beta}$ such that each user is able to choose x_i to solve the problem

$$P: \qquad \max_{x_i} u_i(x_i) - \bar{\beta} x_i \tag{1.25}$$

and therefore, P can be solved simply by setting this price $\bar{\beta}$.

Let $x_i(\beta)$ be the *demand function* of user i, which is the amount of bandwidth he wishes to purchase if the price per unit bandwidth is β. By setting the price $\beta = \bar{\beta}$, the system operator ensures the total bandwidth purchased equals the supply, i.e., $\sum_i x_i(\bar{\beta}) = C$. This allocation leads the total benefit to the social welfare of all the users.

It is also possible to tailor the prices to individual users. For example, nonlinear pricing could be adopted in order to increase the revenue of the system operator or to motivate the social welfare.

How can the wireless system meet the high QoS requirement of its users with the limited resources? The pricing mechanism gives the system regulator an opportunity to ensure the system efficiency and the social welfare. The system regulator needs to adapt the prices smartly. The pricing mechanism in our context is introduced formally as follows.

Let $\mathcal{U}$ be the family of utility functions $u(\boldsymbol{p}, \boldsymbol{\omega})$. $u(\boldsymbol{p}, \boldsymbol{\omega})$ is not jointly concave with respect to $\boldsymbol{p}$ for all $\boldsymbol{w} > 0$. The utility $u(\boldsymbol{p}, \boldsymbol{\omega})$ is a function of the weights $\boldsymbol{\omega}$ and the SINR. Moreover, $u(\boldsymbol{p}, \boldsymbol{\omega})$ is not a convex optimization problem even for linear interference functions [12].

The utility function in (1.15) is a frequently encountered utility maximization problem in wireless systems based on the SINR. The utility $u(\boldsymbol{p}, \boldsymbol{\omega})$ is a strictly monotonic increasing continuous function defined on $\mathbb{R}_+$. Denote $F_k(\beta_k, p_k)$ as the function of the price β_k and power p_k, $\beta_k \geq 0$. Let $\mathcal{F}$ be the family of the pricing functions. The UMP with pricing is defined as

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) = u(\boldsymbol{p}, \boldsymbol{\omega}) - F_k(\beta_k, p_k). \tag{1.26}$$

Denote the optimal power allocation $p^*(\boldsymbol{\beta}, \boldsymbol{\omega})$ of the system as a function of the prices $\boldsymbol{\beta}$ and the weights $\boldsymbol{\omega}$. $p^*(\boldsymbol{\beta}, \boldsymbol{\omega})$ solves the UMP in (1.26), i.e.,

$$p^*(\boldsymbol{\beta}, \boldsymbol{\omega}) = \arg \max_{0 \leq \boldsymbol{p} \leq p_{max}} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) \tag{1.27}$$

$$s.t. \quad g_k\left(\frac{p_k}{I_k(\boldsymbol{p})}\right) \geq \underline{u}_k \qquad \text{for all } k. \tag{1.28}$$

The pricing mechanism in the context of SINR-based utility optimization problem is defined as follows.

1.10 Definition. [12] *Pricing Mechanism*: A pricing mechanism is a mapping from $\underline{\mathcal{U}}(\boldsymbol{\alpha})$ to $\mathcal{F}$.

$\underline{\mathcal{U}}(\boldsymbol{\alpha})$ is the feasibility region for channel states $\boldsymbol{\alpha} = [\alpha_1, \cdots, \alpha_K]$:

$$\underline{\mathcal{U}}(\boldsymbol{\alpha}) = \bigcup_{\boldsymbol{p} \geq 0} \left(g_1(p_1/I_1(\boldsymbol{p})), \cdots, g_K(p_K/I_K(\boldsymbol{p}))\right). \tag{1.29}$$

The pricing mechanism is a tool used by the system regulator to force the resource allocation in such a way that the resulting operation point meets the required point. For the user centric resource allocation of wireless communication, the means of pricing is to choose the pricing parameters $\boldsymbol{\beta}$ such that the QoS requirement of each user is achieved with minimum power. The universal pricing mechanism is introduced in the next subsection.

1.3.3.1 Universal Pricing Problem

The pricing problem is to find the universal pricing parameter $\boldsymbol{\beta}^*$ for given $\boldsymbol{\omega}$ and $\underline{\boldsymbol{u}} \in \underline{\mathcal{U}}(\boldsymbol{\alpha})$, i.e.,

$$\begin{aligned} \text{Find} \quad & \beta^* \\ s.t. \quad & g_k\left(\frac{p_k^*(\boldsymbol{\beta}^*, \boldsymbol{\omega})}{I_k(\boldsymbol{p}^*(\boldsymbol{\beta}^*, \boldsymbol{\omega}))}\right) = \underline{u}_k \end{aligned} \tag{1.30}$$

for all $k \in K$.

1.11 Definition. *Universal Pricing*: A universal pricing scheme finds a pricing vector $\boldsymbol{\beta}$ for all channels $\boldsymbol{\alpha}$ and all weights $\boldsymbol{\omega}$ and their feasible utility requirements $\underline{\boldsymbol{u}} \in \underline{\mathcal{U}}(\boldsymbol{\alpha})$.

In the following chapters, we investigate the universal pricing framework for different scenarios in wireless communication networks. Normally pricing is related to the higher layer revenue. However, pricing on physical layer also plays an important role to affect the resource allocation for wireless systems. There are research works concerning about pricing of different scenarios of wireless networks [1, 36, 37]. We focus on the pricing framework for the physical layer power allocation in order to guarantee the QoS requirement of each user in the wireless system. Particularly, the possible user misbehavior in the system is discussed and the strategy-proof mechanisms using pricing are proposed to counter the malicious behavior in the system. The prices in the current context are rather the control signaling than pecuniary units. The physical layer resource consumption certainly influences the application layer cost and revenue of the system vender. However, the mapping of the physical layer pricing and the higher layer monetary prices is out of the scope of our research. When we refer to cost terms or fee of the power allocation, it is an additional evaluation to indicate the performance of the universal pricing mechanism.

2 General System Model and Problem Formulation

2.1 User Centric System Model

Consider the general MAC or BC as shown in Sec. 1.2. A set $\mathcal{K} := \{1, \ldots, K\}$ of transmitters (or receivers) are communicating with the BS simultaneously on the same spectrum band. Each user has an SINR-based QoS requirement $\underline{\boldsymbol{u}}$ to be guaranteed by the system.

In this thesis, the achievable Shannon rate is adopted as the QoS criterion. Each user suffers from the interference caused by other users in the system. In order to meet the rate requirement of each user with minimum resource, the system regulator should make sure that each user reports its information accurately, which includes the CSI, and/or its preferences, such as the utility function. Denote $\underline{u}_k$ as the rate-based QoS requirement of each user. The achievable rate r_k of each user k should be larger than or equal to its QoS requirement $\underline{u}_k$. From the energy saving point of view, the system guarantees the user QoS requirement by achieving it with the minimum power, i.e., equality holds for (1.16)

$$g_k\left(\frac{p_k}{I_k(\boldsymbol{p})}\right) = \underline{u}_k = \log\left(1 + \frac{\alpha_k p_k}{I_k(\boldsymbol{p})}\right). \tag{2.1}$$

Game theoretic analysis and pricing mechanisms are introduced to tailor the resource allocation amongst the users. From the game theoretic point of view, the rational users are not only interested in achieving its rate requirement $\underline{u}_k$, but also maximizing its own utility function u_k. As denoted in Sec. 1.3.3, pricing is adopted in the described wireless system to control the power allocation such that the QoS requirements are satisfied. The game can be played either between the users and the system regulator or among the users. We propose two types of power allocation games.

In the first game, the system regulator not only controls the power allocation, but also detects and prevents the user misbehavior by careful game design and price selection. The result of the game is that the QoS requirement of each user is achieved with the minimum power consumption and no user has the incentive to cheat for their own user utility.

Given the conditions of the universal pricing in Sec. 1.3.3.1, if the power allocation is centralized at the BS with the given prices $\boldsymbol{\beta}$, the power is allocated by solving the UMP:

$$\begin{aligned} \boldsymbol{p} \quad &= \quad \arg \max_{0 \leq \boldsymbol{p} \leq p_{max}} \sum_{k=1}^{K} w_k r_k(\alpha_k, p_k) - \sum_{k=1}^{K} F_k(\beta_k, p_k) \\ s.t. \quad & \qquad r_k(\alpha_k, p_k) \geq \underline{u}_k \qquad \text{for all } k, \end{aligned} \tag{2.2}$$

where $F_k(\beta_k, p_k)$ is the pricing term as a function of the price β_k and the power p_k of user k.

This optimization solves the social welfare of all users, which maximizes the difference between the weighted sum achievable rates and the cost of power for all users.

In the second game, the noncooperative users choose their transmit power distributively. The NE power allocation is reached in the proposed noncooperative game. By smart price adaptation, the QoS requirement of each user is met with the minimum power at the NE point. A reasonable utility function u_k of each user k is the difference between the achievable rate $r_k(\alpha_k, p_k)$ and the pricing term $F_k(\beta_k, p_k)$.

$$u_k = r_k(\alpha_k, p_k) - F_k(\beta_k, p_k). \tag{2.3}$$

Each user k transmits with power p_k from its feasible *strategy space* $\mathcal{S}_k$ defined as

$$p_k \in \mathcal{S}_k := \{\boldsymbol{p} : 0 < p_k \leq p_{max}\}. \tag{2.4}$$

The *strategy profile* is a set of joint strategies for all transmitters defined as

$$(p_1, \ldots, p_K) \in \mathcal{S}_1 \times \cdots \times \mathcal{S}_K. \tag{2.5}$$

In the noncooperative game formulation, given the strategy profile, each user chooses its own transmit power p_k distributively by maximizing its own utility function.

$$\begin{aligned} \boldsymbol{p} \quad &= \quad \arg \max_{0 \leq \boldsymbol{p} \leq p_{max}} u_k(p_k, \beta_k) \\ s.t. \quad & \qquad r_k(\alpha_k, p_k) \geq \underline{u}_k \qquad \text{for all } k. \end{aligned} \tag{2.6}$$

Given the proper prices $\boldsymbol{\beta}$, (2.2) and (2.6) find the optimal power allocation $\boldsymbol{p}$ to achieve the QoS requirement of each user.

By a user centric approach, the users have access to a broader strategy space due to the following reasons:

- The self-interest driven users have more intelligence and possibility to manipulate the system while ignoring the system objective in order to maximize their own user utility.
- The users have incentives to manipulate their preferences measured on utility functions or their private types such as CSI to the system regulator with the objective of obtaining a better resource allocation.

In order to ensure the QoS requirements of all users in the system, the user misbehavior should be carefully analyzed. By predicting the user misbehavior, the strategy-proof mechanism is designed. Such mechanism should satisfy effectiveness and incentive compatibility with the tool of pricing.

The quasi-static block flat-fading channels are assumed for the general MAC and BC. The CSI is assumed to be known even though the users can manipulate α_k.

2.2 Problem Statement and Contributions

In this section, the problems studied in this thesis are formulated. The methodologies related to these problems are stated. At the end of this section, the papers that are published concerning the solutions to these problems are listed.

Both the centralized and distributed resource allocations for the general MAC and BC are discussed, where pricing is utilized to indirectly force the power allocation of each user. Due to the interference coupling among the users, each user's behavior influences the rate of other users. Therefore, pricing is also employed to feedback the private information about the users and prevent user misbehavior. Different types of games are adopted in order to guarantee the QoS requirement of each user in the system.

Problem 1 and 2 arise in Chapter 3. Universal linear pricing is investigated for the general MAC and BC under QoS requirements.

Problem 1. *Is the pricing mechanism which is linear in both the prices and power a universal pricing mechanism for the general MAC and BC?*

When considering the pricing mechanism, the linear pricing is the simplest and most direct method to apply. We investigate the conditions of the linear pricing to be a universal pricing mechanism for the general MAC and BC, where SIC and DPC are applied respectively at the BS. The prices $\boldsymbol{\beta}$ are proposed for the certain decoding (encoding) order for the general MAC and BC, respectively. With the given prices $\boldsymbol{\beta}$, the power allocation $\boldsymbol{p}$ for the K users is optimized in such a way that the QoS requirement of each user is reached with the minimum power. We also analyze the cost terms for each user under this linear pricing mechanism. The best coding order to minimizing the sum transmit power is obtained.

Problem 2. *What is the user behavior when maximizing its own payoff measured on certain utility? Is it possible to design an incentive compatible mechanism to prevent user cheating?*

From the game theoretic point of view, announcing one's true information may not be the best strategy of rational users when considering to maximize its own payoff. It is the responsibility of the system regulator to detect and prevent the user misbehavior. Otherwise, the QoS requirement of the users are no longer guaranteed. In such a sense, a game is formulated not among the users but between the users and the system regulator who provides the universal prices. The cheating behavior and its results are investigated. The mechanism to prevent cheating is discussed.

Chapter 4 deals with Problem 3 and 4. We focus the scenario on the general MAC, with and without SIC, respectively. The non-linear pricing which is logarithmic in power and linear in the prices is shown to be a universal pricing mechanism.

Problem 3. *Given the linear pricing framework, how does the non-linear pricing which is non-linear in the power and linear in the prices work as the universal pricing mechanism for the general MAC?*

Problem 3 is studied in Chapter 4.2. Given the conditions of the linear pricing to be universal pricing, we analyse other pricing mechanisms for the general MAC with and without SIC, respectively. The pricing mechanism which is logarithmic in power and linear in the pricing parameters are universal pricing mechanism for *log-convex* interference functions[1]. The prices are proposed with the given QoS requirements. The optimal power allocation is derived under the pricing mechanism so that the rate requirement of each user is achieved with minimum sum power. The cost terms corresponding to the universal non-linear pricing of each user are analyzed, where the weights are optimized with respect to the revenue of the system regulator.

Problem 4. *What is the best cheating strategy if the selfish/malicious users maximize their own user utility? How to design an incentive compatible mechanism to prevent cheating with cheat-proof pricing?*

Problem 4 is studied in Chapter 4.3 and 4.4. The best cheating strategy is derived if the selfish/malicious users misrepresent their private information on the purpose of maximizing their own user utility. A worst case strategy is designed in order to guarantee the QoS requirement of all the honest users, where the malicious users are excluded from the system UMP. According to the best cheating strategy, we propose different types of infinite RG to counter the user misbehavior. The cheat-proof pricing is derived so that no user will have incentives to cheat. The simulation results illustrate that the proposed RG is an incentive compatible mechanism.

After the theoretical analysis on the centralized power allocation for the general MAC, we apply the user-centric resource allocation problem to the heterogeneous networks. Chapter 5 investigates Problem 5.

The two-tier macro-femtocell scenario is considered. The MBS adopts certain well-designed compensation framework to motivate the femtocell access points (FAPs) to serve the nearby macrocell user equipments (MUEs). While ensuring the rate requirement of each UE, the total power consumption of the whole two-tier network is minimized.

Problem 5. *How does the proposed centralized power allocation work in the heterogeneous networks?*

Due to the fact that the indoor wireless data traffic explodes rapidly, heterogeneous networks such as the two-tier macro-femtocell networks have attracted high interest in both academy and industry. With the results of the power allocation to fulfill the QoS requirement of each UE, we develop the novel compensation framework to motivate the hybrid access in the uplink transmission of the femtocell network. A Stackelberg game is formulated where the MBS serves as a leader and the FAP serves as a follower. Two compensation frameworks are proposed, where in the first model the regulator exists in the system and the universal power price obtained in Chapter 4 is utilized in the compensation function. In the second model, the

[1] *log-convex* interference functions will be discussed in Sec. 4.1.2

energy efficiency of the whole macro-femtocell network serves as the utility of the MBS. The optimal number of accepted MUEs in the hybrid access and the optimal compensation price are derived in both frameworks. The first model is studied in Chapter 5.1 and the second model is studied in Chapter 5.2.

At last but not the least, the distributed resource allocation for the general MAC is considered. Chapter 6 deals with Problem 6. Each user chooses the transmit power as its best response to maximize its own utility. The individual prices are proposed so that the QoS requirement of each user is achieved at the NE transmit power.

Problem 6. *How is the pricing mechanism for distributed resource allocation of the general MAC with and without SIC?*

We develop the noncooperative game with individual pricing for the general MAC with and without SIC, respectively. Each user allocates its own power by optimizing the individual utility function with clever price adaptation. We show that by the proposed prices, the BR power allocation of each user converges rapidly. The individual prices are proposed such that the Shannon rate-based QoS requirement of each user is achieved at the unique NE point. Different types of user behavior are analyzed and the strategy-proof mechanism is designed with the punishment prices when the types of the malicious users are detected.

2.3 State of the Art

In this section, we first describe works about interference management in the wireless systems, including interference alignment, superposition coding. Then related works regarding resource allocation that apply game theory and microeconomic theory such as pricing are provided. Furthermore, we mention works on the analysis of the user behavior and the mechanism design to prevent the user misbehavior. Afterwards, related works on heterogeneous networks and distributed resource allocation for wireless communications are discussed.

2.3.1 Interference Management

Consider K non-cooperative transmitter-receiver communicating pairs. They interfere each other if they communicate over a wireless channel on the same frequency band. Through a new strategy known as interference alignment [38, 39, 40, 41, 42, 43, 44], it is possible to have each transmitter operate up to $\frac{1}{2}$ its interference-free capacity. The ergodic interference alignment for the K-user interference channel with time-varying fading is developed [45]. If the channel gains have independent, uniform phases, this technique allows each user to achieve at least $\frac{1}{2}$ its interference-free ergodic capacity at any signal-to-noise ratio. The interference alignment, decomposition and performances are analyzed for a multiple-antenna X-channel with two transmitters and two receivers [46]. Based on the idea of interference alignment, authors in [47] show that the degrees of freedom achieves $\frac{K}{2}$ for the K user time-varying interference channel. The results in [48] show that an interference alignment model for the deterministic K-user interference channel can be applied into a fully connected Gaussian interference network.

The superposition coding enhances the achievable rate region for the general interference channel [49]. The capacity of DPC to that of TDMA for a multiple-antenna (multiple input multiple-output (MIMO)) Gaussian BC is compared [50]. They show that the sum-rate capacity (achievable using DPC) of the multiple-antenna BC is larger than single-user capacity (i.e., the TDMA sum-rate) in the system. This result also holds for the sum-rate gain of SIC over TDMA for the uplink channel. In a high-interference regime for cognitive radio, multiuser decoding at the primary receiver is shown to be optimal [51, 52].

2.3.2 Resource Allocation with Game Theory and Pricing

The optimal power allocation is studied to maximize the weighted sum rate under interference power constraints and individual transmit power constraints [53], for a cognitive multiple access channel. The authors [54] introduce hierarchy in energy games modeled by a decentralized MAC. In [55], the energy aware MAC region with and without SIC is studied. In [56], the precoding strategy selection algorithm of the secondary users in cognitive MIMO MAC system is proposed to maximize the sum rate, based on the game-theoretic framework. In [57], the auction mechanisms for sharing spectrum among a group of users is analyzed with the constraint of the interference temperature at a measurement point. Motivated by the idea of cooperative communication, the authors study the cooperation and competition within the cognitive radio networks [58].

Pricing has been successively utilized in the wireless networks to enforce the system efficiency. There exist previous works concerning universal pricing mechanism for interference coupled systems [12]. Traditionally, pricing in communications networks is treated on the service layer. However, pricing also affects how services are used and resources are consumed [35]. On the physical layer, pricing is applied to manage interference and resource allocation. The impact of interference coupling on the convexity of certain utility functions is characterized [59]. The Pareto efficiency of a pricing policy in terms of the transmit power and the Nash equilibria are characterized by using the supermodularity property [2]. Linear pricing in femtocell networks based on Stackelberg games is studied in [60]. By a pricing scheme, the transmitted power is allocated to maximize the total utility summed over all users subject to power constraints in a two CDMA adjacent cell networks [61]. In [62], the power control and beamformer design are investigated for interference networks, based on the exchange of interference prices. A set of prices corresponding to all degree of freedoms (DoFs) must be exchanged to achieve the centralized optimal allocation.

2.3.3 User Misbehavior and Mechanism Design

The behavior of users on networked systems ranges from altruistic on the one end to malicious (adversarial) on the other end. While altruistic users aim to improve the overall network performance, selfish users develop strategies to maximize their own utility and obtain a share of resources. A malicious user, on the other hand, aims to disrupt the whole network. Malicious behavior may be due to the users inherent maliciousness or in competitive scenarios where the loss of a competing user will likely result in future gains for oneself. Well-known examples of such adversarial behavior include jamming in wireless networks and denial-of-service (DoS) attacks [63, 64, 65]. User misbehavior is studied in [66] on the network layer and a clever protocol is designed. In contrast to our work on the physical layer, they typically address trust and misbehavior on the medium access control or network layer. For the inaccurate SINR feedback in interference networks, [67] studies the impact on the distributed power update algorithm. The authors in [68] show that the set of correctly behaving links has the ability to detect the behavior of misrepresenting the utility, if and only if the restricted global dependency matrix $G_{restricted}$ is irreducible. The games for networked systems and the user behavior are analyzed [69]. They also describe the algorithms for cheat-proof mechanism design.

Resource allocation based on d'Aspremont and Gerard-Varet (AGV) mechanism for an incentive compatible spectrum sharing game is proposed in [70]. In [71], finite RG and discounted RG equilibrium are analyzed. A repeated graphical game with incomplete information is proposed in [72] for interaction of legitimate and malicious users.

2.3.4 Heterogeneous Networks

Interference coordination becomes the primary challenge in the heterogeneous networks. Several cognitive radio inspired approaches to enhance the interference coordination for femtocell networks are applied in [73]. Distributed power control scheme for closed access femtocell networks in down-link is formulated in [74] by using a noncooperative game model. In [75], the power allocation to achieve the SINR based QoS requirement is provided for the uplink transmission. The authors [76] propose a game-theoretical mechanism to derive the optimal allocation in the general femtocell channel allocation problem with or without prioritized femtocells.

A Stackelberg Game to investigate the price-based resource allocation strategies for the two-tier spectrum sharing femtocell networks is proposed in [60]. The utility-aware refunding framework for hybrid access femtocell network is analyzed [77], where they use TDMA for data transmission. A resource allocation mechanism is designed for the two-tier orthogonal frequency-division multiple-access (OFDMA) femtocell networks with the analysis of wireless users' selfish characteristic and private traffic information [78]. For the two-tier femtocell networks, the throughput maximization problem subject to QoS constraints in terms of success probabilities and per-tier minimum rates is formulated in [79]. In [80], the uplink interference problem in OFDMA-based femtocell networks is dealt with partial cochannel deployment. An inter-tier interference mitigation strategy offers significant performance improvement over the existing methods. The authors devise a cooperative resource allocation algorithm, which is an enhanced modified iterative water-filling, to improve intercell fairness in femtocell networks [81].

2.3.5 Distributed Resource Allocation

The distributed resource allocation have been discussed plentifully for different wireless communication scenarios. Each user allocates its resources independently to optimize its own utility function. In [82], the authors consider a distributed power control scheme for wireless ad hoc networks, in which each user announces a price that reflects compensation paid by other users for their interference. The MAC game models are discussed in [83] in which each transmitter makes individual decisions regarding their power level or transmission probability. The authors in [84] address the efficient distributed power control via convex pricing of users' transmission power in the uplink of CDMA wireless networks supporting multiple services. The CDMA power control as a noncooperative game is also discussed in [85], where a cost function is introduced as the difference between the pricing and utility functions. A game-theoretic approach is investigated in [86] for power control in ad-hoc networks. The conditions of the unique NE and the global convergence of MIMO iterative waterfilling are discussed in [87]. The distributed joint power and admission control algorithms are proposed [88] for the management of interference in two-tier femtocell networks, where the newly-deployed FUEs share the same frequency band with the MUEs using CDMA. The optimal decentralized power allocation in fast fading MIMO MAC is investigated by the authors in [89], where the players (the mobile terminals) are free to choose their power allocation in order to maximize their individual transmission rates. A distributed interference pricing for allocating power among multiple transmitters is presented [90] in order to optimize the weighted sum-rate in interference channels.

2.4 Contributions and Structure

In the **List of Publications**, the published papers in which results of this thesis were discussed are listed. The results of Problem 1 and 2 are published in [II] and correspond to Chapter 3. The results of Problem 3 and 4 are published in [I] and [III] and correspond to Chapter 4. The results of Problem 5 are published in [IV] and [V] and correspond to Chapter 5. The results of Problem 6 are published in [VI] and [VII] and correspond to Chapter 6 in the thesis. The conclusions and future works are discussed in Chapter 7.

3 Centralized Universal Linear Pricing for MAC and BC under QoS Requirements

In this chapter, we address the problem of power allocation in the uplink MAC and downlink BC with linear pricing framework to ensure that each user in the wireless network can achieve its utility requirement. The prices are provided by the system regulator. As illustrated in Sec. 1.3.3, by introducing prices, the resulting power allocation ensures the QoS requirement of each user. The system optimizer, which can be the BS, is proposed in the framework which maximizes the system utility with pricing function. The existence of the universal linear pricing mechanism is characterized. The algorithms for solving the linear pricing problems in MAC and BC are proposed. The sufficient condition for universal linear pricing in MAC with SIC and its best decoding order are analyzed.

3.1 System Preliminaries

As shown in Fig. 3.1, consider in a wireless system K transmitters with source message are transmitting with power $\boldsymbol{p} = [p_1, \ldots, p_K]^T$, and at least K sinks[1] are interested in their messages. The power is allocated centrally by the system. The system optimizer can be the BS or a separate device. It is a simple dumb device that optimizes the system maximization problem (SMP) with the given parameters such as CSI $\boldsymbol{\alpha}$, prices $\boldsymbol{\beta}$ and weights $\boldsymbol{w}$.

In the wireless system,

- Each user k has a rate requirement $\underline{u}_k$.
- The regulator chooses the optimal universal linear pricing parameter β_k^* and weights (priorities) w_k in order to achieve the rate requirement $\underline{u}_k$ for each user k.
- The system optimizer maximizes the system utility $\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega})$ with respect to the pricing parameter β_k and weight ω_k and allocates power p_k^* to each user k.

In an interference wireless system, each user k is mainly interested in maximizing its own utility, but not the entire system utility. As shown in Fig. 3.1, the regulator chooses linear prices $\boldsymbol{\beta} = [\beta_1, \cdots, \beta_K]$ with the knowledge of channel states $\boldsymbol{\alpha}$ in order to achieve all the

[1] The sources and sinks could be collocated resulting in MAC or BC.

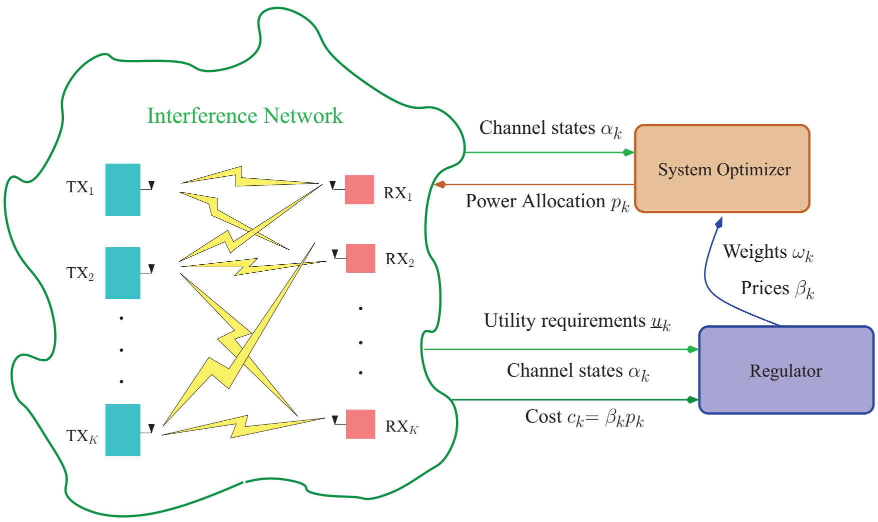

Figure 3.1: System model of centralized universal linear pricing framework for interference network

desired points of QoS requirement $\underline{u}_k$ for each user k. And the system maximizes the system utility $\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega})$ given below with the linear pricing mechanism.

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) \quad = \quad u(\boldsymbol{p}, \boldsymbol{\omega}) - \sum_{k=1}^{K} \beta_k p_k = \sum_{k=1}^{K} \omega_k g_k \left(\frac{p_k}{I_k(\boldsymbol{p})} \right) - \sum_{k=1}^{K} \beta_k p_k. \tag{3.1}$$

We denote the solution to this SMP as the optimal power allocation, i.e.,

$$p^*(\boldsymbol{\beta}, \boldsymbol{\omega}) = \arg\max_{\boldsymbol{p} \geq 0} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}). \tag{3.2}$$

The fee $c_k = \beta_k p_k$ on power of link k is paid by the link to the regulator either directly or via the system optimizer, see Figure 3.1. The pricing serves as a trade off between maximizing the rate and minimizing the power consumption.

The linear pricing which is linear in both the prices $\boldsymbol{\beta}$ and the power allocation $\boldsymbol{p}$ is utilized. From Definition 1.11, the following Lemma states the conditions for the existence of linear pricing mechanism for the utility $u(\boldsymbol{p}, \boldsymbol{\omega})$.

3.1 Lemma. *Let $g_1, \cdots, g_K \in Conc$. And assume $I_1(\boldsymbol{p}), \cdots, I_K(\boldsymbol{p})$ are linear interference functions. If and only if $u(\boldsymbol{p}, \boldsymbol{\omega})$ is jointly concave in $\boldsymbol{p}$ for all $\boldsymbol{\alpha} \in \mathbb{R}_+^K$, and $\boldsymbol{\omega} > 0$, then there exists a universal linear pricing mechanism.*

Proof. The proof is provided in Proof 3.5.1. □

Note that there might occur cases in which the individual utility function does belong to a natural competitive user utility (NCUU) function as defined in [59]. However, the channel realizations or the SINR is by chance chosen to provide a jointly concave system utility function, then all rates can be achieved by linear pricing. This behavior could change if another channel realization leads to a non-concave system utility function.

The result of Lemma 3.1 is related to Theorem 1 in [91]. However here the optimal power allocation is determined centrally by a system utility (3.1) but not the (possibly unique) outcome of a noncooperative game.

3.2 User-Centric Universal Linear Pricing for Multiple Access Channel with SIC

It is well known that with SIC at the BS, the capacity region of the single antenna Gaussian MAC can be achieved. Assume that the BS decides the best decoding order $\boldsymbol{\pi}^i = \{\pi_1^i, \cdots, \pi_K^i\}$ with perfect knowledge of the channel states $\boldsymbol{\alpha} = [\alpha_1, \cdots, \alpha_K]$. The best decoding order will be determined later.

Assume a SIC decoding order as $\pi^1 = [K \to K-1 \to \cdots \to 1]$. Let the SINR-based function $g_k\left(\frac{p_k}{I_k(\boldsymbol{p})}\right) = r_k(\boldsymbol{p})$. Then the rate function without pricing for each user k is

$$r_k(\boldsymbol{p}) = \log\left(1 + \frac{\alpha_k p_k}{1 + \sum_{l=1}^{k-1} \alpha_l p_l}\right) \geq \underline{u}_k. \tag{3.3}$$

Obviously the individual user rate depends on the SIC decoding order. The system optimizer allocates $\boldsymbol{p}$ for the MAC with SIC by solving

$$\max_{\boldsymbol{p}\geq 0} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) = \max_{\boldsymbol{p}} \sum_{k=1}^{K} \omega_k \left(\log\left(1 + \sum_{m=1}^{k} \alpha_m p_m\right) - \log\left(1 + \sum_{m=1}^{k-1} \alpha_m p_m\right)\right) - \beta_k p_k. \tag{3.4}$$

In general, the optimal power allocation is characterized by the first order optimality conditions

$$\begin{aligned} \frac{\partial}{\partial p_l} &= \omega_l \frac{\alpha_l}{1 + \sum_{m=1}^{l} p_m \alpha_m} + \sum_{k=l+1}^{K} \omega_k \left(\frac{\alpha_l}{1 + \sum_{m=1}^{k} \alpha_m p_m} - \frac{\alpha_l}{1 + \sum_{m=1}^{k-1} \alpha_m p_m}\right) \\ &\quad -\beta_l = 0. \end{aligned} \tag{3.5}$$

Calculate the power allocation and substitute it into (3.3), then the linear pricing parameter β_k can be derived. For illustration, we now perform a case study.

3.2.1 Two-User Case in MAC

For simplicity and illustration, we investigate the special case with two users first and assume $\omega_1 \neq \omega_2$.

3.2 Lemma. *For SIC decoding order* $[1 \to 2]$*, the optimal power allocation with respect to* $\boldsymbol{\omega}$ *and* $\boldsymbol{\beta}$ *is* $p_1^{*1\to 2}(\beta_1^*) = \frac{\omega_1}{\beta_1} - \frac{\alpha_2(\omega_1 - \omega_2)}{\alpha_2\beta_1 - \alpha_1\beta_2}$ *for user 1 and* $p_2^{*1\to 2}(\beta_2^*) = \frac{\alpha_1(\omega_1-\omega_2)}{\alpha_2\beta_1 - \alpha_1\beta_2} - \frac{1}{\alpha_2}$ *for user 2.*

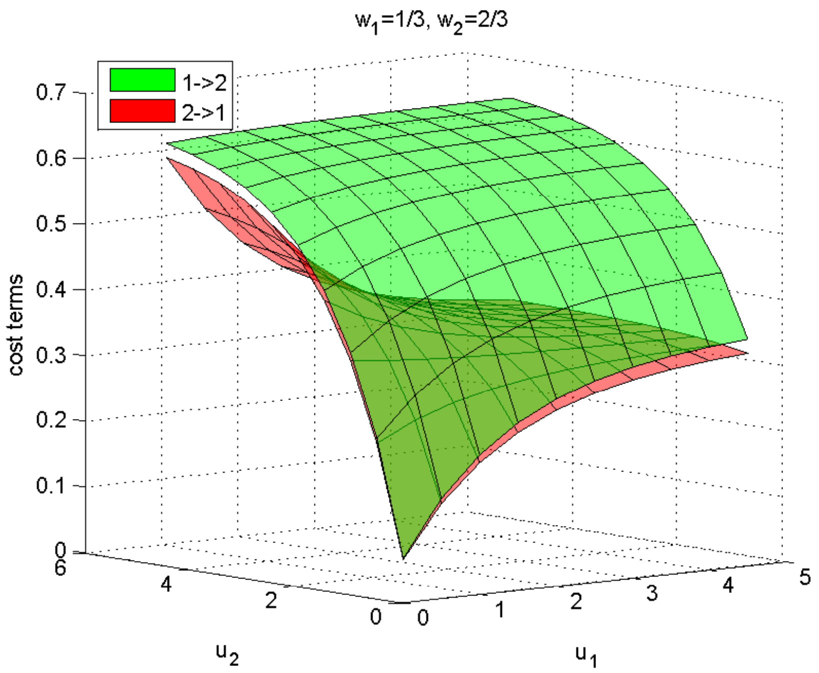

Figure 3.2: Cost terms for 2-user MAC with different SIC decoding order

The corresponding pricing parameters are $\beta_1^{*1\to 2} = \frac{\alpha_1\omega_1}{2^{u_1+u_2}}$ *for user 1 and* $\beta_2^{*1\to 2} = \frac{\alpha_2}{2^{u_2}}\left(\frac{\omega_1}{2^{u_1}} + \omega_2 - \omega_1\right)$ *for user 2.*

For the SIC decoding order $[2 \to 1]$*, the optimal power allocation is* $p_1^{*2\to 1}(\beta_1^*) = \frac{\alpha_2(\omega_2-\omega_1)}{\alpha_1\beta_2-\alpha_2\beta_1} - \frac{1}{\alpha_1}$ *for user 1 and* $p_2^{*2\to 1}(\beta_2^*) = \frac{\omega_2}{\beta_2} - \frac{\alpha_1(\omega_2-\omega_1)}{\alpha_1\beta_2-\alpha_2\beta_1}$ *for user 2.*

The corresponding pricing parameters are $\beta_1^{*2\to 1} = \frac{\alpha_1}{2^{u_1}}\left(\frac{\omega_2}{2^{u_2}} + \omega_1 - \omega_2\right)$ *for user 1 and* $\beta_2^{*2\to 1} = \frac{\alpha_2\omega_2}{2^{u_1+u_2}}$ *for user 2.*

Proof. Please refer to Proof 3.5.2. □

Fig. 3.2 shows the sum of the cost terms for the 2-user MAC with both SIC decoding orders. The $x - y$ domain shows the feasible QoS region. It illustrates that for the weights $\omega_1 = \frac{1}{3}$, $\omega_2 = \frac{2}{3}$ and equal channels $\alpha_1 = \alpha_2$, the sum cost term for decoding order $[1 \to 2]$ is higher than $[2 \to 1]$. This will be analyzed later in Subsection 3.2.5.

3.2.2 K-User Case in MAC

Now we investigate the scenario where K users are transmitting signal to the BS. First, assume all weights ω_i are pairwise disjunct $\omega_1 \neq \cdots \neq \omega_K$.

3.3 Theorem. *In order to guarantee the QoS requirements $\underline{\boldsymbol{u}}$ of each user, the universal linear pricing parameter $\boldsymbol{\beta}$ for K-user MAC with SIC decoding order $\boldsymbol{\pi}^i = [\pi_i^i \to \pi_2^i \to \cdots \to \pi_K^i]$ is given by*

$$\boldsymbol{\beta} = \boldsymbol{A}^{-1} \cdot 2^{\boldsymbol{s}}, \tag{3.6}$$

where the matrix of different channels is denoted by $\boldsymbol{A}$,

$$\boldsymbol{A} = \begin{bmatrix} \alpha_{\pi_{K-1}^i} & -\alpha_{\pi_K^i} & 0 & \cdots & 0 \\ 0 & \alpha_{\pi_{K-2}^i} & -\alpha_{\pi_{K-1}^i} & \cdots & 0 \\ & \cdots\cdots\cdots\cdots\cdots\cdots & & & \\ 0 & 0 & 0 & \cdots & \alpha_{\pi_0^i} \end{bmatrix}.$$

The vector $\boldsymbol{s}$ is given by

$$\boldsymbol{s} = \begin{bmatrix} \log\left((\omega_{\pi_K^i} - \omega_{\pi_{K-1}^i})\alpha_{\pi_K^i}\alpha_{\pi_{K-1}^i}\right) - \underline{u}_{\pi_K^i} \\ \log\left((\omega_{\pi_{K-1}^i} - \omega_{\pi_{K-2}^i})\alpha_{\pi_{K-1}^i}\alpha_{\pi_{K-2}^i}\right) - \underline{u}_{\pi_K^i} - \underline{u}_{\pi_{K-1}^i} \\ \vdots \\ \log(\omega_{\pi_1^i}\alpha_{\pi_1^i}) - \underline{u}_{\pi_K^i} - \cdots - \underline{u}_{\pi_1^i} \end{bmatrix}.$$

The power allocation for the K-user MAC with the SIC decoding order $\boldsymbol{\pi}^i = [\pi_1^i \to \pi_2^i \to \cdots \to \pi_K^i]$ by solving (3.4) is

$$p_{\pi_k^i} = \frac{\tilde{\underline{u}}_{\pi_k^i} - 1}{\alpha_{\pi_k^i}} \cdot \prod_{j=k+1}^{K} \tilde{\underline{u}}_{\pi_j^i}, \tag{3.7}$$

where $\tilde{\underline{u}}_i = 2^{\underline{u}_i}$, $\alpha_{\pi_0^i} = 1$ and $\omega_{\pi_0^i} = 0$.[2]

Proof. The proof is provided in Proof 3.5.3. □

If identical weights $\omega_1 = \cdots = \omega_K = \omega$ are considered, results in Theorem 3.3 are derived as follows.

3.4 Corollary. *The optimal prices $\boldsymbol{\beta}$ and power allocation $\boldsymbol{p}$ for the K-user MAC with equal weights and the SIC decoding order $[K \to \cdots \to 1]$ are*

$$\begin{aligned} \beta_l &= \frac{\alpha_l}{2^{\sum_{k=1}^{K} \underline{u}_k}}, \\ p_l &= \frac{2^{\sum_{k=1}^{l} \underline{u}_k} - 2^{\sum_{k=1}^{l-1} \underline{u}_k}}{\alpha_l}. \end{aligned} \tag{3.8}$$

Proof. Please refer to Proof 3.5.4. □

[2] The power allocation in (3.7) is derived by methods in [92, Chapter 10].

For the K-user MAC, the system regulator provides the prices $\boldsymbol{\beta}$ in (3.6) to the system optimizer. Then the power $\boldsymbol{p}$ is allocated by the system optimizer such that the QoS requirements $\underline{\boldsymbol{u}}$ are achieved.

3.2.3 Condition for Jointly Concave Utility for MAC with SIC

As indicated in Lemma 3.1, the universal linear pricing exists if and only if $u(\boldsymbol{p}, \boldsymbol{\omega})$ if jointly concave in $\boldsymbol{p}$. The following lemma provides the condition of the existence of the universal linear pricing.

3.5 Lemma. *For certain decoding order $\boldsymbol{\pi}^i$, if $\boldsymbol{\pi}^i = [\pi_1^i \to \pi_2^i \to \cdots \to \pi_{K-1}^i \to \pi_K^i]$, a sufficient condition for a jointly concave utility function $u(\boldsymbol{p}, \boldsymbol{\omega})$ irrespective of the channel realizations $\boldsymbol{\alpha}$ is*

$$\omega_{\boldsymbol{\pi}_K^i} \geq \omega_{\boldsymbol{\pi}_{K-1}^i} \geq \cdots \geq \omega_{\boldsymbol{\pi}_2^i} \geq \omega_{\boldsymbol{\pi}_1^i}. \tag{3.9}$$

Proof. Please refer to Proof 3.5.5. □

Fig. 3.2 shows that different SIC decoding orders result in different cost terms for MAC. Therefore, in the next section, the choice of best SIC decoding order is analyzed.

3.2.4 Choosing Best Decoding Order

The idea for the best SIC decoding order is not to compare the system utility functions for different decoding orders but to minimize the sum transmit power in the MAC system with different decoding orders.

3.6 Lemma. *The best SIC decoding order depends on the channel state $\boldsymbol{\alpha}$. In order to maximize the system utility function $\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega})$ fulfilling the rate requirement $\underline{\boldsymbol{u}_{\boldsymbol{k}}}$ with minimum sum power, the decoding order $\boldsymbol{\pi}^i = [\pi_1^i \to \pi_2^i \to \cdots \to \pi_{K-1}^i \to \pi_K^i]$ is induced by*

$$\alpha_{\pi_1^i} \geq \alpha_{\pi_2^i} \geq \cdots \geq \alpha_{\pi_{K-1}^i} \geq \alpha_{\pi_K^i}. \tag{3.10}$$

If the order of weights in (3.9) for some users does not fit the order of channels in (3.10), e.g., if the order of channel states is $\alpha_K \geq \cdots \geq \alpha_{k+1} \geq \alpha_k \geq \cdots \geq \alpha_1$, but the weight $\omega_k < \omega_{k+1}$ for user k and $k+1$, then it is sufficient to use the unweighted sum utility maximization as (3.31) at the system maximizer.

Proof. Please refer to Proof 3.5.6. □

3.2.5 Cost Analysis

Figure 3.2 illustrates the cost terms $c^{[\cdot]} = \sum_i \beta_i p_i$ for different SIC decoding orders.[3] In Section 3.2.4, we analyze the best decoding order regarding the channel states $\boldsymbol{\alpha}$ with respect to min-

[3] $[\cdot]$ denotes the SIC decoding order.

imize the sum transmit power. Now we will analyze the relationship between cost terms and the SIC decoding order. From (3.6), for a certain decoding order $\pi^i = [\pi_1^i \to \pi_2^i \to \cdots \to \pi_K^i]$, the pricing parameters for the K-user MAC can be rewritten as

$$\boldsymbol{\beta} = \begin{bmatrix} \alpha_{\pi_1^i}\Big(\frac{\omega_{\pi_1^i}}{\prod_{j=1}^K \tilde{\underline{u}}_{\pi_j^i}}\Big) \\ \alpha_{\pi_2^i}\Big(\frac{\omega_{\pi_2^i}-\omega_{\pi_1^i}}{\prod_{j=2}^K \tilde{\underline{u}}_{\pi_j^i}} + \frac{\omega_{\pi_1^i}}{\prod_{j=1}^K \tilde{\underline{u}}_{\pi_j^i}}\Big) \\ \vdots \\ \alpha_{\pi_K^i}\Big(\frac{\omega_{\pi_K^i}-\omega_{\pi_{K-1}^i}}{\tilde{\underline{u}}_{\pi_K^i}} + \frac{\omega_{\pi_{K-1}^i}-\omega_{\pi_{K-2}^i}}{\prod_{j=K-1}^K \tilde{\underline{u}}_{\pi_j^i}} + \cdots + \frac{\omega_{\pi_1^i}}{\prod_{j=1}^K \tilde{\underline{u}}_{\pi_j^i}}\Big) \end{bmatrix}.$$

It is shown that by multiplying the power allocation in (3.7), the cost terms $c^{[\cdot]}$ are independent of the channel states $\boldsymbol{\alpha}$.

The cost term c^{π^i} is then

$$\begin{aligned} c^{\pi^i} \;=\; & (\omega_{\pi_K^i} - \omega_{\pi_{K-1}^i})\frac{\tilde{\underline{u}}_{\pi_K^i} - 1}{\tilde{\underline{u}}_{\pi_K^i}} + (\omega_{\pi_{K-1}^i} - \omega_{\pi_{K-2}^i})\Big(\frac{\tilde{\underline{u}}_{\pi_{K-1}^i} - 1}{\tilde{\underline{u}}_{\pi_{K-1}^i}} + \frac{\tilde{\underline{u}}_{\pi_K^i} - 1}{\prod_{K-1}^K \tilde{\underline{u}}_{\pi_j^i}}\Big) + \cdots \\ & + \omega_{\pi_1^i}\Big(\frac{\tilde{\underline{u}}_{\pi_1^i} - 1}{\tilde{\underline{u}}_{\pi_1^i}} + \frac{\tilde{\underline{u}}_{\pi_2^i} - 1}{\prod_{j=1}^2 \tilde{\underline{u}}_{\pi_j^i}} + \cdots + \frac{\tilde{\underline{u}}_{\pi_K^i} - 1}{\prod_{j=1}^K \tilde{\underline{u}}_{\pi_j^i}}\Big). \end{aligned} \tag{3.11}$$

3.7 Lemma. *The cost terms $c^{[\cdot]}$ are only dependent on the weights $\boldsymbol{\omega}$ and the utility requirements $\underline{\boldsymbol{u}}$ of each user for different decoding orders. The regulator can charge highest from the SIC decoding order $[K \to \cdots \to 1]$ if the order of weights is $\omega_1 \geq \cdots \geq \omega_K$.*

Proof. Please refer to Proof 3.5.7. □

It is of interest for the regulator to devise the individual weights $\boldsymbol{\omega}$ in order to achieve the unique power allocation with concave utility function, which indeed coincides with the highest charge from the users. Fig. 3.2 illustrates this for the 2-user MAC.

3.2.6 Reordering Mechanism

Lemma 3.6 shows that the best SIC decoding order π^i is determined by the order of channel states $\boldsymbol{\alpha}$. Lemma 3.5 provides the order of individual wights $\boldsymbol{\omega}$ induced by a given SIC decoding order as a sufficient condition for the utility function $u(\boldsymbol{p}, \boldsymbol{\omega})$ to be jointly concave. Therefore, in order to ensure that the system works with a unique optimal solution, the regulator could set the individual weight ω_k according to the order of channel states $\boldsymbol{\alpha}$ and reorder the k^{th} user according to the channel states as well.

Assume that the channel states are ordered as $\alpha_{\pi_1^i} \geq \alpha_{\pi_2^i} \geq \cdots > \alpha_{\pi_{K-1}^i} \geq \alpha_{\pi_K^i}$ which induce the SIC decoding order as $\boldsymbol{\pi}^i = [\pi_1^i \to \pi_2^i \to \cdots \to \pi_{K-1}^i \to \pi_K^i]$. Set the weights in order $\omega_{\pi_K^i} \geq \omega_{\pi_{K-1}^i} \geq \cdots > \omega_{\pi_2^i} \geq \omega_{\pi_1^i}$ to ensure a jointly concave utility function $u(\boldsymbol{p}, \boldsymbol{\omega})$.

Reorder the user with channel state $\alpha_{\pi_1^i}$ as the K^{th} user, the user with channel state $\alpha_{\pi_2^i}$ as the $K-1^{th}$ user, and so on. Then the SIC decoding order is shifted to $\boldsymbol{\pi}^1 = [K \to \cdots \to 1]$. It is analogue for different decoding orders. Therefore, any fixed SIC decoding order could be obtained by simply reordering the users with the order of their channel states.

If channel states change, then the regulator changes the weights and SIC decoding order accordingly.

3.3 User-Centric Universal Linear Pricing for Broadcast Channel with DPC

Known as the duality between MAC and BC, with the same total transmit power, MAC and BC can achieve the same rate. This duality holds provided that the decoding order of SIC in the uplink MAC is the reverse of the DPC order in the downlink BC [9]. Using this interesting duality, we analyze the universal linear pricing problem in BC.

The general utility function for BC is

$$u(\boldsymbol{q}, \boldsymbol{\omega}) = \sum_{k \in K} \omega_k g_k \left(\frac{q_k}{I_k(\boldsymbol{q})} \right), \tag{3.12}$$

where $\boldsymbol{q}$ is the power allocation in BC. Note that the interference function $\boldsymbol{I}(\boldsymbol{q})$ here for BC is different from that in MAC. For a certain DPC precoding order $\tilde{\boldsymbol{\pi}}^i = [\tilde{\pi}_1^i \to \cdots \to \tilde{\pi}_K^i]$, the interference function for BC is

$$I_{\tilde{\pi}_k^i} = \alpha_{\tilde{\pi}_k^i} \sum_{j=k+1}^{K} q_{\tilde{\pi}_j^i} + \sigma_n^2. \tag{3.13}$$

The regulator chooses linear pricing parameters $\boldsymbol{\beta'} = [\beta'_1, \cdots, \beta'_K]$ and the system utility is

$$\tilde{u}(\boldsymbol{q}, \boldsymbol{\beta'}, \boldsymbol{\omega}) = u(\boldsymbol{q}, \boldsymbol{\omega}) - \sum_{k=1}^{K} \beta'_k q_k. \tag{3.14}$$

3.3.1 Two-User Case in BC

Similar to the analysis in MAC, we consider the special case of two users in the BC first.

3.8 Lemma. *For BC with DPC precoding order as $[1 \rightarrow 2]$ according to the SIC decoding order in MAC as $\pi^1 = [2 \rightarrow 1]$, the optimized power allocation with respect to the utility requirement $\underline{u}_k$ and the pricing parameters are*

$$\begin{aligned} q_1^* &= (2^{\underline{u}_1} - 1)\left(\frac{1}{\alpha_1} + \frac{2^{\underline{u}_2} - 1}{\alpha_2}\right), \\ q_2^* &= \frac{2^{\underline{u}_2} - 1}{\alpha_2}. \\ \beta_1^{*'} &= \frac{\omega_1\alpha_1\alpha_2}{2^{\underline{u}_1}(\alpha_2 - \alpha_1 + \alpha_1 2^{\underline{u}_2})}, \\ \beta_2^{*'} &= \frac{\omega_1\alpha_1\alpha_2(1 + 2^{\underline{u}_1})}{2^{\underline{u}_1}(\alpha_2 - \alpha_1) + \alpha_1 2^{\underline{u}_1 + \underline{u}_2}} - \frac{\omega_2\alpha_2}{2^{\underline{u}_2}}. \end{aligned} \tag{3.15}$$

Proof. Please refer to Proof 3.5.8. □

For the DPC precoding order as $[2 \rightarrow 1]$, the calculations of optimal power allocation and pricing parameters are similar. In the next section, the power allocation for K-user BC using universal linear pricing in order to guarantee the QoS requirement of each user is discussed.

3.3.2 K-User Case in BC

Now, we investigate the universal linear pricing problem in BC for general K-user cases. Due to the duality between MAC and BC, the rate requirement for each user k in BC is the same as in MAC as $\underline{\boldsymbol{u}}_k$.

3.9 Lemma. *Assume the DPC precoding order as $[K \rightarrow K-1 \rightarrow \cdots \rightarrow 2 \rightarrow 1]$, the pricing parameters $\boldsymbol{\beta}^{*'}$ given by regulator for BC are*

$$\beta_l^{*'} = \frac{\omega_l\alpha_l}{Z_l} + \sum_{m=l+1}^{K} \alpha_m\omega_m\left(\frac{1}{Z_m} - \frac{1}{Y_m}\right), \tag{3.16}$$

where $Y_l = 1 + \alpha_l \sum_1^{l-1} q_i$, and $Z_l = 1 + \alpha_l \sum_1^{l} q_i = Y_l + \alpha_l q_l$ with $\omega_{K+1} = 0$.

Proof. Please refer to Proof 3.5.9. □

3.4 Contrary Example

MAC without SIC is one of the contrary example for our universal linear pricing mechanism. The interference function for MAC without SIC is

$$I_k(\boldsymbol{p}) = \sum_{l \neq k} \alpha_l p_l + \sigma^2, \tag{3.17}$$

where σ^2 is the noise power.

Then the utility function $u(\boldsymbol{p},\boldsymbol{\omega}) = \sum_{k\in K}\omega_k g_k(\frac{p_k}{I_k(\boldsymbol{p})})$ is no longer jointly concave with respect to $\boldsymbol{p}$ in general. It becomes the $\mathcal{NU}$ function in [12]. There is no universal linear pricing for these functions in general. For example, if $u_1 = \log\left(1+\frac{\alpha_1 p_1}{1+\alpha_2 p_2}\right)$ and $u_2 = \log\left(1+\frac{\alpha_2 p_2}{1+\alpha_1 p_1}\right)$, the eigenvalues for the Hessian matrix with $\alpha_1 = \alpha_2 = 1$ and $p_1 = p_2 = 1$ are 0.25 and -0.194444. Therefore, $\tilde{u} = u_1 + u_2$ is not jointly concave in p_1 and p_2. It is possible to be jointly concave if the Hessian matrix of the system utility $\tilde{u}(\boldsymbol{q},\boldsymbol{\beta},\boldsymbol{\omega})$ is larger than 0.

3.5 Proofs

3.5.1 Proof of Lemma 3.1

Proof. "⇒": Assume $u(\boldsymbol{p},\boldsymbol{\omega})$ is jointly concave in $\boldsymbol{p}$, then the optimization problem

$$\max_{\boldsymbol{p}\geq 0} \tilde{u}(\boldsymbol{p},\boldsymbol{\beta},\boldsymbol{\omega}) = \max_{\boldsymbol{p}\geq 0}\left(u(\boldsymbol{p},\boldsymbol{\omega}) - \sum_{k=1}^{K}\beta_k p_k\right) \tag{3.18}$$

has a unique solution characterized by the first order optimality condition:

$$\frac{\partial}{\partial p_l}u(\boldsymbol{p}^*,\boldsymbol{\omega}) - \beta_l = 0 \qquad \text{if } p_l^* > 0. \tag{3.19}$$

Let us assume that $\underline{u}_k \in \mathcal{F}(\boldsymbol{\alpha})$ is achieved by a certain power allocation $\underline{\boldsymbol{p}}$, i.e.,

$$g_k(\underline{p}_k/I_k((\underline{\boldsymbol{p}}))) = \underline{u}_k \tag{3.20}$$

for all $k \in K$. For positive utility requirements, the required power p_k^* is always positive and thereby justifying (3.19).

Then choose a pricing parameter

$$\beta_l^*(\underline{\boldsymbol{p}}) = \frac{\partial}{\partial p_l}u(\boldsymbol{p},\boldsymbol{\omega})\mid_{\boldsymbol{p}=\underline{\boldsymbol{p}}}$$

in order to achieve the necessary power allocation.

"⇐": It is proved in Theorem 1 in [12]. □

3.5.2 Proof of Lemma 3.2

Proof. For user 1, the rate requirement for SIC decoding order of $[1 \to 2]$ is fulfilled by $\underline{u}_1 = r_1(p_1^*(\beta_1)) = \log\left(1+\frac{\alpha_1 p_1^*(\beta_1)}{1+\alpha_2 p_2^*(\beta_2)}\right)$. For user 2, the rate requirement is fulfilled by $\underline{u}_2 = r_2(p_2^*(\beta_2)) = \log(1+\alpha_2 p_2^*(\beta_2))$.

Therefore, the power needed to achieve the rate requirement is

$$p_1^*(\beta_1) = \frac{2^{\underline{u}_1}-1}{\alpha_1}(1+\alpha_2 p_2^*(\beta_2)) = \frac{2^{\underline{u}_2}(2^{\underline{u}_1}-1)}{\alpha_1}, \tag{3.21}$$

$$p_2^*(\beta_2) = \frac{2^{u_2} - 1}{\alpha_2}. \tag{3.22}$$

From (3.21) and (3.22), the system maximizes the system utility $\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega})$ with linear pricing term

$$\max_{\boldsymbol{p}\geq 0} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) = \max_{\boldsymbol{p}\geq 0} \Big(\omega_1 \log\big(1 + \frac{\alpha_1 p_1}{1+\alpha_2 p_2}\big) - \beta_1 p_1 + \omega_2 \log(1+\alpha_2 p_2) - \beta_2 p_2\Big). \tag{3.23}$$

The optimal power allocation solves this maximization problem by

$$\frac{\partial}{\partial p_1} = \frac{\omega_1 \alpha_1}{1 + \alpha_1 p_1 + \alpha_2 p_2} - \beta_1 = 0, \tag{3.24}$$

$$\frac{\partial}{\partial p_2} = \frac{\omega_1 \alpha_2}{1 + \alpha_1 p_1 + \alpha_2 p_2} - \frac{(\omega_1 - \omega_2)\alpha_2}{1 + \alpha_2 p_2} - \beta_2 = 0. \tag{3.25}$$

Now we obtain the power allocation p_k^* with respect to the weight ω_k as well as the pricing parameter β_k. Substitute p_k^* into (3.21) and (3.22), the pricing parameter β_k^* is observed. The case for the decoding order $[2 \to 1]$ is analogue. □

3.5.3 Proof of Theorem 3.3

Proof. It is sufficient to consider the case with SIC decoding order $[K \to \cdots \to 1]$. In order to obtain the universal pricing of $\boldsymbol{\beta}$, set $X_l = 1 + \sum_{k=1}^{l} \alpha_k p_k$. Note that $\omega_{K+1} = 0$ and $\alpha_{K+1} = 1$, (3.5) can be written as

$$\frac{\partial}{\partial p_l} = \alpha_l \left(\frac{\omega_l - \omega_{l+1}}{X_l} + \frac{\omega_{l+1} - \omega_{l+2}}{X_{l+1}} + \cdots + \frac{\omega_{K-1} - \omega_K}{X_{K-1}} + \frac{\omega_K}{X_K} \right) - \beta_l = 0. \tag{3.26}$$

Since $\frac{\partial}{\partial p_K} = \frac{\omega_K \alpha_K}{X_K} - \beta_K = 0$, $X_K = \frac{\alpha_K \omega_K}{\beta_K}$. Insert X_K into (3.26), we get $X_l = \frac{(\omega_l - \omega_{l+1})\alpha_l \alpha_{l+1}}{\alpha_{l+1}\beta_l - \alpha_l \beta_{l+1}}$. Therefore,

$$\log(X_l) = \overbrace{\log(\underbrace{(\omega_l - \omega_{l+1})\alpha_l \alpha_{l+1}}_{\tilde{c}_l})}^{c_l} - \log\underbrace{(\alpha_{l+1}\beta_l - \alpha_l \beta_{l+1})}_{D_l}. \tag{3.27}$$

Since ω_l and α_l are given numbers, the first item on the right handside in (3.27) is constant number c_l. Denote $\boldsymbol{D} = [D_1, \cdots, D_K]$, $\boldsymbol{D} = \boldsymbol{A} \cdot \boldsymbol{\beta}$.

From (3.3), the rate of each user l is

$$r_l = \begin{cases} \log(\frac{X_l}{X_{l-1}}) & : \text{ otherwise} \\ \log(X_l) & : \ l = 1 \end{cases} \tag{3.28}$$

Then we obtain $2^{r_1} = X_1$ and $2^{r_l} = \frac{X_l}{X_{l-1}}$ for $1 < l \leq K$, thus $X_l = \prod_{k=1}^{l} 2^{r_k} = 2^{\sum_{k=1}^{l} r_k}$. Therefore, $\log(X_l) = \sum_{k=1}^{l} r_k = \tilde{X}_l$. From (3.27), $\tilde{\boldsymbol{X}} = \boldsymbol{c} - \log(\boldsymbol{A} \cdot \boldsymbol{\beta})$, i.e. $2^{\boldsymbol{s}} = \boldsymbol{A} \cdot \boldsymbol{\beta}$, where $\boldsymbol{s} = \boldsymbol{c} - \tilde{\boldsymbol{X}}$. $\boldsymbol{A}^{-1}$ always exists because $\omega_k > 0, \alpha_k > 0$ for all $k, 1 \leq k \leq K$.

This proves the universal linear pricing parameter $\boldsymbol{\beta}$ in (3.6).

From (3.20) and (3.3), the rate requirement $\underline{u}_k$ for each user with SIC decoding order $[\pi_1^i \to \pi_2^i \to \cdots \to \pi_K^i]$ is achieved by certain power allocation $\boldsymbol{p}$ where

$$\underline{u}_k = \log\left(1 + \frac{\alpha_{\pi_k^i} p_{\pi_k^i}}{1 + \sum_{l=k+1}^{K} \alpha_{\pi_l^i} p_{\pi_l^i}}\right). \tag{3.29}$$

Compute the power allocation $\boldsymbol{p}$ in the SIC decoding order $\boldsymbol{\pi}^i$ as a function of utility requirement $\underline{\boldsymbol{u}}$ and the channel states $\boldsymbol{\alpha}$,

$$\begin{aligned} p_{\pi_k^i} &= \frac{2^{\underline{u}_{\pi_k^i}} - 1}{\alpha_{\pi_k^i}} \cdot (1 + \sum_{l=k+1}^{K} \alpha_{\pi_l^i} p_{\pi_l^i}) \\ &= \frac{2^{\underline{u}_{\pi_k^i}} - 1}{\alpha_{\pi_k^i}} \cdot 2^{\sum_{j=k+1}^{K} \underline{u}_{\pi_j^i}}. \end{aligned} \tag{3.30}$$

This proves the second statement in Theorem 3.3. □

3.5.4 Proof of Corollary 3.4

Proof. When considering the equal weight, the pricing problem is easier to characterize, since the optimization problem of (3.4) becomes

$$\begin{aligned} \max_{\boldsymbol{p} \geq 0, \boldsymbol{\pi}} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{\omega}) &= \max_{\boldsymbol{p}} \sum_{k=1}^{K} \log(1 + \sum_{m=1}^{k} \alpha_m p_m) - \log(1 + \sum_{m=1}^{k-1} \alpha_m p_m) - \beta_k p_k \\ &= \max_{\boldsymbol{p} \geq 0, \boldsymbol{\pi}} \log X_K - \sum_{k=1}^{K} \beta_k p_k. \end{aligned} \tag{3.31}$$

The solution of the optimization problem is

$$\begin{aligned} \frac{\partial}{\partial p_l} &= \frac{\alpha_l}{1 + \sum_{k=1}^{K} \alpha_k p_k} - \beta_l \\ &= \frac{\alpha_l}{X_K} - \beta_l = 0 \end{aligned} \tag{3.32}$$

if $p_l > 0$.

The optimization holds for $p_l = \frac{2^{\sum_{k=1}^{l} \underline{u}_k} - 2^{\sum_{k=1}^{l-1} \underline{u}_k}}{\alpha_l}$ and $\beta_l = \frac{\alpha_l}{X_k}$. This result is similar to equation (6) in [92]. □

3.5.5 Proof of Lemma 3.5

Proof. Recall the utility function $u(\boldsymbol{p},\boldsymbol{\omega})$ for the K users in MAC with SIC. First considering the SIC decoding order is $\boldsymbol{\pi}^1 = [K \to K-1 \to \cdots \to 2 \to 1]$,

$$\begin{aligned} u(\boldsymbol{p},\boldsymbol{\omega}) &= \sum_{k=1}^{K} \omega_k \log(1 + \frac{\alpha_k p_k}{1+\sum_{m=1}^{k-1}\alpha_m p_m}) \\ &= \omega_K \log(1+\sum_{m=1}^{K}\alpha_m p_m) + \cdots + (\omega_{k-1}-\omega_k)\log(1+\sum_{m=1}^{k-1}\alpha_m p_m) \\ &\quad + \cdots + (\omega_1-\omega_2)\log(1+\alpha_1 p_1). \end{aligned} \tag{3.33}$$

(3.33) is the sum of weighted concave functions. Since all weights are non-negative, the overall function is concave, too. For the SIC decoding order $\boldsymbol{\pi}^1$, if the weights are ordered as $\omega_1 \geq \omega_2 \geq \cdots \geq \omega_{K-1} \geq \omega_K$, then the utility $u(\boldsymbol{p},\boldsymbol{\omega})$ is jointly concave.

The analysis is analogue for any given decoding order $\boldsymbol{\pi}^i = [\boldsymbol{\pi}^i_1 \to \boldsymbol{\pi}^i_2 \to \cdots \to \boldsymbol{\pi}^i_{K-1} \to \boldsymbol{\pi}^{\boldsymbol{i}}_{\boldsymbol{K}}]$. □

3.5.6 Proof of Lemma 3.6

Proof. Since the rate requirements $\underline{\boldsymbol{u}}$ are fixed for different decoding orders, the basic idea to prove the first statement in Lemma 3.6 is to find the best decoding order which consumes the lowest sum transmit power. It is sufficient to consider the power allocation $\boldsymbol{p}^{k+1\to k}$ and $\boldsymbol{p}^{k\to k+1}$ for two users $k+1$ and k with the decoding order $k+1 \to k$ and $k \to k+1$, respectively [55]. Assume a decoding order $\pi^1 = [K \to \cdots \to 1]$ and $\alpha_K \geq \cdots \geq \alpha_{k+1} \geq \alpha_k \geq \cdots \geq \alpha_1$. From the power allocation of (3.7),

$$\begin{aligned} p_{k+1}^{k+1\to k} &= \frac{2^{\underline{u}_{k+1}}-1}{\alpha_{k+1}} \cdot 2^{\sum_{i=1}^{k}\underline{u}_i}, \\ p_{k}^{k+1\to k} &= \frac{2^{\underline{u}_{k}}-1}{\alpha_{k}} \cdot 2^{\sum_{i=1}^{k-1}\underline{u}_i}. \end{aligned} \tag{3.34}$$

$$\begin{aligned} p_{k+1}^{k\to k+1} &= \frac{2^{\underline{u}_{k+1}}-1}{\alpha_{k+1}} \cdot 2^{\sum_{i=1}^{k-1}\underline{u}_i}, \\ p_{k}^{k\to k+1} &= \frac{2^{\underline{u}_{k}}-1}{\alpha_{k}} \cdot 2^{\sum_{i=1}^{k-1}\underline{u}_i} \cdot 2^{\underline{u}_{k+1}}. \end{aligned} \tag{3.35}$$

Now compare the sum power $\sum_i p_i^{k+1\to k}$ and $\sum_i p_i^{k\to k+1}$. Define $N = \sum_i p_i^{k+1\to k} - \sum_i p_i^{k\to k+1}$.

$$N = 2^{\sum_{i=1}^{k-1}\underline{u}_i}(2^{\underline{u}_{k+1}}-1)(2^{\underline{u}_k}-1)\left(\frac{1}{\alpha_{k+1}} - \frac{1}{\alpha_k}\right). \tag{3.36}$$

Since the rate requirement $\underline{\boldsymbol{u}} > 0$, $2^{\underline{u}_k} > 1$, $2^{\underline{u}_{k+1}} > 1$ and $2^{\sum_{i=1}^{k-1}\underline{u}_i} > 0$. With the assumption $\alpha_{k+1} > \alpha_k$, $N < 0$. Therefore, decoding order $k+1 \to k$ consumes lower transmit power than decoding order $k \to k+1$ for $[K \to \cdots \to 1]$. For any arbitrary decoding orders $\boldsymbol{\pi} \neq [K \to \cdots \to 1]$ with the channel states $\alpha_K \geq \cdots \geq \alpha_{k+1} \geq \alpha_k \geq \cdots \geq \alpha_1$, reordering the successive two neighbor indices lowers the sum transmit power. It is analogue for any other orders of channel states $\boldsymbol{\alpha}$ and π^i.

This proves the first statement in Lemma 3.6.

Deduced by (3.10), the SIC decoding order for the order of channel states $\alpha_K \geq \cdots \geq \alpha_{k+1} \geq \alpha_k \geq \cdots \geq \alpha_1$ is $[K \to \cdots \to 1]$. If $\omega_k < \omega_{k+1}$, then $\omega_k - \omega_{k+1} \leq 0$, using $\omega_k = \omega_{k+1}$ maximizes the utility function $\boldsymbol{u}(\boldsymbol{p}, \boldsymbol{\omega})$. This proves the second statement in Lemma 3.6. □

3.5.7 Proof of Lemma 3.7

Proof. It is sufficient to compare the cost terms $c^{k+1\to k}$ and $c^{k\to k+1}$ of two successive users k and $k+1$ with the decoding order $k+1 \to k$ and $k \to k+1$, respectively. Assume the weights for each user are ordered by $\omega_1 \geq \cdots \geq \omega_K$, which induce the SIC decoding order as $[K \to \cdots \to 1]$. By changing the decoding order of two successive users $k+1$ and k, the corresponding pricing parameters are

$$\begin{aligned}
\beta_{k+1}^{k+1\to k} &= \alpha_{k+1} \cdot \Big(\frac{\omega_{k+1} - \omega_{k+2}}{\prod_{i=i}^{k+1} \tilde{\underline{u}}_i} + \cdots + \frac{\omega_K}{\prod_{i=1}^{K} \tilde{\underline{u}}_i} \Big), \\
\beta_{k}^{k+1\to k} &= \alpha_{k} \cdot \Big(\frac{\omega_{k} - \omega_{k+1}}{\prod_{i=i}^{k} \tilde{\underline{u}}_i} + \cdots + \frac{\omega_K}{\prod_{i=1}^{K} \tilde{\underline{u}}_i} \Big).
\end{aligned} \tag{3.37}$$

$$\begin{aligned}
\beta_{k+1}^{k\to k+1} &= \alpha_{k+1} \cdot \Big(\frac{\omega_{k+1} - \omega_{k}}{\prod_{i=i}^{k-1} \tilde{\underline{u}}_i \cdot \tilde{\underline{u}}_{k+1}} + \frac{\omega_{k} - \omega_{k+2}}{\prod_{i=i}^{k+1} \tilde{\underline{u}}_i} + \cdots + \frac{\omega_K}{\prod_{i=1}^{K} \tilde{\underline{u}}_i} \Big), \\
\beta_{k}^{k\to k+1} &= \alpha_{k} \cdot \Big(\frac{\omega_{k} - \omega_{k+2}}{\prod_{i=i}^{k+1} \tilde{\underline{u}}_i} + \cdots + \frac{\omega_K}{\prod_{i=1}^{K} \tilde{\underline{u}}_i} \Big).
\end{aligned} \tag{3.38}$$

Note that $\omega_{K+1} = 0, \tilde{\underline{u}}_0 = 1$, and $\tilde{\underline{u}}_i = 2^{\underline{u}_i}$. Now we compare the cost terms $c^{k+1\to k}$ and $c^{k\to k+1}$. Define $M = c^{k+1\to k} - c^{k\to k+1}$, where $c^{k+1\to k} = \beta_{k+1}^{k+1\to k} p_{k+1}^{k+1\to k} + \beta_{k}^{k+1\to k} p_{k}^{k+1\to k}$ and $c^{k\to k+1} = \beta_{k+1}^{k\to k+1} p_{k+1}^{k\to k+1} + \beta_{k}^{k\to k+1} p_{k}^{k\to k+1}$. From (3.34) and (3.35), the difference between the cost terms of the two decoding orders for user $k+1$ and k is

$$M = \frac{(\tilde{\underline{u}}_k - 1)(\tilde{\underline{u}}_{k+1} - 1)}{\tilde{\underline{u}}_k \cdot \tilde{\underline{u}}_{k+1}} \left(\omega_k - \omega_{k+1}\right). \tag{3.39}$$

Since $\underline{\boldsymbol{u}} \geq 0$, $\tilde{\underline{\boldsymbol{u}}} \geq 1$. With $\omega_k \geq \omega_{k+1}$, $M \geq 0$. Therefore. the cost term for decoding order $k+1 \to k$ is higher than decoding order $k \to k+1$. For any arbitrary decoding order $\boldsymbol{\pi} \neq [K \to \cdots \to 1]$ with the weights $\omega_1 \geq \cdots \geq \omega_K$, reordering the successive two neighbor indices increases the cost term. It is analogue for any other orders of weights $\boldsymbol{\alpha}$ and decoding orders π^i. □

3.5.8 Proof of Lemma 3.8

Proof. According to the MAC and BC duality, the sum transmit power in BC is

$$\begin{aligned} \sum_i q_i &= \sum_i p_i, \\ q_1 + q_2 &= \frac{2^{\underline{u}_1} - 1}{\alpha_1} + \frac{2^{\underline{u}_1}(2^{\underline{u}_2} - 1)}{\alpha_2} \\ &= \frac{2^{\underline{u}_1}(\alpha_2 - \alpha_1) + \alpha_1 2^{\underline{u}_1 + \underline{u}_2} - \alpha_2}{\alpha_1 \alpha_2}. \end{aligned} \tag{3.40}$$

And solve the optimization problem in (3.14), $\frac{\partial}{\partial q_1} = \frac{\omega_1 \alpha_1}{1+\alpha_1 q_1 + \alpha_1 q_2} - \beta_1 = 0$ and $\frac{\partial}{\partial q_2} = \frac{\omega_1 \alpha_1}{1+\alpha_1 q_1 + \alpha_1 q_2} - \frac{\omega_1 \alpha_1}{1+\alpha_1 q_2} + \frac{\omega_2 \alpha_2}{1+\alpha_2 q_2} - \beta_2 = 0$. Hence, knowing the sum power in (3.40), the optimal pricing parameters $\beta_1^{*'}$ and $\beta_2^{*'}$ are solved. □

3.5.9 Proof of Lemma 3.9

Proof. From (3.14), the system utility for BC is

$$\max_{\boldsymbol{q} \geq 0} \tilde{u}(\boldsymbol{q}, \boldsymbol{\beta'}, \boldsymbol{\omega}) = \max_{\boldsymbol{q} \geq 0} \sum_{k=1}^{K} \omega_k \log \left(1 + \frac{\alpha_k q_k}{1 + \alpha_k \sum_{j=1}^{k-1} q_j} \right) - \sum_{k=1}^{K} \beta'_k q_k. \tag{3.41}$$

The first optimization condition with respect to q_l is

$$\frac{\partial}{\partial q_l} = \sum_{m=l+1}^{K} \left(\frac{\omega_m \alpha_m}{Z_m} - \frac{\omega_m \alpha_m}{Y_m} \right) + \frac{\omega_l \alpha_l}{Z_l} - \beta_l = 0. \tag{3.42}$$

Then the rate requirement $\underline{\boldsymbol{u}}$ is

$$\underline{u}_l = \log \left(1 + \frac{\alpha_l q_l}{1 + \alpha_l \sum_{m=1}^{l-1} q_m} \right) = \log \left(\frac{Z_l}{Y_l} \right). \tag{3.43}$$

To solve Y_l and Z_l, the power given in Chapter 10.3.2 of [9] could be used.

$$\boldsymbol{q} = (\boldsymbol{D}_a - \boldsymbol{B})^{-1} \mathbf{1},$$

where $\boldsymbol{D}_a := \operatorname{diag}\left(\frac{1}{a_1}, \cdots, \frac{1}{a_K}\right)$, and $\mathbf{1}$ is the vector of all 1's. And $\boldsymbol{B}$ have components of α_k,

$$a_k := \frac{2^{\underline{u}_k} - 1}{2^{\underline{u}_k} \alpha_k}. \tag{3.44}$$

By inserting $\boldsymbol{D}_a$ into Y_l and Z_l, the optimal pricing parameters $\boldsymbol{\beta'}$ are solved. □

3.6 Summary

We propose a linear pricing framework in which a general system utility function is optimized under the QoS requirements of each user in the uplink MAC as well as in the downlink BC. For the MAC with SIC, we characterize the conditions for the system utility to be jointly concave with respect to power allocation which support the universal linear pricing. Furthermore, we provide an algorithm of the pricing parameters to achieve the QoS requirement for each user. The best decoding order for SIC in MAC which minimizes the sum transmit power is proposed. A reordering mechanism for the K-user MAC with regard to the order of individual weight w_k is proposed so that the SIC decoding order can be fixed.

In the downlink BC, due to the duality to MAC under the sum power constraint, the universal linear pricing algorithm is also proposed.

The contrary example shows that linear pricing is not a universal pricing mechanism for the general MAC without SIC. Because the SINR-based utility function for MAC without SIC is no longer jointly concave with respect to the power allocation.

In the next chapter, the universal nonlinear pricing mechanism for the general MAC both with and without SIC is analyzed. Moreover, the user misbehavior is discussed and the strategy-proof mechanism to prevent cheating is proposed.

4 Centralized Universal Cheat-Proof Non-Linear Pricing Framework for MAC

In this chapter we analyze the universal cheat-proof non-linear pricing framework for the general MAC system with and without SIC, respectively. It serves as a benchmark. The detailed system model are introduced and described.

4.1 System Overview and Universal Pricing for General MAC

In order to achieve the utility requirement of each user in the system, we adopt a universal non-linear pricing mechanism at the system optimizer to enforce the power allocation of the whole system.

4.1.1 System Preliminaries

We study the system operation with universal cheat-proof non-linear pricing for a wireless MAC with three types of **agents** as shown in Fig. 4.1: the system operator serving as the benevolent regulator, the BS serving as the dumb system optimizer and the transmitters serving as the selfish (malicious) users. In total, there are K transmitters (users) in the MAC system, each with single antenna. Each user k has an SINR-based utility requirement $\underline{u}_k$ to be guaranteed by the system and maximizes its short-term user-utility as well as the long-term total payoff in the RG. The pricing mechanism is designed as a virtual currency in the system to help the regulator to shift the system operating point to the utility requirement of each user. Each user has to pay some virtual money to the system operator based on their utility requirement. We regard this cost term as the virtual fee for the power allocation in the MAC system. The cost terms might be a basis for the operator to develop a tariff model. However, the pricing framework influences more on the physical layer processing than on the application layer revenue. Therefore the time scale is based on the real time physical layer power allocation. These agents interact and behave in each round i, $i = 0, \dots, \infty$ (for infinite RG), according to the following characteristics:

The regulator applies pricing to i) maximize revenue, ii) satisfy the QoS requirements of all users and iii) guarantee the correct system operation (e.g. punishing the misbehavior of agents).

1. Obtain the utility requirements $\underline{\boldsymbol{u}}$ from the K users (higher layer)
2. Compute the universal non-linear pricing parameters $\boldsymbol{\beta}^i = [\beta_1^i, \dots, \beta_K^i] \geq 0$ and charge the total cost c_K^i from users

3. Choose weights $\boldsymbol{w} = [w_1, \dots, w_K] > 0$ with $\sum_{j=1}^{K} w_j = 1$
4. Send $\boldsymbol{\beta^i}$ and $\boldsymbol{w}$ to the system optimizer
5. Punish user k with trigger strategy V_k involving the trigger pricing β_k^{tr} once detecting the user misbehavior.

The system optimizer automatically allocates the power to the users by solving the system utility maximization problem (UMP) $\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w})$ with given parameters.

1. Obtain prices $\boldsymbol{\beta^i}$ and weights $\boldsymbol{w}$ from the regulator
2. Obtain CQI $\hat{\alpha}_1, \dots, \hat{\alpha}_K$ from the users, $\hat{\boldsymbol{\alpha}} > 0$
3. Solve the UMP to allocate the power $p_1^i, \dots, p_K^i$ with maximum single user power constraint p_{max}, $0 < p_k^i \leq p_{max}$
4. Send the power allocation to users and the regulator

The users require system service $\underline{\boldsymbol{u}} = [\underline{u}_1, \cdots, \underline{u}_K]$ with the proper power allocation $\boldsymbol{p}$ and pay the fee to the system regulator.

1. Receive the pricing parameters $\beta_1^i, \dots, \beta_K^i$ from the regulator
2. Report CQI $\hat{\alpha}_1^i, \dots, \hat{\alpha}_K^i$ to system optimizer by calculating their own short-term user-utility
3. Receive transmit power allocation $p_1^i, \dots, p_K^i$
4. Pay cost $c_k^i(\boldsymbol{\beta}, \boldsymbol{p}) = \beta_k \log p_k$ to the regulator
5. Transmit with power p_k^i over the *true channel* α_k
6. Anticipate the long-term total payoff $\bar{u}_k$ in the repeated game.

4.1.2 Universal Non-linear Pricing

Let us start from the correct operation for the physical layer power allocation with truthful agents using the universal pricing. We discuss the general MAC system with and without SIC, respectively. Denote the operation with SIC with $\cdot^{SIC}$. Consider a general utility function

$$u(\boldsymbol{p}, \boldsymbol{\omega}) = \sum_{k=1}^{K} \omega_k \log \left(1 + \frac{\alpha_k p_k}{I_k(\boldsymbol{p})} \right). \tag{4.1}$$

$I_k(\boldsymbol{p})$ is from the set of simple linear interference (plus noise) functions where for MAC without SIC, it is a linear interference function $I_k^{lin}(\boldsymbol{p}) = \sum_{l \neq k} \alpha_l p_l + \sigma_n^2$, and for MAC with SIC decoding order $\pi = [\pi_1 \to \cdots \to \pi_K]$, $I_{\pi_k}^{SIC}(\boldsymbol{p}) = \sum_{l=k+1}^{K} \alpha_{\pi_l} p_{\pi_l} + \sigma_n^2$.

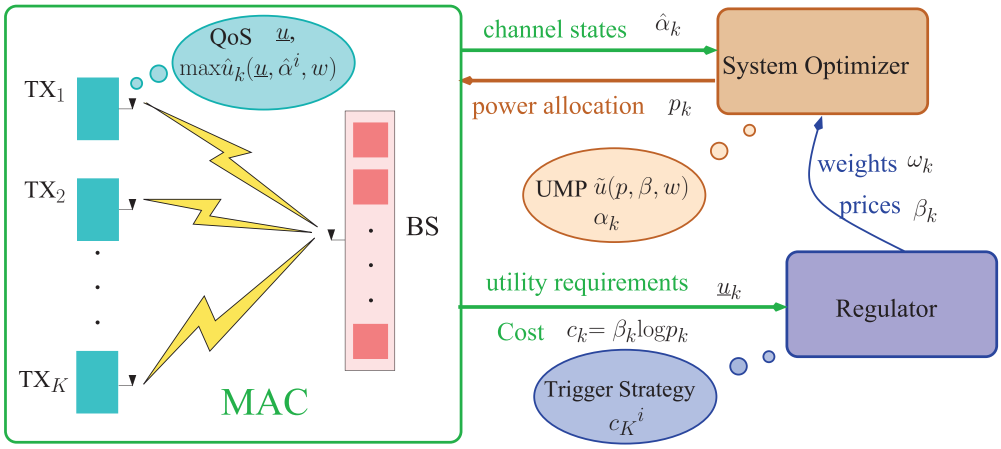

Figure 4.1: System model for general MAC with three agents: regulator, system optimizer and mobile users

A universal pricing mechanism is a tool where the regulator can utilize to shift the operating point of the wireless communication system to the desired utility requirement of each user k. Theorem 1 in [12] shows that linear pricing in power p_k is not sufficient for achieving all points if the links are interference coupled, e.g., for the linear interference function. Theorem 2 and 3 in [12] show that linear pricing in β_k and logarithmic in p_k is a universal pricing mechanism for *log-convex* interference functions. An interference function F: $\mathbb{R}_+^{K+1} \to \mathbb{R}_+$ is said to be a *log-convex* function if F is log-convex on $\mathbb{R}^{K+1}$.

Linear interference functions are also *log-convex* interference functions. Therefore, after the transformation $p_k = e^{s_k}$, the utility function $\sum_{k=1}^{K} w_k \log(1 + \frac{\alpha_k p_k}{I_k(\boldsymbol{p})})$ is jointly concave with respect to $\boldsymbol{s}$ for both MAC with and without SIC. The system utility with pricing mechanism which is linear in β_k and logarithmic in p_k is given by

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w}) = u(\boldsymbol{p}, \boldsymbol{w}) - \sum_k \beta_k \log p_k. \tag{4.2}$$

4.1 Definition. The pricing term $\beta_k \log p_k$ which is linear in β_k and non-linear in p_k is said to be **universal non-linear pricing** if the utility function (4.1) is jointly concave in s_k.

In the following section, we consider the rate based utility maximization function as follows.

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w}) = \sum_{k=1}^{K} w_k \log\left(1 + \frac{\alpha_k e^{s_k}}{I_k(e^{\boldsymbol{s}})}\right) - \sum_{k=1}^{K} \beta_k s_k, \tag{4.3}$$

where w_k is the weight, β_k is the universal non-linear price and $s_k = \log p_k$.

4.2 System Operation with Truthful Agents

First we analyze the standard procedure to allocate power p_k with corresponding price β_k and weight w_k for the truthful agents in the K-user MAC with and without SIC, respectively, using the universal non-linear pricing mechanism. Therefore, we assume that the CQI $\alpha_1, ..., \alpha_K$ are known perfectly and reported truthfully. We omit the notation i for round i in this section for simplicity. The UMP is to maximize

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w}) = \sum_{k=1}^{K} w_k \log\left(1 + \frac{\alpha_k e^{s_k}}{1 + \sum_{j \neq k} \alpha_j e^{s_j}}\right) - \sum_{k=1}^{K} \beta_k s_k \tag{4.4}$$

for MAC without SIC and similarly

$$\begin{aligned} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w})^{SIC} \quad = \quad & \sum_{k=1}^{K} w_{\pi_k}^{SIC} \log\left(1 + \frac{\alpha_{\pi_k} e^{s_{\pi_k}^{SIC}}}{1 + \sum_{j=k+1}^{K} \alpha_{\pi_j} e^{s_{\pi_j}^{SIC}}}\right) \\ & - \sum_{k=1}^{K} \beta_{\pi_k}^{SIC} s_{\pi_k}^{SIC} \end{aligned} \tag{4.5}$$

for MAC with SIC decoding order $\pi = [\pi_1 \to \cdots \to \pi_K]$.

4.2.1 Linear Receiver without SIC

For MAC without SIC, we characterize the optimal power allocation as a function of utility requirements and the reported CQI. Then, the corresponding pricing parameters are derived.

4.2.1.1 Power Allocation and Universal Non-linear Pricing

The system optimizer allocates the power to each user by solving

$$\begin{aligned} \boldsymbol{p} \quad &= \quad \arg\max_{\boldsymbol{p}} \tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w}). \\ s.t. \quad & \quad 0 \leq \boldsymbol{p} \leq p_{max} \end{aligned}$$

4.2 Proposition. *In the K-user MAC without SIC, the power of each user k allocated by the system optimizer in order to optimize UMP is a function of the QoS requirements $\underline{\boldsymbol{u}}$ and the CQI α_k.*

$$p_k = \frac{B_K}{\alpha_k} \cdot \frac{2^{\underline{u}_k} - 1}{2^{\underline{u}_k}}, \tag{4.6}$$

where $B_K = \frac{1}{\sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} - K + 1}$ is a constant for given $\underline{u}_j, j = 1, \cdots, K$.

The regulator can ensure the QoS requirements $\underline{\mathbf{u}}$ by pricing parameters ($k = 1, \cdots, K$)

$$\beta_k = \left(1 - \frac{1}{2^{\underline{u}_k}}\right)\left(1 - \sum_{j \neq k} w_j 2^{\underline{u}_j}\right) \tag{4.7}$$

and weights $\mathbf{w}$ from the following interval

$$\frac{1 + \frac{1}{2^{\underline{u}_k}} - \frac{1}{K-1} \cdot \sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}}}{K-1} < w_k < \frac{1}{2^{\underline{u}_k}(K-1)}. \tag{4.8}$$

Proof. See Proof 4.5.1. □

The achievable rate of each user in the general MAC without SIC is restrict by the total number of users in the wireless system.

4.3 Corollary. *The feasible region $\mathcal{U}$ for the K-user MAC system without SIC is*

$$K - 1 < \sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} < K, \tag{4.9}$$

where feasible *means that the utility requirements are achievable in the K-user MAC system.*

Proof. From (4.6), the utility requirement $\underline{u}_k$ of user k is achievable with positive power allocation p_k if and only if $B_K > 0$ so that $K - 1 < \sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}}$. For positive $\underline{u}_k$, $2^{\underline{u}_k} > 1$ and $0 < \frac{1}{2^{\underline{u}_k}} < 1$, therefore $\sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} < K$ is proved. □

The definition of the utility requirement $\underline{u}_k$ allows us to rewrite the criterion of feasible utility region (4.9) through an *effective bandwidth* characterization: $\sum_{j=1}^{K} \frac{2^{\underline{u}_j}-1}{2^{\underline{u}_j}} < 1$ and $\sum_{j=1}^{K} \frac{SINR_j}{1+SINR_j} < 1$, where the *effective bandwidth* $\sum_{j=1}^{K} \frac{2^{\underline{u}_j}-1}{2^{\underline{u}_j}}$ is a simple monotonic function of $\underline{u}_j$. Therefore the utility region is feasible if and only if the sum of the effective bandwidths of the K users is less than one. This region is similarly characterized in [93], where the authors focus on the user capacity of synchronous CDMA systems with linear MMSE multiuser receivers. The right handside (RHS) one of the criterion represents the *degrees of freedom* in the system.

4.4 Corollary. *The feasible utility region $\mathcal{U}_{p_{max}}$ with single user power constraint p_{max} for the K-user MAC system without SIC is*

$$\max_{1 \leq k \leq K} \left(\frac{1 - \frac{1}{2^{\underline{u}_k}}}{p_{max} \cdot \alpha_k}\right) + K - 1 < \sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} < K. \tag{4.10}$$

Proof. By solving $p_k < p_{max}$, we obtain $\sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} > \frac{1-\frac{1}{2^{\underline{u}_k}}}{p_{max} \cdot \alpha_k} + K - 1, \quad k = 1, \ldots, K$. Since $\left(\frac{1-\frac{1}{2^{\underline{u}_k}}}{p_{max} \cdot \alpha_k}\right)$ is always positive, $K > \max_{1 \leq k \leq K}\left(\frac{1-\frac{1}{2^{\underline{u}_k}}}{p_{max} \cdot \alpha_k}\right) + K - 1 > K - 1$. □

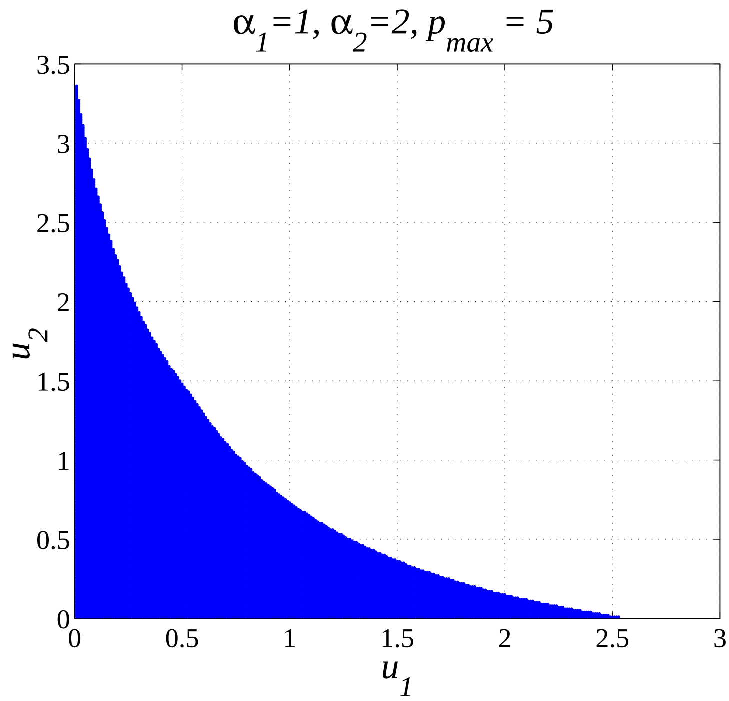

Figure 4.2: Feasible utility region $\mathcal{U}_{p_{max}}$ for 2-user MAC with p_{max} and no SIC

Fig. 4.2 shows the feasible utility region $\mathcal{U}_{p_{max}}$ for the 2-user MAC without SIC.

4.5 Remark. If $p_{max} \to \infty$, then the feasible utility region $\mathcal{U}_{p_{max}} \to \mathcal{U}$.

4.6 Remark. The power allocation p_k for user k is only dependent on its own channel α_k and the utility requirements $\underline{\boldsymbol{u}}$ of all the users. The power allocation satisfies

$$\frac{1}{\alpha_k}(1 - \frac{1}{2^{\underline{u}_k}}) < p_k < p_{max}, \tag{4.11}$$

since $B_K > 1$ from Corollary 1. Note that the CQI $\boldsymbol{\alpha} \neq 0$ due to the single power constraint p_{max}. Since the system guarantees the utility requirement $\underline{u}_k$ of each user k, the power allocation p_k is inversely proportional to its CQI α_k.

4.7 Remark. The pricing parameter β_k is independent of the CQI $\boldsymbol{\alpha}$. This observation is important because the regulator does not need to know the channels $\alpha_1, \ldots, \alpha_K$ and can adapt the prices $\boldsymbol{\beta}$ to the less fluctuating QoS requirements $\underline{\boldsymbol{u}}$. This property reduces the computational complexity of the regulator and since $\underline{\boldsymbol{u}}$ is a long-term constant, the update of the universal pricing parameters is slow.

Given the weights $\boldsymbol{w}$ in (4.8), the pricing parameters are within the interval

$$0 < \beta_k < 1 - \frac{1}{2^{\underline{u}_k}},$$

since $0 < 1 - \frac{1}{2^{\underline{u}_k}}$ and $0 < 1 - \sum_{j \neq k} w_j 2^{\underline{u}_j} < 1$.

4.2.1.2 Cost Terms and Optimal Weights

We assume all the users pay the virtual fee to the system operator for the service depending on their transmit power allocation. The total cost paid to the regulator by all the users is

$$c_K(\boldsymbol{\beta}, \boldsymbol{p}) = \sum_{j=1}^{K} \beta_j \log p_j. \tag{4.12}$$

On the basis of guaranteeing the rate requirement of each user, the regulator will choose the weight vector $\boldsymbol{w}$ in order to maximize the revenue c_K from the users, i.e., $\boldsymbol{w} := \max_{\boldsymbol{w}} c_K(\boldsymbol{\beta}, \boldsymbol{p})$.

Inserting the results in Proposition 4.2,

$$\begin{aligned} c_K(\boldsymbol{\beta}, \boldsymbol{p}) &= \sum_{j=1}^{K}(1 - \frac{1}{2^{\underline{u}_j}})\Big(1 - \sum_{l \neq j} w_l 2^{\underline{u}_l}\Big) \log p_j \\ &= \xi - \sum_{j=1}^{K}(1 - \frac{1}{2^{\underline{u}_j}}) \log p_j \cdot \sum_{l \neq j} w_l 2^{\underline{u}_l}, \end{aligned}$$

where $\xi = \sum_{j=1}^{K}(1 - \frac{1}{2^{\underline{u}_j}}) \log p_j$ is a constant with respect to weights $\boldsymbol{w}$.

Since p_j is independent of $\boldsymbol{w}$, we formulate a linear programming (LP) problem to solve $\boldsymbol{w}$.

$$\begin{aligned} \min_{\boldsymbol{w}} \quad & \boldsymbol{l}^T \cdot \boldsymbol{w} \\ \text{s.t.} \quad & \frac{1 + \frac{1}{2^{\underline{u}_k}} - \frac{1}{K-1} \cdot \sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}}}{K-1} < w_k < \frac{1}{2^{\underline{u}_k}(K-1)}, \end{aligned} \tag{4.13}$$

where $\boldsymbol{l}^T = [2^{\underline{u}_1} \sum_{j=2}^{K}(1-\frac{1}{2^{\underline{u}_j}}) \log p_j, \cdots, 2^{\underline{u}_k} \sum_{j \neq k}(1-\frac{1}{2^{\underline{u}_j}}) \log p_j, \cdots, 2^{\underline{u}_K} \sum_{j=1}^{K-1}(1-\frac{1}{2^{\underline{u}_j}}) \log p_j]$.

4.8 Example. The LP problem for the general K-user MAC system without SIC can be solved easily. Here we provide the result of the 2-user MAC without SIC. With $w_1 = 1 - w_2$, if $2^{\underline{u}_2}(1 - \frac{1}{2^{\underline{u}_1}}) \log p_1 - 2^{\underline{u}_1}(1 - \frac{1}{2^{\underline{u}_2}}) \log p_2 \geq 0$, then $w_1 = \frac{1}{2^{\underline{u}_1}}$ for user 1 and $w_2 = 1 - \frac{1}{2^{\underline{u}_1}}$ for user 2. Otherwise $w_1 = 1 - \frac{1}{2^{\underline{u}_2}}$ and $w_2 = \frac{1}{2^{\underline{u}_2}}$. Fig. 4.3 shows the contour result of the corresponding cost terms in the feasible utility region $\mathcal{U}_{p_{max}}$ using optimal pricing and weights.

4.2.2 Non-linear Receiver with SIC

In Chapter 3 [94], universal linear pricing for MAC with SIC was presented. To gain a comprehensive understanding and to compare the pricing mechanism with and without SIC, we consider the same universal non-linear pricing mechanism of the MAC with SIC.

4.2.2.1 Power Allocation and Universal Non-linear Pricing

Without loss of generality, we assume the SIC decoding order as $\pi = [K \to \cdots \to 1]$ and denote the variables with ^{SIC}. This decoding order remains the same throughout the whole paper if not specified otherwise.

4.9 Proposition. *In the MAC system with SIC decoding order of $\pi = [K \to \cdots \to 1]$, the power of each user k allocated by the system optimizer in order to maximize the UMP is*

$$p_k^{SIC} = \frac{2^{\underline{u}_k} - 1}{\alpha_k} \cdot \prod_{j=1}^{k-1} 2^{\underline{u}_j}. \tag{4.14}$$

The pricing parameter charged by the regulator for ensuring the user QoS requirement $\underline{\boldsymbol{u}}$ is

$$\beta_k^{SIC} = (2^{\underline{u}_k} - 1) \sum_{j=k}^{K} \frac{w_j - w_{j+1}}{\prod_{m=k}^{j} 2^{\underline{u}_m}}. \tag{4.15}$$

Proof. See Proof 4.5.2. □

4.10 Remark. The power allocation p_k^{SIC} is only dependent on its own channel α_k and utility requirement $\underline{u}_k$, and $\underline{u}_l$ of all the users l which are decoded after user k. p_k^{SIC} is the same as (3.7). In contrast to the results of Theorem 1 in [94] ((3.6) in Chapter 3), the pricing parameter β_k^{SIC} is only dependent on the weights w_l and all the $\underline{u}_l$ of user l which are decoded earlier than user k. In particular, same as β_k for MAC without SIC, β_k^{SIC} is independent of the CQI $\boldsymbol{\alpha}$.

4.11 Corollary. *If the regulator provides weights*

$$w_1^{SIC} \geq \cdots \geq w_k^{SIC} \geq \cdots w_K^{SIC}, \tag{4.16}$$

then the corresponding pricing parameters are in the range $0 \leq \beta_k^{SIC} < 1 - \frac{1}{2^{\underline{u}_k}}$.

Proof. Another form of the pricing parameter β_k^{SIC} in (4.15) is

$$\beta_k^{SIC} = \big(1 - \frac{1}{2^{\underline{u}_k}}\big) \cdot \Big(w_k + w_{k+1}\big(\frac{1}{2^{\underline{u}_{k+1}}} - 1\big) + \cdots + w_K \cdot \frac{1}{\prod_{j=k+1}^{K-1} 2^{\underline{u}_j}}\big(\frac{1}{2^{\underline{u}_K}} - 1\big)\Big). \tag{4.17}$$

Since $\underline{\boldsymbol{u}} \geq 0$, $\frac{1}{2^{\underline{u}_j}} - 1 < 0$. From $\sum_{j=1}^{K} w_j = 1$, β_k^{SIC} is always smaller than $1 - \frac{1}{2^{\underline{u}_k}}$. From (4.15), if the weights given by the regulator are in order (4.16), then β_k^{SIC} is always larger than 0. □

4.2.2.2 Cost Terms and Optimal Weights for MAC with SIC

As in the MAC system without SIC, the regulator in the MAC system with SIC chooses weights $\boldsymbol{w}^{SIC}$ in order to maximize its total revenue, i.e.,

$$\boldsymbol{w}^{SIC} \quad := \quad \max_{\boldsymbol{w}} c_K^{SIC}(\boldsymbol{\beta^{SIC}}, \boldsymbol{p^{SIC}}),$$

from all the K users. Here $c_K^{SIC}(\boldsymbol{\beta^{SIC}}, \boldsymbol{p^{SIC}}) = \sum_{j=1}^{K} \beta_j^{SIC} \log p_j^{SIC}$.

The weight vector $\boldsymbol{w}^{SIC}$ can be solved by the LP problem as follows.

$$\begin{aligned} \max\nolimits_{\boldsymbol{w}^{SIC}} \quad & \boldsymbol{l}^{SIC} \cdot \boldsymbol{w}^{SIC} \\ \text{s.t.} \quad & w_1^{SIC} > \cdots > w_k^{SIC} > \cdots > w_K^{SIC}, \\ & \sum_{j=1}^{K} w_j^{SIC} = 1, \end{aligned} \tag{4.18}$$

where $\boldsymbol{l}^{SIC} = [(1-\frac{1}{2^{\underline{u}_1}})\log p_1^{SIC}, (1-\frac{1}{2^{\underline{u}_1}})(\frac{1}{2^{\underline{u}_2}}-1)\log p_1^{SIC} + (1-\frac{1}{2^{\underline{u}_2}})\log p_2^{SIC}, \cdots, \sum_{j=1}^{K-1}(1-\frac{1}{2^{\underline{u}_j}})(\frac{1}{2^{\underline{u}_K}}-1)\cdot\frac{1}{\prod_{i=j+1}^{K-1}2^{\underline{u}_i}}\log p_j^{SIC} + (1-\frac{1}{2^{\underline{u}_K}})\log p_K^{SIC}]$.

4.12 Example. We address the result for the 2-user MAC with SIC decoding order of $\pi = [2 \rightarrow 1]$. This order is the best by means of minimizing the sum power [94]. If $(1-\frac{1}{2^{\underline{u}_1}})(\frac{1}{2^{\underline{u}_2}} - 2)\log p_1^{SIC} + (1-\frac{1}{2^{\underline{u}_2}})\log p_2^{SIC} \geq 0$, then $w_2^{SIC} = \max w_2^{SIC} < w_1^{SIC}$. Otherwise $w_2^{SIC} = \min w_2^{SIC}$. Fig. 4.4 shows the contour result of the corresponding cost terms in the feasible rate region. We use $\max w_2 = 0.4$ and $\min w_2 = 0.1$ in Fig. 4.4.

The curves in the $\underline{u}_1 - \underline{u}_2$ plane in Fig. 4.3 and Fig. 4.4 show the cost terms for different QoS requirements in the feasible utility region with optimal weights. It is clear that the higher the utility requirements, the higher the cost. Notice that the cost terms are below zero for small $\underline{\boldsymbol{u}}$ because the power allocation for small utilities is low. This can be seen as a stimulation measure, that the users with good channels and low utility requirements could even get payback from the system because they consume less power and produce lower interference to the others. Of course, this negative cost terms can be compensated by adding a constant cost, so the system which provides service will in total always get positive fees or become at least budget balanced.

4.3 Cheating Problem

From a game theoretic point of view, the users have incentives not to report their true types. It is possible for the user k to manipulate the universal non-linear pricing scheme by reporting the CQI $\hat{\alpha}_k$ instead of the true α_k in order to maximize its own short-term user-utility.

In this section, we analyze the incentives of the user misbehavior and their best cheating strategy. Based on this, the cheat-proof pricing strategy is proposed in the next section. First

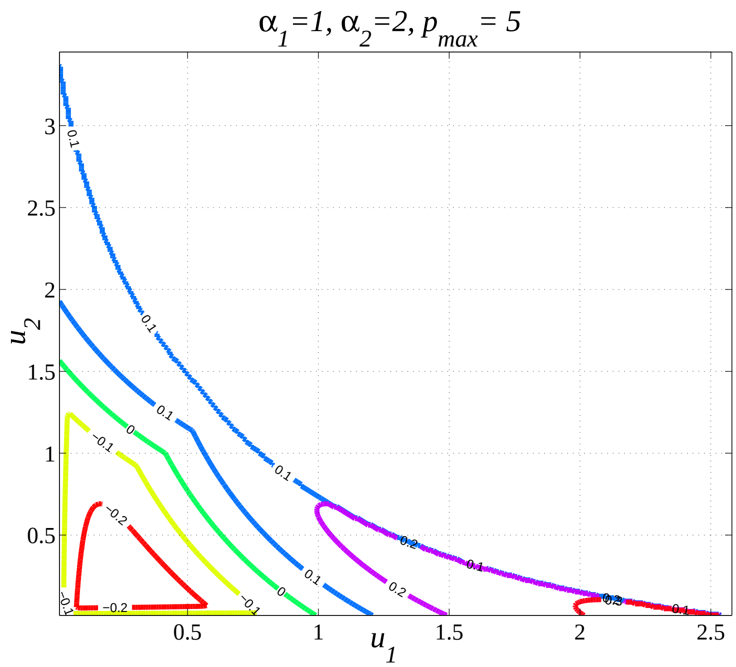

Figure 4.3: Cost term for the 2-user MAC without SIC in the feasible utility region $\mathcal{U}_{p_{max}}$ with the optimal pricing and weights given in Example 4.8

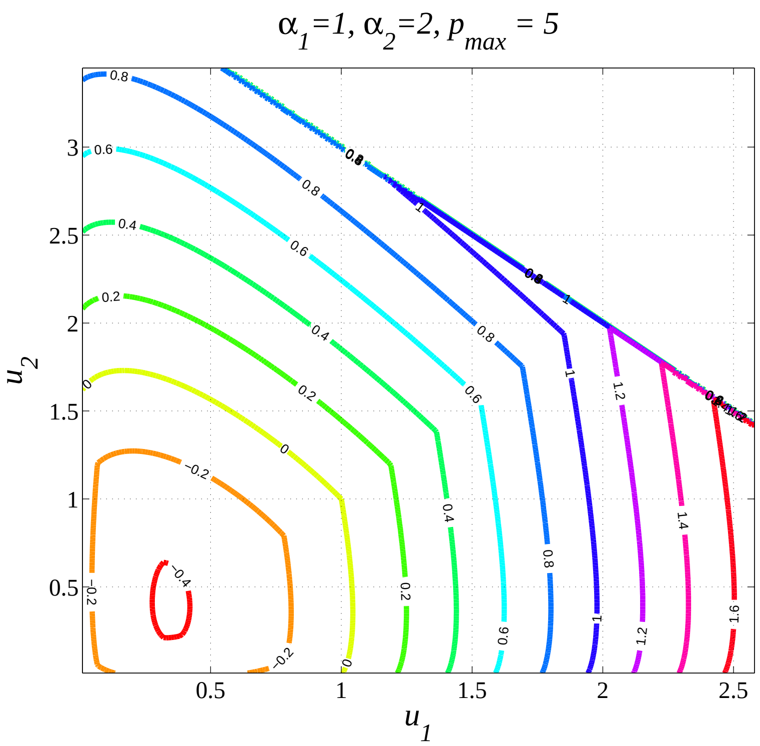

Figure 4.4: Cost term for the 2-user MAC with SIC decoding order $[2 \to 1]$ in the feasible utility region with the optimal pricing and weights given in Example 4.12

we investigate the influence on power allocation and the resulting achievable rate if there exists a cheater, namely user k, who cheats on its CQI by reporting $\hat{\alpha}_k \neq \alpha_k$. Then, we study the optimal cheating strategy of the cheater for the MAC system with and without SIC, respectively.

4.3.1 Rate Analysis

Since the power $p_k(\hat{\boldsymbol{\alpha}})$ allocated by the system optimizer is only dependent on $\underline{\boldsymbol{u}}$ and $\hat{\alpha}_k$, $p_k(\hat{\boldsymbol{\alpha}})$ satisfies the QoS requirements $\underline{\boldsymbol{u}}$ with the reported channels $\hat{\boldsymbol{\alpha}}$, i.e.,

$$\begin{aligned} \underline{u}_k &= \log\left(1 + \frac{\hat{\alpha}_k p_k(\hat{\boldsymbol{\alpha}})}{I_k(\boldsymbol{p})}\right), \quad \text{and} \\ \underline{u}_l &= \log\left(1 + \frac{\alpha_l p_l(\hat{\boldsymbol{\alpha}})}{I_l(\boldsymbol{p})}\right), \qquad l \neq k. \end{aligned} \tag{4.19}$$

When $l \neq k$ for MAC without SIC and $l > k$ for MAC with SIC, the component $\hat{\alpha}_k p_k(\hat{\boldsymbol{\alpha}})$ of the cheated CQI $\hat{\alpha}_k$ and the power allocation $p_k(\hat{\boldsymbol{\alpha}})$ after cheating is involved in $I_l(\boldsymbol{p})$. i.e.,

$$I_l^{lin}(\boldsymbol{p}) = 1 + \sum_{j \neq l, j \neq k} \alpha_j p_j(\hat{\boldsymbol{\alpha}}) + \hat{\alpha}_k p_k(\hat{\boldsymbol{\alpha}}) \tag{4.20}$$

for $l \neq k$ in MAC without SIC and

$$I_l^{SIC}(\boldsymbol{p}) = 1 + \sum_{j=1, j \neq k}^{l-1} \alpha_j p_j(\hat{\boldsymbol{\alpha}}) + \hat{\alpha}_k p_k(\hat{\boldsymbol{\alpha}}) \tag{4.21}$$

for $l > k$ in MAC with SIC. We interpret the optimal power allocation as a function of $\hat{\boldsymbol{\alpha}}$, i.e., $\boldsymbol{p}(\hat{\boldsymbol{\alpha}})$ solves (4.19). The actual rate achieved after cheating for each user k is $r_k(\hat{\boldsymbol{\alpha}})$.

4.13 Lemma. *By cheating only the own power allocation does change. e.g., if $\hat{\alpha}_k > \alpha_k$ ($\hat{\alpha}_k < \alpha_k$), then the power allocation is*

1. $p_k(\hat{\boldsymbol{\alpha}}) < p_k(\boldsymbol{\alpha})$ $(p_k(\hat{\boldsymbol{\alpha}}) > p_k(\boldsymbol{\alpha}))$,
2. $p_l(\hat{\boldsymbol{\alpha}}) = p_l(\boldsymbol{\alpha})$ *for all* $l \neq k$.

The actual rate $r_l(\hat{\boldsymbol{\alpha}})$ achieved after cheating deviates from the rate requirement $\underline{u}_l$. If $\hat{\alpha}_k < \alpha_k$, then the actual rate

1. $r_k(\hat{\boldsymbol{\alpha}}) > \underline{u}_k$ *for the cheater* k;
2. $r_l(\hat{\boldsymbol{\alpha}}) < \underline{u}_l$ *for* $l \neq k$ *in MAC without SIC;*
3. $r_l^{SIC}(\hat{\boldsymbol{\alpha}}) < \underline{u}_l$ *for* $l > k$ *and* $r_l^{SIC}(\hat{\boldsymbol{\alpha}}) = \underline{u}_l$ *for* $l < k$ *in MAC with SIC.*

And vice versa.

Proof. See Proof 4.5.3. □

In round i the regulator is able to detect the misbehavior of user k in round $i-1$ since the rates achieved by some other users are lower than the utility requirements while the rate of user k is higher than its utility requirement if $\hat{\alpha}_k < \alpha_k$.

4.3.2 Optimal Cheating by User Utility Maximization

Besides achieving its SINR-based QoS requirement $\underline{u}_k$, each user k has its own short-term user utility $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$ in each round i to maximize with respect to the reported CQI $\hat{\alpha}_k$. Denote $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$ and $\hat{u}_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^i, \boldsymbol{w})$ as the user-utility with and without cheating, respectively. Since the pricing parameter is independent of the CQI, β_k^i is the same for both $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$ and $\hat{u}_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^i, \boldsymbol{w})$, where

$$\begin{aligned} \hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w}) &= r_k^i(\hat{\boldsymbol{\alpha}}) - \beta_k^i \log p_k^i(\hat{\boldsymbol{\alpha}}) \qquad (4.22) \\ &= \log\left(1 + \frac{\alpha_k}{\hat{\alpha}_k}(2^{\underline{u}_k} - 1)\right) - \beta_k^i \log\left(\frac{y_k}{\hat{\alpha}_k^i}\right), \\ \hat{u}_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^i, \boldsymbol{w}) &= \underline{u}_k - \beta_k^i \log\left(\frac{y_k}{\alpha_k}\right). \qquad (4.23) \end{aligned}$$

For MAC without SIC, $y_k = B_K \frac{2^{\underline{u}_k}-1}{2^{\underline{u}_k}}$, $\beta_k = (1 - \frac{1}{2^{\underline{u}_k}})(1 - \sum_{j \neq k} w_j 2^{\underline{u}_j})$ and for MAC with SIC, $y_k^{SIC} = (2^{\underline{u}_k} - 1)\prod_{j=1}^{k-1} 2^{\underline{u}_j}$ and $\beta_k^{i,SIC} = (2^{\underline{u}_k} - 1)\sum_{j=k}^{K} \frac{w_j - w_{j+1}}{\prod_{m=k}^{j} 2^{\underline{u}_m}}$, respectively.

From Lemma 4.13, the users do not have incentives to cheat for a higher CQI $\hat{\alpha}_k > \alpha_k$ since its rate requirement $\underline{u}_k$ will not be fulfilled after cheating. Due to single user power constraint p_{max} in the wireless system, the minimum effective CQI in transmission for each user k is

$$\alpha_{min,k} = \frac{B_K}{p_{max}} \frac{2^{\underline{u}_k} - 1}{2^{\underline{u}_k}}$$

for MAC without SIC and

$$\alpha_{min,k}^{SIC} = \frac{2^{\underline{u}_k} - 1}{p_{max}} \prod_{j=1}^{k-1} 2^{\underline{u}_j}$$

for MAC with SIC.

4.14 Theorem. *Assume $\underline{\boldsymbol{u}} \in \mathcal{U}_{p_{max}}$. If the regulator provides weights as in (4.8) for MAC without SIC or in (4.16) for MAC with SIC, then in round i the malicious (selfish)[1] user always reports its lowest CQI $\alpha_{min,k}$ or $\alpha_{min,k}^{SIC}$ in order to maximize its own user-utility $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$, respectively.*

Proof. See Proof 4.5.4. □

[1] Note that the cheating user is selfish (because it maximizes its own user-utility $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$) and also malicious (because all other users in the system suffer according to Lemma 4.13).

After cheating with the CQI $\alpha_{min,k}$, the user utility of user k in round i is

$$\max \hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w}) \quad = \quad \log\left(1 + z_k(2^{\underline{u}_k} - 1)\right) - \beta_k^i \log\left(\frac{y_k}{\alpha_{min,k}}\right), \tag{4.24}$$

where $z_k = \frac{\alpha_k}{\alpha_{min,k}} = \frac{2^{r_k^i(\hat{\boldsymbol{\alpha}})}-1}{2^{\underline{u}_k}-1}$ and y_k is defined below (4.23). The real rate for the cheater k in MAC without SIC achieved after cheating in round i is

$$r_k^i(\hat{\boldsymbol{\alpha}}) = \log\left(1 + \frac{\alpha_k p_{max}}{B_K} \cdot 2^{\underline{u}_k}\right). \tag{4.25}$$

The real rate for MAC with SIC after cheating with $\hat{\alpha}_k^{SIC} = \alpha_{min,k}^{SIC}$ is

$$r_k^{i,SIC}(\hat{\boldsymbol{\alpha}}) = \log\left(1 + \frac{\alpha_k p_{max}}{\prod_{j=1}^{k-1} 2^{\underline{u}_j}}\right). \tag{4.26}$$

In Theorem 4.14, we derive how the user, who cheats, misbehaves by reporting the smallest CQI $\alpha_{min,k}$ and $\alpha_{min,k}^{SIC}$ for the MAC without and with SIC. In the next section, we propose a repeated game mechanism with trigger pricing which counters such misbehavior.

4.4 Cheat-proof Pricing and Repeated Game

In this section, we calculate the incentive compatible mechanism to prevent cheating in the general MAC system with and without SIC. The mechanism includes two parts: 1) Worst case strategy to ensure the utility requirement of all the honest users: We propose the worst case power allocation with the worst case pricing parameters. 2) Repeated game formulation with trigger strategy: We show that it is possible to provide the proper trigger price in order to prevent user misbehavior analysed in Sec. 4.3.

4.4.1 Repeated Game Design

We assume the regulator adopts the repeated game so that the user misbehavior is detected and the cheating on the CQI is prevented. A typical repeated game is played in several or infinite rounds, denoted as $i = [0, \cdots]$. We adopt the infinite RG in this section in order to prevent the users cheating. A model with an infinite horizon is appropriate if, after each round, the players believe that the game will continue for an additional round, while a model with a finite horizon is appropriate if the players clearly perceive a well-defined final round [95]. In this case, the finite RG is not appropriate. Because the players can change their strategy profile in each round of the finite RG. It is possible that the selfish (malicious) users cheat in the last round of the finite repeated game while pretend to be honest in the first played rounds. If so, then no punishment can be applied to the cheaters and the utility requirements of the other users can not be guaranteed.

For the case in which one user misbehaves, e.g., user k, we assume that in each round i, the selfish user k maximizes its own short-term user-utility $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w}) = r_k^i(\hat{\boldsymbol{\alpha}}) - \beta_k \log p_k(\hat{\boldsymbol{\alpha}})$. The users may have incentives to cheat on their CQI ($\hat{\boldsymbol{\alpha}} \neq \boldsymbol{\alpha}$) to achieve additional profits in $\hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w})$. In order to prevent cheating, a RG is operated among all the users in the system and the regulator. Whenever the regulator detects a user misbehavior, the trigger strategy V_k is applied on the cheater k from that round on with the trigger pricing parameter β_k^{tr}.

Instead of adjusting the strategy in each stage game, the players in the infinite RG choose their best strategy once at the beginning of the game by anticipating the expected total payoff. The mechanism of RG serves as a deterrence (threat) for the players who utilize it, since by anticipating the long-term total payoff in RG, the cheater will gain nothing and the honest users will always fulfill their utility requirements with the worst-case strategy.

It is always apposite to consider user k cheats for $\alpha_{min,k}$ in the 0-th round in the RG. In order to guarantee the utility requirements $\underline{u}_l$ for users $l \neq k$, the worst case strategy is performed for all the $K-1$ honest users, where user k is removed from the system optimization.

4.4.2 Worst Case Strategy for Honest Users

From the cheating round on, the system optimizes UMP of the $K-1$ users with the standard procedure given in Sec. 4.2. We denote the parameters in worst case strategy with notation wc. We refer to it as worst case strategy because the best cheating strategy of the malicious user is to report $\hat{\alpha}_k = \alpha_{min,k}$. If the regulator can ensure the rate requirement of all the honest users in this case, then $\underline{\boldsymbol{u}}$ can always be guaranteed.

$$\tilde{u}(\boldsymbol{p}, \boldsymbol{\beta}, \boldsymbol{w})^{wc} = \sum_{l \neq k} w_l \log\left(1 + \frac{\alpha_l p_l^{i,wc}}{I_l^{wc}(\boldsymbol{p}^{wc})}\right) - \sum_{l \neq k} \beta_l^{i,wc} \log\left(p_l^{i,wc}\right), \tag{4.27}$$

where for MAC without SIC, $I_{l,wc}^{lin}(\boldsymbol{p}^{wc}) = N + \sum_{j \neq k,l} \alpha_j p_j^{i,wc}$ and for MAC with SIC, $I_{l,wc}^{SIC}(\boldsymbol{p}^{wc}) = N^{SIC} + \sum_{j=1,\neq k}^{l-1} \alpha_j p_{j,wc}^{i,SIC}$. $N = 1 + \alpha_k p_{max}$ is the *worst-case noise-plus-interference*.

The system optimizer in round i observes the misbehavior of user k by its actual rate $r_k^{i-1}(\hat{\boldsymbol{\alpha}})$. Then the *real CQI*[2] α_k of user k for MAC without SIC is calculated by

$$\alpha_k = \frac{2^{r_k^{i-1}(\hat{\alpha})} - 1}{2^{\underline{u}_k} - 1} \alpha_{min,k} = \frac{2^{r_k^{i-1}(\hat{\alpha})} - 1}{p_{max}} \left(B_K \cdot \frac{1}{2^{\underline{u}_k}}\right). \tag{4.28}$$

And for MAC with SIC,

$$\alpha_k^{SIC} = \frac{2^{r_k^{i-1,SIC}}(\hat{\boldsymbol{\alpha}}) - 1}{p_{max}} \cdot \prod_{j=1}^{k-1} 2^{\underline{u}_j}. \tag{4.29}$$

[2]Note that the calculation of the real channel α_k is different for MAC systems with and without SIC.

Since users $l \neq k$ are honest, by observing α_k of the cheater k in N, the utility requirement $\underline{u}_l$ for all $l \neq k$ needs to be achieved in the worst-case, which solves (4.27).

4.15 Proposition. *For the MAC system without SIC, the worst case power allocation $p_l^{i,wc}$ for all the honest users $l \neq k$, after user k cheated in the $i-1$th round, is*

$$p_l^{i,wc} = \frac{N}{\alpha_l} \cdot \frac{2^{\underline{u}_l} - 1}{2^{\underline{u}_l}} \cdot B_{K-1}, \qquad l \neq k, \tag{4.30}$$

where $B_{K-1} = \frac{1}{\sum_{j\neq k} \frac{1}{2^{\underline{u}_j}} - K + 2}$ and $N = 1 + (2^{r_k^{i-1}(\hat{\boldsymbol{\alpha}})} - 1)\frac{B_K}{2^{\underline{u}_k}}$. The real rate achieved by user k in the $(i-1)$-th round $r_k^{i-1}(\hat{\boldsymbol{\alpha}})$ is obtained by (4.25).

The worst case pricing parameter is

$$\beta_l^{i,wc} = \Big(1 - \frac{1}{2^{\underline{u}_l}}\Big)\Big(\sum_{j\neq k} w_j^i - \sum_{j\neq l,k} w_j^i \cdot 2^{\underline{u}_j}\Big). \tag{4.31}$$

If the regulator gives $w_k^i = 0$ for the cheating user k, then $\sum_{j\neq l,k} w_j^i = 1$.

Proof. See Proof 4.5.5. □

4.16 Proposition. *For the MAC with SIC decoding order $\pi = [K \to \cdots \to 1]$, the worst-case power allocation $p_{l,wc}^{i,SIC}$ for all the honest users $l \neq k$, after user k cheated in the $i-1$th round, is*

1. $p_{l,wc}^{i,SIC} = p_l^{i,SIC}$*, for $l < k$*
2. $p_{l,wc}^{i,SIC} = \frac{(2^{\underline{u}_l}-1)}{\alpha_l} \prod_{j=1,j\neq k}^{l-1} 2^{\underline{u}_j} \cdot 2^{r_k^{i-1,SIC}(\hat{\boldsymbol{\alpha}})}$*, for $l > k$.*

The worst case pricing parameter is

1. $\beta_{l,wc}^{i,SIC} = (2^{\underline{u}_l} - 1)\Big(\sum_{j=l}^{k-1} \frac{w_j - w_{j+1}}{\prod_{i=l}^{j} 2^{\underline{u}_i}} + \sum_{j=k}^{K} \frac{w_j - w_{j+1}}{\prod_{i=l,\neq k}^{j} 2^{\underline{u}_i} \cdot 2^{r_k^{i-1,SIC}(\hat{\boldsymbol{\alpha}})}} \Big)$*, for $l < k$*
2. $\beta_{l,wc}^{i,SIC} = \beta_l^{i,SIC}$*, for $l > k$.*

Proof. See Proof 4.5.6. □

4.17 Corollary. *After user k cheated in the $i-1$th round, the worst case power allocation for all the honest users $l \neq k$ is always larger than or equal to the power in (4.6) and (4.14), respectively.*

Proof. For MAC without SIC, since $r_k^{i-1}(\hat{\boldsymbol{\alpha}}) > \underline{u}_k$, $N > 1 + (2^{\underline{u}_k} - 1)\frac{B_K}{2^{\underline{u}_k}} = \frac{\sum_{j\neq k} \frac{1}{2^{\underline{u}_j}} - K + 2}{\sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} - K + 1} = \frac{B_K}{B_{K-1}} > 1$. Substituting (4.30) with $N > \frac{B_K}{B_{K-1}}$, then $p_l^{i,wc} > \frac{B_K}{\alpha_i}\frac{2^{\underline{u}_i}-1}{2^{\underline{u}_i}} = p_l$ is proved.

For MAC with SIC, from Lemma 4.13 and Theorem 4.14, $r_k^{i-1,SIC}(\hat{\boldsymbol{\alpha}}) > \underline{u}_k$, therefore, comparing $p_{l,wc}^{i,SIC}$ with p_k^{SIC} in (4.14), the worst case power allocation $p_{l,wc}^{i,SIC} \geq p_k^{SIC}$. □

4.4.3 Repeated Game with Cheat-proof Pricing

Finally, a repeated game is designed to prevent cheating. All the users participating in the RG know the rules and the trigger strategy. Since in real life, the players are not patient and thereby they discount the future payoff in the infinite RG, we will focus our analysis in the δ-discounting infinite RG at first. Later on, the extension to other specification of the time-average infinite games is also discussed (See Proof 4.5.8). We conclude that by adopting the well designed infinite RG using the trigger strategy with the proper trigger price β_k^{tr}, no player will have incentive to cheat on their reported CQI.

For the δ-discounting infinite RG, each user anticipates its long-term total payoff in the RG[3] as

$$\bar{u}_k = (1-\delta_k)\sum_{i=0}^{\infty}\delta_k^i \hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w}), \tag{4.32}$$

where δ_k is the discount factor, $0 < \delta_k < 1$. When the honest users report their real CQI $\hat{\alpha}_k^i = \alpha_k$ to the system optimizer, their total payoff is

$$\begin{aligned}\bar{u}_k(\boldsymbol{\alpha}) &= u_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^0, \boldsymbol{w}) \cdot (1-\delta_k)\sum_{i=0}^{\infty}\delta_k^i \\ &= u_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^0, \boldsymbol{w}) = \underline{u}_k - \beta_k^0 \log p_k^0. \end{aligned}\tag{4.33}$$

When cheating occurs, without loss of generality, we assume that user k cheats $\alpha_{min,k}$ in round zero. Then the system optimizer detects it by (4.25) and (4.26) and reports it to the regulator in the first round. From then on, the trigger strategy works on the malicious user k and leads to a certain trigger utility V_k. The long-term total payoff $\bar{u}_k(V_k)$ for user k to cheat with $\alpha_{min,k}$ is

$$\begin{aligned}\bar{u}_k(V_k) &= (1-\delta_k)\cdot \hat{u}_k(\underline{\boldsymbol{u}}, \alpha_{min,k}^0, \boldsymbol{w}) + (1-\delta_k)\sum_{i=1}^{\infty}\delta_k^i V_k \\ &= (1-\delta_k)\cdot \big(r_k^0(\hat{\boldsymbol{\alpha}}) - \beta_k^0 \log(p_{max})\big) + \delta_k V_k. \end{aligned}\tag{4.34}$$

In order to prevent users from cheating about their channels, the overall long-term payoff $\bar{u}_k(V_k)$ with cheating should be smaller than the honest total payoff $\bar{u}_k(\boldsymbol{\alpha})$ with true CQI α_k. Thereby, the overall payoff gain $\Delta u_k(V_k) = \bar{u}_k(\boldsymbol{\alpha}) - \bar{u}_k(V_k)$ of user k should be positive, where

$$\begin{aligned}\Delta \bar{u}_k(V_k) &= \underline{u}_k - \beta_k^0 \log p_k^0 - (1-\delta_k) \\ &\quad \cdot \big(r_k^0(\hat{\boldsymbol{\alpha}}) - \beta_k^0 \log(p_{max})\big) - \delta_k V_k. \end{aligned}\tag{4.35}$$

We claim that the RG formulation is an incentive compatible strategy-proof mechanism.

[3] We will use $\bar{u}_k$ with different arguments depending on the context.

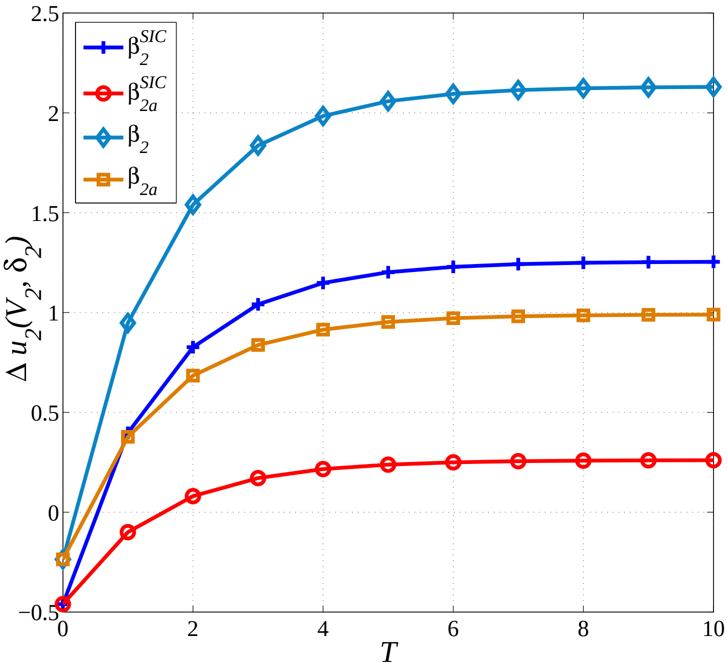

Figure 4.5: Overall payoff gain $\Delta\bar{u}_2(V_2)$ between honesty and cheating as a function of the number of rounds T with $\beta_{2a}^{tr} < \beta_2^{tr}$. $p_{max} = 5, \underline{u}_1 = 0.5, \underline{u}_2 = 1$, $\underline{u}_3 = 0.1, \alpha_2 = 1, w_2 = 0.3, w_3 = 0.2, \delta_2 = 0.5$ for 3 users MAC

4.18 Proposition. *In an infinite repeated game, it is possible for the regulator to compute a trigger pricing parameter β_k^{tr} such that misbehavior is prevented for the MAC with and without SIC.*

Proof. See Proof 4.5.7 for the δ-discounting infinite RG and Proof 4.5.8 for the time-average RG. □

4.4.4 Numerical Illustration

All the illustrations are made for the δ-infinite RG.

Fig. 4.5 shows the overall payoff gain $\Delta\bar{u}_2(V_2)$ of user two with and without cheating in both the 3-user MAC systems with and without SIC, respectively, if the upper limit of rounds is T (where $T \to \infty$, it is $\bar{u}_k$ in (4.32)). The SIC decoding order is $[3 \to 2 \to 1]$. It can be observed that, only after one round, the total payoff $\bar{u}_2(V_2)$ with cheating is smaller than the honest total payoff $\bar{u}_2(\boldsymbol{\alpha})$. With the punishment trigger strategy, the users will always report their true CQI $\boldsymbol{\alpha}$ in order to maximize their total payoff in the RG.

Fig. 4.6 shows how fast $\Delta\bar{u}_2(V_2, \delta_2)$ is changing with δ_2. The overall payoff gain $\Delta\bar{u}_2(V_2, \delta_2)$ of user two without and with cheating is always positive for all discount factor $0 < \delta_2 < 1$. Notice that $\Delta\bar{u}_2(V_2, \delta_2)$ using $\beta_{2a}^{tr,SIC}$ is constant with respect to δ_2. This is because by substituting $\beta_{ka}^{tr,SIC}$ into (4.35), $\Delta\bar{u}_k^{SIC}(V_k) = \beta_k^{0,SIC} \log\left(\frac{p_{max}}{p_k^{0,SIC}}\right)$ is independent of the discount factor δ_k.

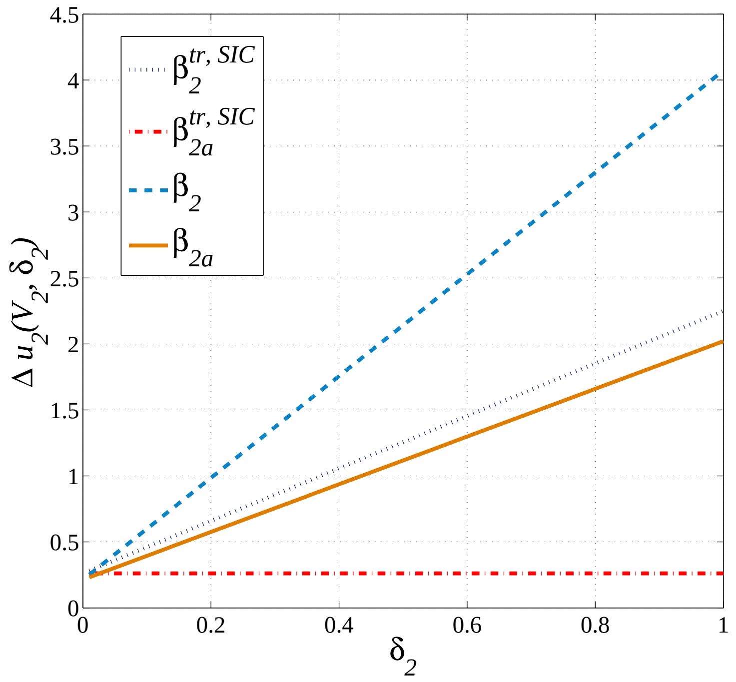

Figure 4.6: Overall payoff gain $\Delta\bar{u}_2(V_2, \delta_2)$ between cheating and honesty as a function of δ_2 with $\beta_{2a}^{tr} < \beta_2^{tr}$. $p_{max} = 5, \underline{u}_1 = 0.5, \underline{u}_2 = 1$, $\underline{u}_3 = 0.1, \alpha_2 = 1, w_2 = 0.3, w_3 = 0.2$ for 3 users MAC

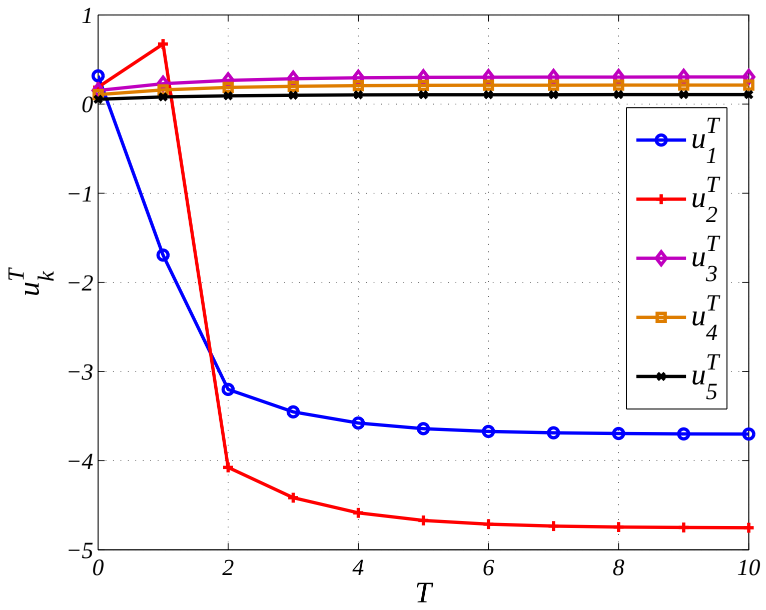

Figure 4.7: Sum utility of each user up to different rounds for the 5-user MAC without SIC. $p_{max} = 5, \underline{u}_1 = 0.3, \underline{u}_2 = 0.5, \underline{u}_3 = 0.1, \underline{u}_4 = 0.2, \underline{u}_5 = 0.1, \alpha_1 = 1, \alpha_2 = 2, \alpha_3 = 0.5, \alpha_4 = 1, \alpha_5 = 0.2, w_1 = 0.2, w_2 = 0.3, w_3 = 0.2, w_4 = 0.1, w_5 = 0.2$. User 1 cheats in the 0th round, user 2 cheats in the 1st round and all the others are honest.

Fig. 4.7 shows the sum utility of each user up to different rounds for the 5-user MAC without SIC. We assume user 1 cheats in the 0-th round, user 2 cheats in the first round and all the others are honest. Trigger strategy is applied immediately after the misbehavior is detected. It is shown that by cheating, the short-term utility is higher. However, with the trigger strategy as a punishment, the sum utility decreases rapidly. Therefore, with the proposed RG, no user will have incentive to cheat.

4.5 Proofs

4.5.1 Proof of Proposition 4.2

The power allocation for the uplink MAC can be obtained by $\boldsymbol{p} = (\boldsymbol{D}_a - \boldsymbol{A}^t)^{-1} \cdot \boldsymbol{1}$ [9, Chapter 10.3.2], where $\boldsymbol{D}_a := Diag(\frac{1}{a_1}, \ldots, \frac{1}{a_K})$ with $a_k = \frac{SINR_k}{(1+SINR_k)\alpha_k}$ and $\boldsymbol{A}^t$ is a $K \times K$ matrix with index of $\boldsymbol{\alpha}$. $\boldsymbol{1}$ is a vector with all 1s. Define the coupling matrix $\boldsymbol{C}_K = \boldsymbol{D}_a - \boldsymbol{A}^t$, then $\boldsymbol{C}_K \cdot \boldsymbol{p} = \boldsymbol{1}$. With QoS requirement $\underline{u}_k = \log(1 + SINR_k)$, so $a_k = \frac{2^{\underline{u}_k}-1}{2^{\underline{u}_k}\alpha_k}$ and the matrices

$$\boldsymbol{A}^t = \begin{bmatrix} \alpha_1 & \ldots & \alpha_k & \ldots & \alpha_K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \alpha_1 & \ldots & \alpha_k & \ldots & \alpha_K \end{bmatrix},$$

$$\boldsymbol{C}_K = \begin{bmatrix} \frac{\alpha_1}{2^{\underline{u}_1}-1} & -\alpha_2 & \ldots & -\alpha_K \\ -\alpha_1 & \frac{\alpha_2}{2^{\underline{u}_2}-1} & \ldots & -\alpha_K \\ \vdots & \vdots & \ddots & \vdots \\ -\alpha_1 & -\alpha_2 & \ldots & \frac{\alpha_K}{2^{\underline{u}_K}-1} \end{bmatrix}. \tag{4.36}$$

From Cramer's rule [96], the power allocation p_i, $i = 1, \ldots, K$, is solved by

$$p_i = \frac{\det(\boldsymbol{C}_K^i)}{\det(\boldsymbol{C}_K)}, \qquad i = 1, \ldots, K, \tag{4.37}$$

where $\boldsymbol{C}_K^i$ is the matrix formed by replacing the ith column of $\boldsymbol{C}_K$ by the column vector $\boldsymbol{1}$. Thereby, p_i is solved by $\det(\boldsymbol{C}_K^i) = \prod_{j \neq i} \frac{\alpha_j}{2^{\underline{u}_j}-1} \cdot 2^{\underline{u}_j}$ and $\det(\boldsymbol{C}_K) = \prod_j \alpha_j \cdot \det(\boldsymbol{C}_K^{'})$, where $\boldsymbol{C}_K^{'}$ is a matrix with diagonal indices of $\frac{1}{2^{\underline{u}_i}-1}$ and all the other components of -1, so that $\det(\boldsymbol{C}_K^{'}) = (-1)^K \cdot \prod_{j=1}^K \frac{2^{\underline{u}_j}}{1-2^{\underline{u}_j}} \cdot \left(\frac{1}{2^{\underline{u}_1}} - \sum_{j=2}^K \frac{2^{\underline{u}_j}-1}{2^{\underline{u}_j}}\right) = \prod_{j=1}^K \frac{2^{\underline{u}_j}}{2^{\underline{u}_j}-1} \cdot (\sum_{j=1}^K \frac{1}{2^{\underline{u}_j}} - K + 1)$. Then from (4.37), the power allocation (4.6) for the K-user MAC without SIC is proved.

The pricing parameters $\boldsymbol{\beta}$ can be solved by the first optimality condition $\frac{\partial \tilde{u}(\boldsymbol{p},\boldsymbol{\beta},\boldsymbol{w})}{\partial s_k} = 0$. With $p_k = e^{s_k}$, the pricing parameter is $\beta_k = \alpha_k p_k \left(\frac{1}{1+\sum_{j=1}^K \alpha_j p_j} - \sum_{j \neq k} \frac{w_j}{1+\sum_{i \neq j} \alpha_i p_i}\right)$. By substituting p_k in (4.6), the closed form of the pricing parameter β_k is obtained as (4.7).

The regulator always provide positive prices, so the weights should ensure the range of $1 - \sum_{j \neq k} w_j 2^{\underline{u}_j} > 0$. We use a matrix formulation to solve w_j for $\sum_{j \neq k} w_j 2^{\underline{u}_j} < 1, j = 1, \ldots, K$, as $\boldsymbol{U}_K \cdot \boldsymbol{W} < \boldsymbol{1}$. The indices of $\boldsymbol{U}_K$ are $[\boldsymbol{U}_K]_{m,m} = 0$ and $[\boldsymbol{U}_K]_{m,n} = 2^{\underline{u}_n}$, $m \neq n$. Applying Cramer's rule, $0 < w_i < \frac{\det(\boldsymbol{U}_K^i)}{\det(\boldsymbol{U}_K)}$, where $\boldsymbol{U}_K^i$ is the matrix formed by replacing the ith column of $\boldsymbol{U}_K$ by the column vector $\boldsymbol{1}$. w_i is solved by $\det(\boldsymbol{U}_K^i) = (-1)^{K-1} \cdot \prod_{j\neq i} 2^{\underline{u}_j}$ and $\det(\boldsymbol{U}_K) = (-1)^{K-1}(K-1)\prod_{j=1}^{K} 2^{\underline{u}_j}$ so that the upper bound of w_i is $w_i < \frac{\det(\boldsymbol{U}_K^i)}{\det(\boldsymbol{U}_K)} = \frac{1}{2^{\underline{u}_i}\cdot(K-1)}$.

Since $\sum_{j=1}^{K} w_j = 1$, $0 < 1 - \sum_{j\neq k} w_j < \frac{1}{2^{\underline{u}_k}\cdot(K-1)}$. In order to obtain the lower bound of w_k, we calculate $1 - \frac{1}{2^{\underline{u}_j}\cdot(K-1)} < \sum_{j\neq k} w_j < 1$ by the matrix $\boldsymbol{E}\cdot\boldsymbol{W} > \boldsymbol{F}$, where $\boldsymbol{E} = \boldsymbol{1} - \boldsymbol{I}$ is a $K \times K$ matrix and each row i of $\boldsymbol{F}$ is $1 - \frac{1}{2^{\underline{u}_i}(K-1)}$. Use the Cramer's rule, $w_i > \frac{\det(\boldsymbol{E}^i)}{\det(\boldsymbol{E})}$, where $\det(\boldsymbol{E}) = (-1)^{(K-1)}\cdot(K-1)$ and $\det(\boldsymbol{E}^i) = (-1)^{(K-1)}\cdot\left[1 + \frac{1}{2^{\underline{u}_i}} - \frac{1}{K-1}\cdot\sum_{j=1}^{K}\frac{1}{2^{\underline{u}_j}}\right]$. Therefore, $w_i > \frac{\det(\boldsymbol{E}^i)}{\det(\boldsymbol{E})} = \frac{1+\frac{1}{2^{\underline{u}_i}}-\frac{1}{K-1}\cdot\sum_{j=1}^{K}\frac{1}{2^{\underline{u}_j}}}{K-1}$, and in $\mathcal{U}_{p_{max}}$, (4.8) is always true.

4.5.2 Proof of Proposition 4.9

For MAC system with SIC and universal non-linear pricing mechanism, the result for power allocation is the same as in [94], because the pricing mechanism does not change the system power allocation in order to achieve the single user utility requirement $\underline{\boldsymbol{u}}$. However it can also be calculated by $\boldsymbol{p}^{SIC} = (\boldsymbol{D}_a^{SIC} - \boldsymbol{A}_{SIC}^t)^{-1}\cdot\boldsymbol{1}$, where $\boldsymbol{D_a}^{SIC}$ is same as $\boldsymbol{D_a}$ for the K-user MAC without SIC. For the SIC decoding order of $\pi = [K \to \cdots \to 1]$, $\boldsymbol{A}_{SIC}^t$ and the coupling matrix $\boldsymbol{C}_K^{SIC} = (\boldsymbol{D}_a^{SIC} - \boldsymbol{A}_{SIC}^t)$ are lower-triangular matrices of $\boldsymbol{A}^t$ and $\boldsymbol{C}_K$, respectively.

The regulator offers the pricing parameters $\boldsymbol{\beta}^{SIC}$ by solving the first optimality condition $\frac{\partial\tilde{u}(\boldsymbol{p},\boldsymbol{\beta},\boldsymbol{w})^{SIC}}{\partial s_k} = \alpha_k e^{s_k}\left(\sum_{j=k}^{K}\frac{w_j^{SIC}}{1+\sum_{i=1}^{j}\alpha_i e^{s_i}} - \sum_{j=k+1}^{K}\frac{w_j^{SIC}}{1+\sum_{i=1}^{j-1}\alpha_i e^{s_i}}\right) - \beta_k^{SIC} = 0$. Substitute p_k^{SIC} in (4.14) for e^{s_k} and denote $x_j^{SIC} = 1 + \sum_{i=1}^{j}\alpha_i p_i^{SIC} = \prod_{i=1}^{j} 2^{\underline{u}_i}$ (see Theorem 1 in [94]), then

$$\beta_k^{SIC} = \alpha_k p_k^{SIC}\cdot\Big(\frac{w_k^{SIC} - w_{k+1}^{SIC}}{x_k^{SIC}} + \cdots + \frac{w_{K-1}^{SIC} - w_K^{SIC}}{x_{K-1}^{SIC}} + \frac{w_K^{SIC}}{x_K^{SIC}}\Big). \tag{4.38}$$

With $\alpha_k p_k^{SIC} = (2^{\underline{u}_k} - 1)\prod_{j=1}^{k-1} 2^{\underline{u}_j}$, β_k^{SIC} in (4.15) is proved. For other SIC decoding orders than $\pi = [K \to \cdots \to 1]$, the process is similar.

4.5.3 Proof of Lemma 4.13

Since all the utility requirements $\underline{u}_j, j = 1, \ldots, K$ are fixed, both the power allocation in (4.6) and (4.14) are only dependent on and are monotonically decreasing in the reported CQI $\hat{\alpha}_k$. If $\hat{\alpha}_k < \alpha_k$, then $p_k(\hat{\boldsymbol{\alpha}}) > p_k(\boldsymbol{\alpha})$ and vice versa. For all honest users, $\hat{\alpha}_l = \alpha_l, l \neq k$, thereby $p_l(\hat{\boldsymbol{\alpha}}) = p_l(\boldsymbol{\alpha})$.

The actual rate $r_k(\hat{\boldsymbol{\alpha}})$ achieved by power allocation $p_k(\hat{\boldsymbol{\alpha}})$ for the cheater k with the real CQI α_k is $r_k(\hat{\boldsymbol{\alpha}}) = \log\left(1 + \frac{\alpha_k p_k(\hat{\boldsymbol{\alpha}})}{I_k(\boldsymbol{p})}\right) = \log\left(1 + \frac{\alpha_k}{\hat{\alpha}_k}(2^{\underline{u}_k} - 1)\right)$. Compare with the rate requirement $\underline{u}_k$ calculated in (4.19). If $\hat{\alpha}_k < \alpha_k$ then $r_k(\hat{\boldsymbol{\alpha}}) > \log(1 + 2^{\underline{u}_k} - 1) = \underline{u}_k$ and vice versa.

For MAC without SIC, the actual rate achieved by the honest user $l, l \neq k$, is

$$r_l(\hat{\boldsymbol{\alpha}}) = \log\left(1 + \frac{\alpha_l p_l}{1 + \sum_{m \neq l,k} \alpha_m p_m + \alpha_k p_k(\hat{\boldsymbol{\alpha}})}\right). \tag{4.39}$$

For MAC with SIC decoding order $\pi = [K \to \cdots \to 1]$, the actual rate achieved by each user $l, l < k$, remains the same as $\underline{u}_l$ since the misbehavior of user k has no influence on those users who are decoded later than it. But the actual rate achieved by each user $l, l > k$, is

$$r_l^{SIC}(\hat{\boldsymbol{\alpha}}) = \log\left(1 + \frac{\alpha_l p_l}{1 + \sum_{m=1, m \neq k}^{l-1} \alpha_m p_m + \alpha_k p_k(\hat{\boldsymbol{\alpha}})}\right). \tag{4.40}$$

If $\hat{\alpha}_k < \alpha_k$, then $p_k(\hat{\boldsymbol{\alpha}}) > p_k(\boldsymbol{\alpha})$ and $\alpha_k p_k(\hat{\boldsymbol{\alpha}}) > \hat{\alpha}_k p_k(\hat{\boldsymbol{\alpha}})$. Comparing with (4.19), $r_l(\hat{\boldsymbol{\alpha}}) < \underline{u}_l$, and vice versa. Note that for all users $l \neq k$ in MAC with SIC, $r_l(\hat{\boldsymbol{\alpha}}) = \underline{u}_l$ holds if and only if the cheater is the first decoded user at the receiver by SIC. This completes the proof.

4.5.4 Proof of Theorem 4.14

First we make a curve analysis of $\hat{u}_k^i(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})$. Rewrite (4.23) as

$$\begin{aligned} \hat{u}_k^i(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w}) &= \log\left(\frac{(\hat{\alpha}_k + \alpha_k(2^{\underline{u}_k} - 1))\hat{\alpha}_k^{\beta_k^i}}{\hat{\alpha}_k \cdot y_k^{\beta_k^i}}\right) \\ &= \log\left(\frac{\hat{\alpha}_k^{\beta_k^i} + \alpha_k(2^{\underline{u}_k} - 1) \cdot \hat{\alpha}_k^{(\beta_k^i - 1)}}{y_k^{\beta_k^i}}\right), \end{aligned}$$

where $y_k > 0$ in $\mathcal{U}_{p_{max}}$. From (4.7) and (4.15), $0 < \beta_k^i < 1 - \frac{1}{2^{\underline{u}_k}}$, $\beta_k^i - 1 < 0$. Therefore, $\lim_{\hat{\alpha}_k \to 0} u_k^i(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w}) \to \infty$ and $\lim_{\hat{\alpha}_k \to \infty} u_k^i(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w}) \to \infty$. It is important to check the utility $\hat{u}_k^i(\underline{\boldsymbol{u}}, \underline{\hat{\boldsymbol{\alpha}}}, \underline{\boldsymbol{w}})$ with respect to the reported CQI $\hat{\alpha}_k^i$. Assume that user k cheats for $\hat{\alpha}_k$ in round 0, the first and second derivative of $\hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})$ are $\frac{\partial \hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})}{\partial \hat{\alpha}_k} = \frac{1}{\hat{\alpha}_k + \alpha_k(2^{\underline{u}_k} - 1)} + \frac{\beta_k^i - 1}{\hat{\alpha}_k}$ and $\frac{\partial^2 \hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})}{\partial \hat{\alpha}_k^2} = \frac{-1}{(\hat{\alpha}_k + \alpha_k(2^{\underline{u}_k} - 1))^2} + \frac{1 - \beta_k^i}{\hat{\alpha}_k^2}$, respectively. There is only one valid $\hat{\alpha}_k^* = \frac{1 - \beta_k^i}{\beta_k^i}\alpha_k(2^{\underline{u}_k} - 1)$ fulfilled with $\frac{\partial \hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})}{\partial \hat{\alpha}_k} = 0$. Since the second derivative at $\hat{\alpha}_k^*$ $\left.\frac{\partial^2 \hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})}{\partial \hat{\alpha}_k^2}\right|_{\hat{\alpha}_k = \hat{\alpha}_k^*} = \frac{\beta_k^{i2}}{\alpha_k^2(2^{\underline{u}_k} - 1)^2} \left(\frac{\beta_k^i}{1 - \beta_k^i}\right)$ is always positive, $\hat{\alpha}_k^*$ is the **global minimum** of the user own utility $u_k^i(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})$.

As shown in Fig 4.8, in the feasible utility region for both MAC systems, the short-term user utility $\hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})$ is convex in $\hat{\alpha}_k$ with global minimum $\hat{\alpha}_k^* = \frac{1 - \beta_k^i}{\beta_k^i}\alpha_k(2^{\underline{u}_k} - 1)$. At $\hat{\alpha}_k = \alpha_k$, the user utility is decreasing since its first derivative $\left.\frac{\partial \hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})}{\partial \hat{\alpha}_k}\right|_{\hat{\alpha}_k = \alpha_k} = \frac{1 + (\beta_k^i - 1)2^{\underline{u}_k}}{\alpha_k 2^{\underline{u}_k}}$ is always negative. Therefore, in order to maximize its own utility, the user will always report $\alpha_{min,k}$.

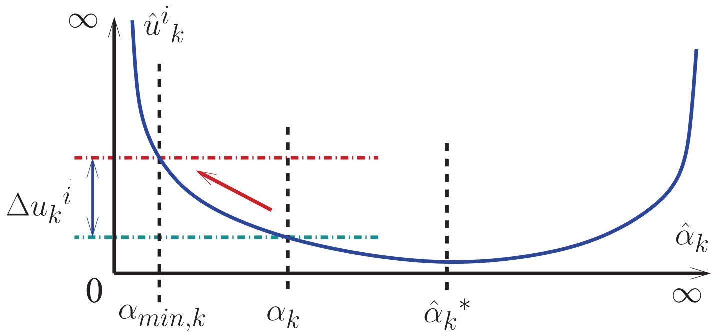

Figure 4.8: User utility $\hat{u}_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w})$ vs. reported channel $\hat{\alpha}_k$

4.5.5 Proof of Proposition 4.15

The system optimizer allocates the power by solving the worst-case UMP in (4.27) for all the $K-1$ honest users with the same procedure as in Sec. 4.2. The differences lie in $\boldsymbol{A}_{K-1}^t$ and the corresponding coupling matrix $\boldsymbol{C}_{K-1} = \boldsymbol{D}_a - \boldsymbol{A}_{K-1}^t$, where the indices of $[\boldsymbol{A}_{K-1}^t]_{m,n} = \alpha_n$ for $m, n \neq k$ and $[\boldsymbol{C}_{K-1}]_{m,m} = \frac{\alpha_m}{2^{\underline{u}_m}-1}$, $[\boldsymbol{C}_{K-1}]_{m,n} = -\alpha_n$ for $m \neq n$ and $m, n \neq k$. Solve $\boldsymbol{C}_{K-1} \cdot \boldsymbol{p}^{i,wc} = \boldsymbol{N}$ by using the Cramer's rule, $p_l^{i,wc} = \frac{\det \boldsymbol{C}_{K-1}^i}{\det \boldsymbol{C}_{K-1}}$. Since $\det \boldsymbol{C}_{K-1} = \prod_{j\neq k} \alpha_j \frac{2^{\underline{u}_j}}{1-2^{\underline{u}_j}} \cdot \left[\sum_{j\neq k} \frac{1}{2^{\underline{u}_j}} - K + 2\right]$ and $\det \boldsymbol{C}_{K-1}^i = N \prod_{j\neq k,l} \alpha_j \frac{2^{\underline{u}_j}}{2^{\underline{u}_j}-1}$, the worst-case power (4.30) is proved.

The derivation of β_l^{wc} is similar to Section 4.2. Substitute N and B_{K-1} for p_l^{wc} to solve $\beta_l^{wc} = \alpha_l p_l^{wc} \left(\sum_{j\neq k} \frac{w_j}{N + \sum_{i\neq k} \alpha_i p_i^{wc}} - \sum_{j\neq k,l} \frac{w_j}{N+\sum_{i\neq j,k} \alpha_i p_i^{wc}}\right)$. Then Proposition 4.15 is proved.

4.5.6 Proof of Proposition 4.16

From Remark 4.10, when user k cheats, since the power allocation of user l for MAC with SIC is only dependent on $\underline{\boldsymbol{u}}$ of users which are decoded later than l, $p_{l,wc}^{i,SIC} = p_l^{SIC}$ for $l < k$.

For the users $l > k$, their QoS requirements are achieved even though the cheater k uses p_{max}

$$\begin{aligned} r_l^{wc,SIC} &= \log\left(1 + \frac{\alpha_l p_{l,wc}^{i,SIC}}{x_{l-1}^{wc} + \alpha_k p_{max}}\right) \\ &= \log\left(\frac{q_l^{wc}}{q_{l-1}^{wc}}\right) \geq \underline{u}_l, \qquad l > k \end{aligned} \tag{4.41}$$

where $x_{l-1}^{wc} = 1 + \sum_{j=1, j\neq k}^{l-1} \alpha_j p_j^{wc}$. Denote $q_l^{wc} = x_l^{wc} + \alpha_k p_{max}$. Since $p_{l,wc}^{i,SIC} = p_l^{SIC}$ for $l < k$, $x_{k-1}^{wc} = x_{k-1} = \prod_{j=1}^{k-1} 2^{\underline{u}_j}$ (see proof of Theorem 1 in [94]). Thereby, $q_k^{wc} = x_{k-1} + \alpha_k p_{max} =$

$\prod_{j=1}^{k-1} 2^{\underline{u}_j} + \alpha_k p_{max}$. Then $q_{k+1}^{wc} = 2^{\underline{u}_{k+1}} \cdot (\prod_{j=1}^{k-1} 2^{\underline{u}_j} + \alpha_k p_{max})$ and $q_l^{wc} = \prod_{j=k+1}^{l} 2^{\underline{u}_j} \cdot (\prod_{j=1}^{k-1} 2^{\underline{u}_j} + \alpha_k p_{max})$, $l > k$, if equality holds in (4.41). From $\underline{u}_l = \log\left(1 + \frac{\alpha_l p_{l,wc}^{i,SIC}}{q_{l-1}^{wc}}\right)$ and $p_{l,wc}^{i,SIC} = \frac{2^{\underline{u}_l} - 1}{\alpha_l} \cdot q_{l-1}^{wc}$,

$$p_{l,wc}^{i,SIC} = \frac{2^{\underline{u}_l} - 1}{\alpha_l} \cdot \prod_{j=k+1}^{l-1} 2^{\underline{u}_j} \cdot (\prod_{j=1}^{k-1} 2^{\underline{u}_j} + \alpha_k p_{max}), \quad (4.42)$$

for $l > k$.

Then substitute α_k given in (4.29), $p_{l,wc}^{i,SIC} = \frac{2^{\underline{u}_l} - 1}{\alpha_l} \cdot \prod_{j=k+1}^{l-1} 2^{\underline{u}_j} \cdot 2^{r_k^{i-1,SIC}(\boldsymbol{\alpha})}$ is proved.

For the pricing parameters for MAC with SIC, $\beta_{l,wc}^{i,SIC}$ remains the same as $\beta_l^{i,SIC}$ for $l > k$ since it is only dependent on w_j and $\underline{u}_j$ where $j > l$. For $l < k$, the system optimizer will solve the UMP^{SIC} of (4.27). With the result of $p_{l,wc}^{i,SIC}$ and α_k, the worst case pricing parameter $\beta_{l,wc}^{i,SIC}$ is solved. The trick is that the regulator chooses the weight $w_{k,wc}^{SIC} = 0$. Thereby, in the pricing $\beta_{l,wc}^{i,SIC}$, there is no component of $w_{k,wc}^{SIC}$ and all the components of $2^{\underline{u}_k}$ are replaced with $r_k^{SIC}(\hat{\boldsymbol{\alpha}})$.

4.5.7 Proof of Proposition 4.18 (for δ-discount RG criterion)

The road map of the proof is that the MAC system with and without SIC are treated together at the beginning. Later on, they will be analyzed separately with ^{SIC} to denote the MAC with SIC. The trigger utility V_k is some realization of the utility function with the trigger pricing parameter β_k^{tr} when p_{max} is allocated to the cheater k since $\hat{\alpha}_k = \alpha_{min,k}$, i.e.,

$$V_k \;:=\; \log\left(1 + \frac{\alpha_k p_{max}}{I_k(\boldsymbol{p}^{wc})}\right) - \beta_k^{tr} \log(p_{max}). \quad (4.43)$$

In order to ensure $\Delta\bar{u}_k(V_k) \geq 0$, the trigger strategy V_k fulfills

$$\begin{aligned} V_k \;\leq\; & \frac{\underline{u}_k}{\delta_k} - \frac{1-\delta_k}{\delta_k} r_k^0(\hat{\boldsymbol{\alpha}}) \\ & - \frac{\beta_k^0}{\delta_k}\left(\log(p_k^0) - (1-\delta_k)\cdot\log(p_{max})\right). \end{aligned} \quad (4.44)$$

For MAC system without SIC, the interference function in (4.43) is $I_k^{lin}(\boldsymbol{p}^{wc}) = 1 + \sum_{l \neq k} \alpha_l p_l^{i,wc}$. With the worst case power allocation (4.30), $I_k^{lin}(\boldsymbol{p}^{wc}) = 1 - N + N \cdot B_{K-1}$.

For convenience, we define the RHS of (4.43) as V_k^l, and RHS of (4.44) as V_k^r so that β_k^{tr} is solved by fulfilling $V_k^l \leq V_k^r$. Since $p_k^0 < p_{max}$, $\delta_k < 1$ and $\beta_k^0 < (1 - \frac{1}{2^{\underline{u}_k}})$, we obtain

$$V_k^r \;>\; \frac{1-\delta_k}{\delta_k}\left(\frac{\underline{u}_k}{1-\delta_k} - r_k^0(\hat{\boldsymbol{\alpha}})\right) - \beta_k^0 \log(p_{max}) \quad (4.45)$$

$$\;>\; \frac{1-\delta_k}{\delta_k}\left(\frac{\underline{u}_k}{1-\delta_k} - r_k^0(\hat{\boldsymbol{\alpha}})\right) - \log(p_{max}). \quad (4.46)$$

V_k^l is upper bounded by the utility with no interference and p_{max} allocated to user k. Therefore $V_k^l \leq \log(1+\alpha_k p_{max}) - \beta_k^{tr} \log(p_{max})$. If the regulator gives the trigger pricing parameter

$$\beta_k^{tr} \geq 1 + \frac{1}{\log(p_{max})} \cdot \left(E - \frac{\underline{u}_k}{\delta_k} + \frac{1-\delta_k}{\delta_k} r_k^0(\hat{\boldsymbol{\alpha}}) \right) \tag{4.47}$$

by applying (4.46), or more tightly

$$\beta_{ka}^{tr} \geq \beta_k^0 + \frac{1}{\log(p_{max})} \cdot \left(E - \frac{\underline{u}_k}{\delta_k} + \frac{1-\delta_k}{\delta_k} r_k^0(\hat{\boldsymbol{\alpha}}) \right) \tag{4.48}$$

by applying (4.45), where $E = \log(1+\alpha_k p_{max})$, then $\Delta \bar{u}_k(V_k)$ is always positive.

For MAC with SIC decoding order $[K \to \cdots \to 1]$, the interference function in (4.43) is $I_k^{SIC}(\boldsymbol{p}^{wc}) = 1 + \sum_{l<k} \alpha_l p_{l,wc}^{i,SIC}$. From Proposition 4.16, $p_{l,wc}^{i,SIC} = p_l^{i,SIC}$ for all $l < k$, therefore

$$V_k^{SIC} = r_k^{0,SIC}(\hat{\boldsymbol{\alpha}}) - \beta_k^{tr,SIC} \log(p_{max}). \tag{4.49}$$

Substitute V_k^{SIC} into (4.34) and (4.35), respectively. The overall payoff difference for MAC with SIC is

$$\Delta u_k(V_k^{SIC}) = \underline{u}_k - r_k^{0,SIC}(\hat{\boldsymbol{\alpha}}) - \beta_k^{0,SIC} \log p_k^{0,SIC} + \log(p_{max}) \left((1-\delta_k)\beta_k^{0,SIC} + \delta_k \beta_k^{tr,SIC} \right).$$

Solve for $\Delta u_k(V_k^{SIC}) \geq 0$, the regulator should provide the trigger pricing parameter

$$\begin{aligned} \beta_k^{tr,SIC} \quad > \quad & \frac{1}{\delta_k \cdot \log p_{max}} \Big(r_k^{0,SIC}(\hat{\boldsymbol{\alpha}}) + \beta_k^{0,SIC} \log p_k^{0,SIC} \\ & - \underline{u}_k - (1-\delta_k)\beta_k^{0,SIC} \log(p_{max}) \Big) \end{aligned} \tag{4.50}$$

in order to prevent cheating. Since $p_k^{SIC} \leq p_{max}$ and $\beta_k^{0,SIC} < (1 - \frac{1}{2^{\underline{u}_k}})$, the regulator could provide the trigger pricing parameter in MAC system with SIC as

$$\beta_k^{tr,SIC} > \frac{\left(r_k^{0,SIC}(\hat{\boldsymbol{\alpha}}) - \underline{u}_k + \log(p_{max})\delta_k \right)}{\delta_k \cdot \log p_{max}}. \tag{4.51}$$

$$\beta_{ka}^{tr,SIC} > \frac{\left(r_k^{0,SIC}(\hat{\boldsymbol{\alpha}}) - \underline{u}_k + \beta_k^{0,SIC} \log(p_{max})\delta_k \right)}{\delta_k \cdot \log p_{max}}.$$

4.5.8 Proof of Proposition 4.18 (for time-average RG criterion)

If the players are completely patient, corresponding to the limit $\delta = 1$, the time-average criterion can be implemented. Any forms of time-average criterion implies that players are unconcerned not only about the timing of payoffs but also their payoff in finite number of periods. The objective of each player in the 'limit of means' RG is

$$\bar{u}_k = \lim_{T\to\infty} \frac{1}{T} \sum_{i=0}^{T} \hat{u}_k(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}^i, \boldsymbol{w}). \tag{4.52}$$

Now we will describe shortly if the 'limit of means' RG is adopted, how it works for the general MAC system without SIC. For the honest users, since they do not cheat on their reported CQI, i.e. $\hat{\alpha}_k = \alpha_k$, their expected total payoff is

$$\begin{aligned}\bar{u}_k(\boldsymbol{\alpha}) &= \lim_{T\to\infty} \frac{1}{T} \sum_{i=0}^{T} u_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^0, \boldsymbol{w}) \\ &= \lim_{T\to\infty} \frac{1}{T} \cdot T u_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^0, \boldsymbol{w}) \\ &= u_k(\underline{\boldsymbol{u}}, \boldsymbol{\alpha}^0, \boldsymbol{w}). \end{aligned} \tag{4.53}$$

This result is the same as the total payoff for honest users in the discounting RG.

For the cheater k, the resulting total payoff for the cheater k in the 'limit of means' RG is

$$\begin{aligned}\bar{u}_k(V_k) &= \lim_{T\to\infty} \frac{1}{T} \left(u_k^0(\underline{\boldsymbol{u}}, \hat{\boldsymbol{\alpha}}, \boldsymbol{w}) + \sum_{t=1}^{T} V_k \right) \\ &= V_k. \end{aligned} \tag{4.54}$$

In order to prevent cheating in the 'limit of means' RG, the regulator should provide the trigger price β_k^{tr} as follows,

$$\beta_k^{tr} > \frac{\log\left(1 + \frac{\alpha_k p_{max}}{I_k(\boldsymbol{p}^{wc})}\right) - \underline{u}_k + \beta_k^0 \log p_k^0}{\log(p_{max})}, \tag{4.55}$$

so that no users will have incentives to cheat. Since $\log(p_{max}) > \log p_k^0$, any trigger price $\beta_k^{tr} > \beta_k^0 + \frac{\log\left(1+\frac{\alpha_k p_{max}}{I_k(\boldsymbol{p}^{wc})}\right) - \underline{u}_k}{\log p_k^0}$ will work.

The procedure for the MAC system with SIC using the 'limit of means' RG is similar. Therefore we skip it here.

We can conclude that if the players are completely patience, the counter mechanism using the trigger strategy with the trigger price β_k^{tr} in the time-average infinite RG such as 'limit of means' RG also works for our proposed scenario.

4.6 Summary

For the general MAC, we propose a universal non-linear pricing framework. At first, we characterize the feasible utility region, the optimal power allocation and pricing for ensuring the rate requirements. Then, the user behavior is studied with reporting the false CQI values. It is shown that the selfish users have incentives to cheat for a smaller CQI value than their real one to achieve a higher short-term user utility. In order to prevent cheating, we introduce a repeated game mechanism and derive a suitable trigger strategy which satisfies the rate requirements for the honest users and punishes the cheating users. Numerical results confirm that the long-term total payoff after cheating is made smaller than the honest total payoff leading to a stable incentive-compatible operation.

Serving as a benchmark, the power allocation to ensure the QoS requirement of each user in the wireless system and the properly proposed universal prices are implemented into the heterogeneous networks in Chapter 5.

The research of the universal pricing framework can be continued to the distributed topology. Chapter 6 investigated the distributed resource allocation for the general MAC system with and without SIC using the linear and nonlinear pricing framework, respectively. The noncooperative game is adopted, where the QoS requirement of each user is achieved at the unique NE power allocation.

5 Applications of User-Centric Resource Allocation in Heterogeneous Networks

Due to the services of 3G and 4G, more and more wireless data traffic is expected from indoor users. The femtocells, also known as home BS, due to their small and low power characteristics to provide high-quality indoor coverage, have recently attracted significant research consideration. These FAPs, working as BSs, are connected to the operators' macrocell networks by backhaul DSL, optical fibre or other connections [4].

A limited number of UEs can be supported by femtocells and therefore the access control mechanism is pivotal. Currently, three access modes are adopted: open access, closed access and hybrid access. By allowing unregistered MUEs to access the nearby FAP and guaranteeing the QoS of each UE with low cost, the hybrid access shows the most potential. The compensation framework, which not only motivates the FAP for hybrid access, but also benefits the MBS is challenging.

The QoS requirement of each UE is a dominant issue. Hence, how to utilize communications resource such as power and spectrum fairly and more efficiently is of great importance. The uplink transmission is considered in this chapter, both for the macrocell and the femtocell. Since the FAPs are small and simple devices, SIC is not applied in the femtocells. The resource allocation for MAC without SIC analyzed in Chapter 4 can be adopted in this scenario of heterogeneous networks.

Both the MBS in the macrocell and FAP in the femtocell networks are considered selfish and rational. On the one hand, due to the low cost and better indoor coverage, the traffic load and power consumption of the MBS will be greatly reduced with the help of FAP to accept some MUEs which are nearby. On the other hand, the FAP has no incentive to open access to other MUEs since the utility of its own reserved FUEs is diminished by sharing the radio and power resource with the unregistered MUEs. Based on this, we develop the compensation frameworks such that the utilities of both the MBS and the FAP are maximized respectively.

Two compensation frameworks of motivating the hybrid access of the femtocell are investigated in this chapter. The first part utilizes the compensation as a function of the universal nonlinear price β_i given in Chapter 4. The second part focuses on the system global energy efficiency. The MBS compensates the FAP in order to maximize its utility which is the energy efficiency of the whole two-tier system.

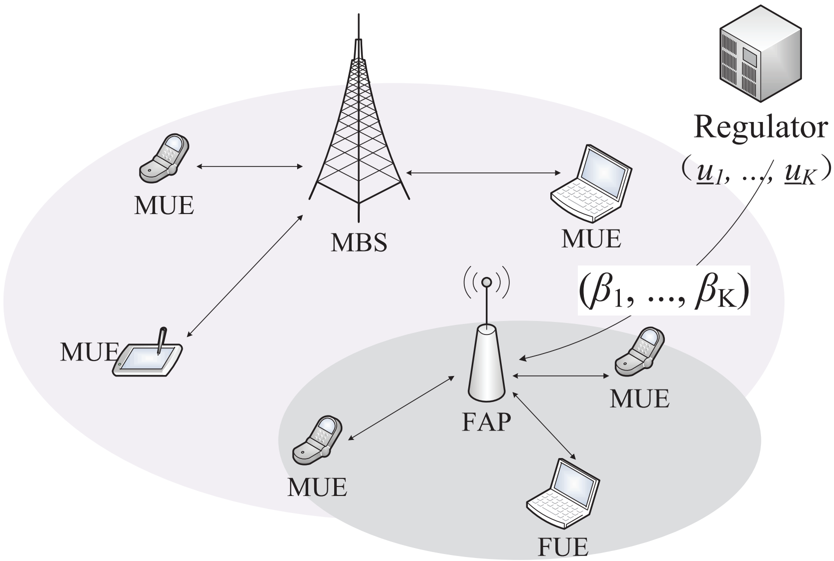

Figure 5.1: System model of compensation framework with regulator using universal non-linear pricing

5.1 Compensation Framework with Regulator using Universal Nonlinear Pricing

In this section, we integrate the universal non-linear pricing into the compensation framework for the two-tier macro-femtocell wireless networks which motivates the FAP to apply the hybrid access. By adopting the proposed compensation framework, both the utilities of the MBS and the FAP are maximized. The protocol of hybrid access is provided and numerical simulations are conducted.

5.1.1 Problem Formulation

As depicted in Fig. 5.1, there is a MBS in the macrocell and a FAP in each femtocell network. In our model, we consider the single macro-femtocell cluster. We assume in total N MUEs are subscribed by the MBS and M FUEs are subscribed by the FAP, respectively. Due to the mobility of UEs, some MUEs are in the coverage of the FAP. The MBS is willing to compensate the FAP by the compensation function for accepting a certain number of MUEs in the hybrid access since on the one hand, the total power consumption of the MBS is reduced which significantly lowers the cost. On the other hand, the revenue of the FAP is improved by fully utilizing its wireless resource.

In the user-centric wireless system, the main task is to satisfy the QoS requirement $\underline{u}_j$ of each user j. Otherwise the UEs will leave the service package and as a result, the revenue of the system vendor is declined significantly. The uplink transmissions within the macrocell and the femtocell are exactly the same as MAC model set up in Chapter 4. The MBS and the FAP are considered as the BSs. Both the multiple mobile UEs and the BSs are equipped with single antenna. Therefore the interference management is dealt with the power allocation given in (4.6).

We propose a compensation framework to motivate the hybrid access for the femtocell network. The power allocation and the universal non-linear prices are used for interference management and the compensation paid by the MBS to motivate the hybrid access. A Stackelberg game is introduced to optimize the utility functions of both the MBS in the macrocell and the FAP in the femtocell. Denote K as the number of accepted MUEs in the hybrid access. The compensation function c_K is paid by the MBS to the FAP for serving K MUEs nearby.

The larger the amount of compensation c_K paid to the FAP by the MBS, the more MUEs should the FAP accept since this will benefit its own revenue while ensuring the QoS requirements of its own subscribed FUEs. In contrast, the MBS wishes to assign maximum number K of MUEs to the FAP with minimum compensation in order to maximize the utility of the macrocell. This tradeoff can typically be modeled with game theory.

The MBS and the FAP are players in a game. They maximize their own utilities, respectively. The strategy of the MBS is the compensation price κ and the strategy of the FAP is the optimal accepted number of MUEs when hybrid access is motivated by the compensation framework. The utilities of the MBS and the FAP are as follows.

The utility of the MBS is

$$U_M = v_M(K) - c_K(K, \kappa), \tag{5.1}$$

where $v_M(K)$ is the utility of the macrocell itself when K MUEs are served by the nearby FAP in the hybrid access. We call it self-utility of macrocell. κ is introduced as the compensation price so that the MBS can influence the strategy of the FAP in choosing the optimal number K^* of accepted MUEs. Both the self-utility of macrocell $v_M(K)$ and the compensation function $c_K(K, \kappa)$ are functions of K.

The utility of the FAP is

$$U_F = v_F(K) - F + c_K(K, \kappa). \tag{5.2}$$

where F is the fixed fee paid by the FAP to the MBS for the backhaul network support. F is independent of the number K of accepted MUEs. Similarly, the self-utility of femtocell is $v_F(K)$.

5.1.2 Hybrid Access Protocol between Macro- and Femtocell

In this section, the process of the hybrid access with the compensation framework is discussed. We adopt the Stackelberg game between the MBS and the FAP and apply the market clearance[1].

[1] The market clears if the quantity of supply is equal to the quantity of demand [14].

The hybrid access protocol between the two-tier macro- and femtocell works as follows. The MBS and the FAP compete for the number of MUEs which are served by the FAP in the hybrid access. This can be modeled as a market. The MBS and FAP can be considered as the consumer and producer in the market, where the supply of the FAP s_F is the optimal number of served MUEs by maximizing its utility U_F, i.e.

$$s_F = K_F^* := \arg \max_{0 \le K_F \le N} U_F. \tag{5.3}$$

The demand of the MBS d_M is the optimal number of out-served MUEs accepted by the FAP,

$$d_M = K_M^* := \arg \max_{0 \le K_M \le N} U_M. \tag{5.4}$$

The utility functions of the MBS and the FAP must be concave functions with respect to K so that the number of accepted MUEs in the hybrid access can be optimized.

The MBS must take steps to motivate, monitor, and enforce the FAP's interaction with the compensation in the hybrid access. If the market clears, the optimal compensation price κ^* provided by the MBS solves the function where the market demand equals the supply, i.e.,

$$\begin{aligned} \text{Find} \quad & \kappa^* \\ \text{s.t.} \quad & d_M = s_F. \end{aligned} \tag{5.5}$$

The protocol is formulated as a Stackelberg game, where the MBS acts as a leader with the compensation price κ as its strategy and the FAP acts as a follower with the accepted number K of MUEs in the hybrid access as its strategy. The MBS first predicts the best response of the FAP with the given compensation price κ, and then optimizes its own best response in choosing the optimal κ^* so that the resulting optimal number of accepted MUEs K_F^* is equal to K_M^*. They interact as follows.

- **Optimal Compensation Price κ Selection for MBS**

  The MBS will maximize its own utility U_M with the compensation by choosing the optimal compensation price κ. Since the MBS has all the information about the femtocell from the backhaul support, it can force the FAP to meet the demand of K_M^* by providing a proper compensation price κ.

- **Utility Optimization of FAP with Given κ**

  The FAP will automatically find the optimal number K of MUEs it would open access to by maximizing its own utility U_F with the compensation function c_K of the given compensation price κ. As a result, this optimized K_F^* coincides with the number K_M^* which maximizes the utility U_M of the MBS with c_K. Indeed, $K_F^* = K_M^*$ makes the market clear and leaves the market stable.

The mechanism which forces the best response of the FAP to be equal to the need of the MBS is summarised in the following Lemma.

5.1 Lemma. *The condition of market clearance for the hybrid access protocol in the two-tier macro-femtocell networks is that U_F and U_M are concave functions with respect to K and*

$$\frac{\partial v_M(K)}{\partial K} = -\frac{\partial v_F(K)}{\partial K}. \tag{5.6}$$

The self-utility v_M of the MBS is an increasing function with respect to K and the self-utility v_F of the FAP is a decreasing function of K.

Proof. In order to achieve market clearance in (5.5), the utility functions of the MBS U_M and the FAP U_F should be concave to K. Solving their first derivatives, it results in

$$\begin{aligned} \frac{\partial v_M(K)}{\partial K} - \frac{\partial c_K(K,\kappa)}{\partial K} &= 0 \\ \frac{\partial v_F(K)}{\partial K} + \frac{\partial c_K(K,\kappa)}{\partial K} &= 0. \end{aligned} \tag{5.7}$$

Since the more MUEs are out-served by the FAP, the higher self-utility the MBS should achieve. v_M is an increasing function of K and therefore v_F is a decreasing function of K. □

Due to the utility requirement $\underline{u}_k$ of each UE, the total number of acceptable UEs in each cell is restricted as follows.

5.2 Corollary. *If all the users belong to the same service class, i.e., $\underline{u}_1 = \ldots = \underline{u}_N = \underline{u}$, then the number of supportable UEs N in the system to fulfill $\underline{u}$ is bounded by*

$$0 < N < \frac{1}{1 - 2^{-\underline{u}}}. \tag{5.8}$$

Proof. It is easy to prove from Corollary 4.3. □

If there exist M registered FUEs served by the FAP and K MUEs assigned by the MBS and all the UEs belong to the same service class $\underline{u}$, then from (5.8), the achievable rate region for serving $M + K$ FUEs and MUEs in the FAP is

$$1 < 2^{\underline{u}} < \frac{K+M}{K+M-1}. \tag{5.9}$$

So it follows $0 < \underline{u} < \log\left(\frac{1}{1-\frac{1}{K+M}}\right)$. We define for serving $K + M$ UEs,

$$2^{\underline{u}} = \frac{1}{\lambda} \cdot \frac{M+K}{M+K-1}, \tag{5.10}$$

where $\lambda > 1$ is a load factor due to the inequality in (5.8).

5.3 Remark. For any given class of QoS requirements $\underline{u}$, the maximum number K_{max} of UEs that can be served in the system to ensure the user $\underline{u}$ is restricted by $\frac{1}{1-2^{-\underline{u}}}$. It shows that the FAP cannot serve too many additional MUEs. This restriction is reflected later in the compensation paid by the MBS to the FAP and the optimal K of accepted FUEs is influenced by the number M of subscribed FUEs as well.

5.4 Corollary. *For identical QoS requirement (5.10) of each UE, the number of UEs in the system is restricted by $\underline{u}$ and the system load factor λ,*

$$\max(N, M+K) \leq \frac{1}{2^{\underline{u}}\lambda - 1} + 1, \tag{5.11}$$

where N is the total number of MUEs in the macrocell, M is the total number of FUEs subscribed by the FAP and K is the MUEs served by the FAP as well if hybrid access is operated in the system.

Proof. The relationship between the total number N (not necessarily equal to the total number of MUEs in the MBS) of UEs in the system and their QoS requirements $\underline{u}$ is $\frac{N}{N-1} = 2^{\underline{u}}\lambda$. The number of supportable UEs is a function of $\underline{u}$ and λ,

$$N(\underline{u}, \lambda) = \frac{1}{2^{\underline{u}}\lambda - 1} + 1. \tag{5.12}$$

Since $\frac{N}{N-1}$ is a decreasing function with respect to N, $N(\underline{u}, \lambda) \geq \max(N, M+K)$, which indicates that no matter all the N MUEs are served by the MBS or the hybrid access is adopted by the FAP to serve M FUEs and K MUEs, the QoS requirement $\underline{u}$ is guaranteed in the wireless system. □

The compensation framework which benefits not only both the MBS in the macrocell and the FAP in the femtocell, but also all UEs in the whole wireless system to fulfill their QoS requirements $\underline{\boldsymbol{u}}$ is of great importance.

In the following, we will conduct the utility functions of the MBS and the FAP, respectively, as well as the suitable compensation function c_K.

5.1.3 Utility of FAP in Femtocell

Concerning in a single femtocell, the FAP is only motivated to serve K MUEs if its own utility U_F is maximized with the given compensation from the MBS. The utility of the FAP is defined as the rate-based utility v_F of its own registered FUEs plus the compensation function c_K when accepting K MUEs. The self utility v_F of the total M FUEs served by the FAP itself is defined as

$$v_F = \sum_{k=1}^{M} 2^{\underline{u}_k}. \tag{5.13}$$

Obviously, from the analysis in Remark 5.3, v_F is monotonically decreasing in K because the more MUEs are served, the less utility for FUEs in the femtocell is available.

For identical $\underline{u}$, we define the rate-based utility v_F as a M-fold rate-based utility function

$$v_F \quad = \quad M \cdot 2^{\underline{u}} = \frac{M}{\lambda} \frac{M+K}{M+K-1}. \tag{5.14}$$

Since v_F is a decreasing function of the number K of accepted MUEs and an increasing function of the number M of registered FUEs, the larger K the less the first term of U_F.

5.1.4 Utility of MBS in Macrocell

One of the main reasons why the MBS would like to compensate the FAP for hybrid access is the physical layer energy savings, which will result in cost reduction in the higher (application) layers. The question is how much benefit the MBS can earn from the hybrid access for the K out-served MUEs by paying the compensation c_K to the FAP. Therefore we define the utility U_M of the MBS as the profit from energy saving minus the compensation paid to the FAP.

The utility of the MBS is

$$U_M \quad = \quad \eta(N-K) \log \frac{E[P_{sum}^{MBS}(N)]}{E[P_{sum}^{MBS}(N-K)]} - c_K, \tag{5.15}$$

where N is the total number of MUEs subscribed by the MBS, K is the number of MUEs served by the FAP. $E[\,\cdot\,]$ denotes the expectation of the sum power. η is the equivalent revenue per unit of relative energy savings. The energy saving part $ES = \frac{E[P_{sum}^{MBS}(N)]}{E[P_{sum}^{MBS}(N-K)]}$ is denoted as the ratio of sum power consumption of the total N MUEs to that of N minus K MUEs if hybrid access is adopted by the FAP.

It can be interpreted that ES is an increasing function of K. The larger K is, the more revenue from ES will the MBS earn.

However in practice, the MBS should not assign all the MUEs to other FAPs. One possible scenario could be that some MUEs will leave the service package provided by the MBS since they are always served by the FAPs. Besides, from Corollary 5.2, it is not possible for the FAP to accept too many MUEs as well because the QoS requirement cannot be reached if the total number of served UEs is too large. Therefore, $N-K$ in U_M serves as a barrier function to prevent the slope of the ES part monotonically increasing.

5.1.5 Compensation Function

We assume that the compensation c_K is a function of the power price β_j (4.7) and it is averaged over the CSI α_j of each UE j. This represents the power consumption and the cost for serving different UEs with variable channel states. It indeed provides an explicit connection of the physical layer cost to the upper (application) layer revenue. Since the MBS has the whole information about the femtocell with the backhaul network support, such as the number M

of registered FUEs, it can influence the outcome of the hybrid access with the compensation price (will be discussed in Sec. 5.1.6.2).

The compensation function c_K paid by the MBS to the FAP for hybrid access serving K MUEs is given by

$$c_K = \frac{\kappa\lambda}{\lambda - 1} \sum_{k=1}^{K} \beta_k \mu_k, \tag{5.16}$$

where κ is the compensation price determined by the MBS. The power price β_k is described in (4.7). The averaged CSI is $\mu_j = E[\log(\frac{1}{\alpha_j})]$. The compensation c_K is a function of $\frac{1}{\alpha_k}$ since the power allocation p_k (4.6) of each UE k is inversely proportional to the CSI α_k.

Equation (5.16) shows the relationship between the compensation function in the macro-femtocell networks and the total cost for the power allocation in the general MAC system without SIC in Chapter 4.

From (4.7), the regulator can ensure the identical QoS requirements $\underline{\boldsymbol{u}}$ in (5.10) of the K MUEs and M FUEs served by the FAP by providing the power price

$$\begin{aligned} \beta_k = \beta &= (1 - 2^{-\underline{u}}) \left(1 - \frac{K+M-1}{K+M} 2^{\underline{u}}\right) \\ &= (1 - 2^{-\underline{u}}) \left(1 - \frac{1}{\lambda}\right) \\ &= \left(1 - \lambda + \frac{\lambda}{K+M}\right) \frac{\lambda - 1}{\lambda}. \end{aligned} \tag{5.17}$$

Since $\beta > 0$, the system load factor λ satisfies

$$1 < \lambda < \frac{K+M}{K+M-1}. \tag{5.18}$$

Note that the QoS requirement $\underline{u}$ is the same for all the users regardless of the total number of UEs in the macrocell or the femtocell. Therefore, the load factor λ should fulfill Corollary 5.2 for different total numbers in the single cells.

In order to ensure the rate requirement $\underline{u}$ of each UE with a positive power price β, the following Lemma holds.

5.5 Lemma. *In the two-tier macro-femtocell system, in which there are N MUEs in total and M registered FUEs in the femtocell, if the FAP adopts hybrid access and accepts K MUEs, then the system load factor λ is bounded by*

$$\frac{M+K}{M+K-1} > \lambda > \begin{cases} \frac{M+K-1}{M+K} \cdot \frac{N}{N-1} & \text{if } M+K > N \\ \frac{M+K}{M+K-1} \frac{N-1}{N} & \text{otherwise.} \end{cases} \tag{5.19}$$

Proof. For different numbers of UEs in the single cells, the load factor λ should fulfill $2^{\underline{u}} = \frac{1}{\lambda}\frac{M+K}{M+K-1} = \frac{1}{\lambda'}\frac{N}{N-1} < \min\left(\frac{M+K}{M+K-1}, \frac{N}{N-1}\right)$. $\frac{N-K}{N-K-1}$ is ignored because $\frac{x}{x-1}$ is a monotonically decreasing function. If $N > M+K$, then $\frac{1}{\lambda} \cdot \frac{M+K}{M+K-1} < \frac{N}{N-1}$. For $N < M+K$ it is similar. Concluding the above, we get the lower bound for the load factor λ as

$$\begin{aligned}\lambda &> \frac{M+K}{M+K-1} \cdot \frac{N-1}{N} \qquad \text{if} \quad N > M+K \\ \lambda &> \frac{M+K-1}{M+K} \cdot \frac{N}{N-1} \qquad \text{otherwise.}\end{aligned} \tag{5.20}$$

Since $\beta > 0$, the load factor λ should also fulfill (5.18). Then Lemma 5.5 is proved. □

5.6 Remark. The load factor λ with restriction in Lemma 5.5 is very close to 1 when M and K are not too small, so $\frac{\lambda}{\lambda-1}$ is multiplied in c_K in order to amplify the influence of the power price β_k and the CSI α_k, which illustrates the physical layer power consumption. Moreover, it enhances the influence of the compensation c_K in the utility function of the FAP.

5.1.6 Analysis of Compensation Framework and Stackelberg Game Formulation

For simplicity of analysis, we have the following assumptions:

1. All the UEs belong to the same service class and have equal weights, i.e., $\underline{u}_k = \underline{u}$ and $w_k = w$ with $\sum_{k=1}^{K} w_k = 1$, so the power pricing parameter $\beta_k = \beta$.

2. The system load factor ($\lambda > 1$) satisfies Lemma 5.5.

3. We assume the quasi-static block flat-fading channels apply the exponential distribution $e^{-\alpha_k}$. All the UEs are symmetric distributed. According to Rayleigh fading,

$$\begin{aligned}\mu_k &= E[-\log \alpha_k] \\ &= -\int_0^{\infty} e^{-\alpha_k} \cdot \log \alpha_k d\alpha_k = \gamma,\end{aligned} \tag{5.21}$$

   for all k where $\gamma \approx 0.5772$ is the Euler-Mascheroni constant.

With the power price β in (5.17) and μ_k in (5.21), the compensation c_K becomes

$$\begin{aligned}c_K &= \frac{\kappa\lambda}{\lambda-1}\sum_{k=1}^{K}\left(1-\lambda+\frac{\lambda}{K+M}\right)\frac{\lambda-1}{\lambda}\cdot\mu_k \\ &= \kappa K\gamma\left(1-\lambda+\frac{\lambda}{K+M}\right).\end{aligned} \tag{5.22}$$

Fig. 5.2 shows the compensation function c_K with respect to the number K of accepted MUEs in the femtocell. It is a concave but not monotonically increasing function of K, which very well illustrates the characteristics of the two-tier system. The compensation should be

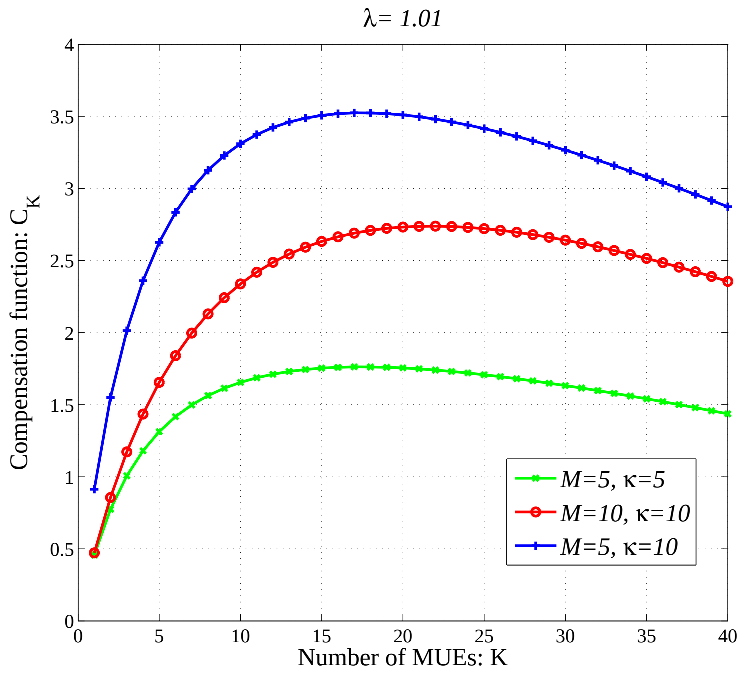

Figure 5.2: Compensation function with respect to K for power-price based compensation framework.

larger with the increment of K MUEs served by the FAP, while in the mean time should also put certain restriction on K due to Corollary 5.2 and 5.4. The maximum affordable number of UEs is restricted by the users' QoS requirements $\underline{u}$.

With all the aforementioned utilities of the MBS and the FAP, the two-tier macro-femtocell networks can apply the hybrid access by maximizing their own U_M and U_F, respectively.

We will apply the backward induction in the following analysis.

5.1.6.1 Utility Optimization of FAP with Given κ

As analyzed before, with the compensation function c_K, the expected utility U_F at the FAP is

$$U_F = \frac{M(K+M)}{\lambda(K+M-1)} - F + \kappa K \gamma \left(1 - \lambda + \frac{\lambda}{K+M}\right). \tag{5.23}$$

The FAP optimizes the number of acceptable MUEs K in order to maximize U_F, i.e.,

$$K^* := \arg \max_{0 \le K \le N} U_F. \tag{5.24}$$

5.7 Corollary. *The utility U_F of the FAP with the compensation function c_K is bounded with*

$$\underline{U}_F \le U_F \le \bar{U}_F, \tag{5.25}$$

where the lower bound of U_F is

$$\underline{U}_F = \frac{M}{\lambda}\left(\frac{K+M+1}{K+M}\right) - F + \kappa K\gamma\Big(1-\lambda+\frac{\lambda}{K+M}\Big) \tag{5.26}$$

and the upper bound of U_F is

$$\bar{U}_F = \frac{M}{\lambda}\left(\frac{K+M}{K+M-1}\right) - F + \kappa K\gamma\Big(1-\lambda+\frac{\lambda}{K+M-1}\Big). \tag{5.27}$$

Proof. Function $\frac{x+1}{x}$ and $\frac{1}{x}$ are decreasing functions of x, so that changing the variables in U_F results in the lower and upper bounds $\underline{U}_F$ and $\bar{U}_F$, respectively. □

5.8 Proposition. *If the utility of the FAP U_F is the utility function in (5.23) and the compensation term paid by the MBS to the FAP for hybrid access is c_K in (5.22), then the optimal number K^* of MUEs will the FAP serve (solving (5.24)) is bounded by*

$$\underline{K}^* \leq K^* \leq \bar{K}^*, \tag{5.28}$$

where the upper bound of the optimal number of MUEs $\bar{K}^*$ will the FAP serve (solving $\bar{K}^* := \arg\max_{0\leq K\leq N} \underline{U}_F$) is

$$\bar{K}^* = \left\lfloor \sqrt{\frac{\kappa\gamma M\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)}} - M \right\rceil^+, \tag{5.29}$$

and the lower bound of the optimal number of MUEs $\underline{K}^*$ will the FAP serve (solving the optimization problem $\underline{K}^* := \arg\max_{0\leq K\leq N} \bar{U}_F$) is

$$\underline{K}^* = \left\lfloor \sqrt{\frac{\kappa\gamma (M-1)\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)}} - M + 1 \right\rceil^+. \tag{5.30}$$

Proof. Please refer to Proof 5.3.1. □

Fig. 5.3 shows the utility function U_F of the FAP with respect to the number of accepted MUEs K comparing with the rate-based utility v_F and the compensation function c_K. It is shown that U_F is concave with respect to K and v_F is a decreasing function of K.

Fig. 5.4 shows that the higher the compensation price κ is, the more number of MUEs K^* the FAP will serve to maximize its own utility U_F.

Table 5.1 provides the comparison of the number of optimal accepted MUEs K^* with the lower and upper bound $\underline{K}^*$ and $\bar{K}^*$, respectively, for given parameters. It is shown that when the compensation price $\kappa > 5$, the numerically obtained K^* is the same as $\underline{K}^*$ even though M and K are in small values.

Table 5.1: Comparison of approximation $\bar{K}^*$ and $\underline{K}^*$ to numerical results K^*.

$M=5$, $\lambda=1.01$, $\gamma=0.5772$				
κ	$\bar{K}^*$	$\underline{K}^*$	K^*	$\max U_F$
3	9	7	8	6.3008
4	12	10	11	6.4297
5	13	12	13	6.9717
6	14	13	14	7.3180
25	17	16	17	13.9951

In order to ensure U_F as a concave function to a positive K^*, the compensation price κ decided by the MBS to optimize its own utility U_M is restricted as follows.

5.9 Lemma. *The compensation price κ provided by the MBS in order to motivate the FAP to accept K MUEs in the hybrid access fulfills*

$$\kappa > \max\left[\frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))}, \frac{1}{\gamma\lambda(\lambda-M(\lambda-1))}\right]. \tag{5.31}$$

Proof. Please refer to Proof 5.3.2. □

5.1.6.2 Optimization of the Compensation Price at MBS

With the power allocation in (4.6), $E[P_{sum}^{MBS}(N)] = E[\sum_{j=1}^{N} p_j]$ and $E[P_{sum}^{MBS}(N-K)] = E[\sum_{j=1}^{N-K} p_j]$, respectively. Therefore the utility function of the MBS is

$$\begin{aligned} U_M &= \eta(N-K)\log\frac{E[\sum_{j=1}^{N}\frac{B_N}{\alpha_j}(1-2^{-\underline{u}})]}{E[\sum_{j=1}^{N-K}\frac{B_{N-K}}{\alpha_j}(1-2^{-\underline{u}})]} - c_K \\ &= \eta(N-K)\log\frac{E[\frac{1}{\alpha_j}]\left(\frac{(1-2^{-\underline{u}})}{N(2^{-\underline{u}}-1)+1}\right)N}{E[\frac{1}{\alpha_j}]\left(\frac{(1-2^{-\underline{u}})}{(N-K)(2^{-\underline{u}}-1)+1}\right)(N-K)} - c_K \\ &= \eta(N-K)\log\frac{N(N-K)(2^{-\underline{u}}-1)+N}{N(N-K)(2^{-\underline{u}}-1)+N-K} - c_K. \end{aligned} \tag{5.32}$$

We propose two methods for the MBS to optimize its compensation price κ. On the one hand to maximize its own utility $U_M(K^*(\kappa))$, and on the other hand to make sure that the FAP will accept the optimal number of MUEs K^* given κ.

5.1.6.3 Close to Optimal Compensation Pricing

The first method is based on the market clearance. Since the optimal number of MUEs accepted by the FAP is only numerically obtained, the following proposition is calculated with

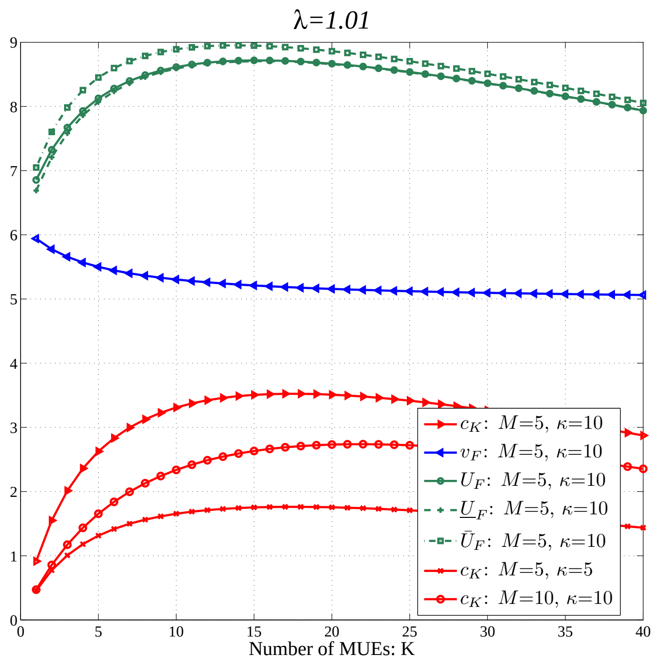

Figure 5.3: Utility of femtocell with respect to K, comparing with the rate-based utility v_F and compensation function. The lower three curves show the compensation function of different parameters. The upper curves are corresponding to the parameters as $\lambda = 1.01$ $M = 5$, $K = 10$.

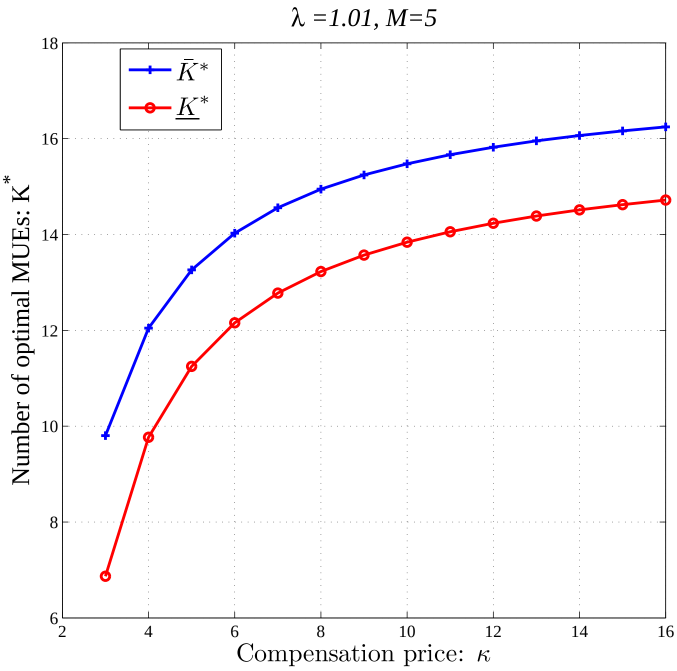

Figure 5.4: Optimal acceptable number K of MUEs with respect to compensation price κ for power price based compensation framework.

the lower and upper bound of K^*. In order to clear the market, i.e., find κ^*, s.t. $K_M^* = K^*$ (5.5), the MBS applies the following compensation price κ^*.

5.10 Proposition. *The FAP will automatically accept $K^* = K_M^*$ MUEs from the MBS in order to maximize its own utility U_F, if the MBS provides the compensation price $\kappa^* = \frac{M}{\gamma\left((K_M^*+M)^2\lambda(1-\lambda)+M\lambda^2\right)}$ for the upper bound $\bar{K}^*$ and $\kappa^* = \frac{M}{\gamma\lambda((\lambda-1)(K+M-1)^2-(M-1)\lambda)}$ for the lower bound $\underline{K}^*$.*

Proof. The proof is straightforward and omitted here. □

5.1.6.4 Numerical Search for Compensation Price

The second method is to search the compensation price κ numerically by solving the equation $\arg\max_\kappa U_M(K^*(\kappa)) = K^*$. Fig. 5.5 illustrates the numerical search of the optimal compensation price κ^*. The MBS predicts the results for $\underline{K}^*$ and $\bar{K}^*$ of the FAP first. The blue and red curves correspond to the upper and lower bound $\bar{K}^*$ and $\underline{K}^*$ that the FAP will serve in the hybrid access with respect to different κ. The green line shows the optimal number K_M^* of out-served MUEs at the MBS side as an example. The intersection points are the optimal compensation prices $\bar{\kappa}^*$ and $\underline{\kappa}^*$. K_M^* can be obtained by numerical results solving (5.4). Therefore the MBS decides its optimal compensation price and pays the compensation c_K to the FAP to motivate the hybrid access in the femtocell. With the given compensation price κ^*, the FAP will automatically accept K^* MUEs by maximizing its own utility $U_F(\kappa^*)$. In general, both the utilities of the MBS and the FAP are maximized with the proposed compensation framework while at the same time, the utility requirement $\underline{u}$ of each UE is guaranteed.

In this section, the compensation framework is established to motivate the hybrid access of the femtocell based on the power allocation and universal non-linear price β in Chapter 4. In the next section, the energy efficiency of the whole two-tier system is considered as the utility function of the MBS.

5.2 Energy-Aware Compensation Framework for Hybrid Macro-femtocell Networks

The user-centric compensation structure is suggested in Sec. 5.1, which is based on the universal non-linear price controlled by a regulator in the system. In this section, we focus on the energy efficiency of the whole macro-femtocell system as depicted in Fig. 5.6, where the power price β is released. The compensation function is free of β and therefore no regulator is required. We investigate the utility functions of both the MBS and the FAP with proper compensation and power allocation. The compensation is a function of the channels which depend on the positions of the UEs. A Stackelberg game is formulated and the strategies of the MBS and the FAP adjust due to the mobility of UEs. The novel hybrid access protocol for the uplink transmission of the two-tier macro-femtocell networks is proposed and the following contributions are made.

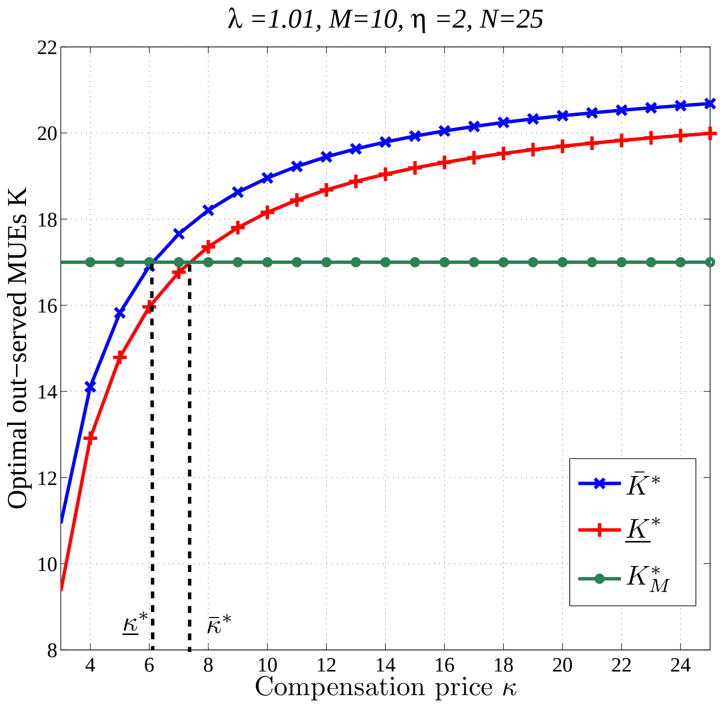

Figure 5.5: Illustration of optimal compensation price κ, where the green line shows the optimal number of MUEs K_M^* that the MBS wants the FAP to serve as an example.

- The utility functions of the MBS in the macrocell and the FAP in the femtocell are provided, in which the MBS maximizes the energy efficiency of the whole system and the FAP maximizes its own revenue with the given compensation function.
- The compensation which is a function of the CSI of the out-served MUEs and the compensation price is established.
- The hybrid access protocol is investigated, where the optimal acceptable MUEs in the femtocell is drawn with the proposed optimal compensation price.
- Numerous simulations are conducted to illustrate the compensation framework for motivating hybrid access.

5.2.1 Energy Aware Compensation Framework

In this section, the compensation framework applied by the MBS to motivate the hybrid access in the femtocell is proposed based on the power consumption of all the UEs (MUEs and FUEs). The MBS is able to save the energy of the whole system while guaranteeing the QoS requirement $\underline{u}$ of each UE by utilizing the femtocell wireless resource. The FAP serves the nearby MUEs with its spare resource for the compensation paid by the MBS such that its own utility is maximized.

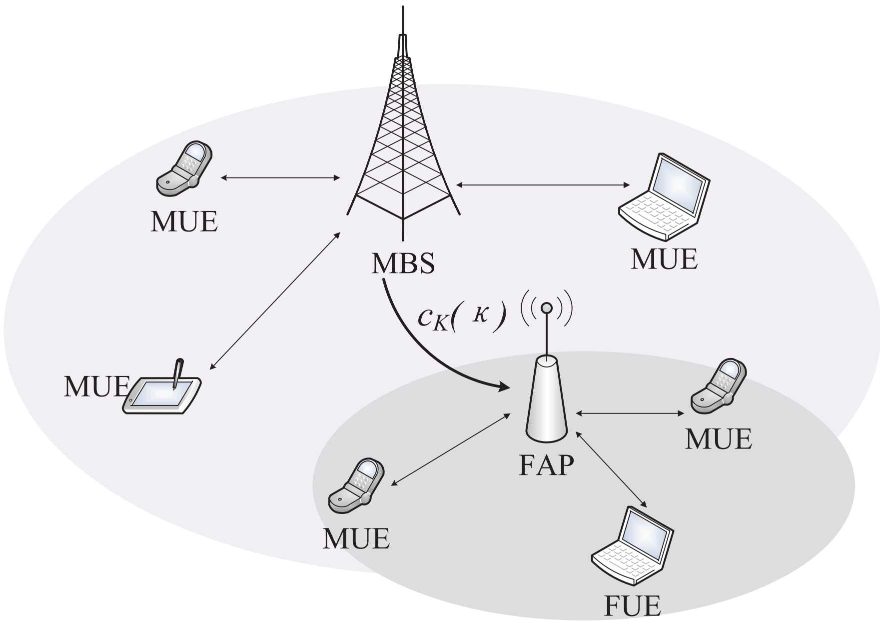

Figure 5.6: System model of energy-aware compensation framework for hybrid macro-femtocell networks.

We define the energy aware utility U_M of the MBS and the utility U_F of the FAP as follows.

5.2.1.1 Utility of MBS in Macrocell

As analyzed above, the power p_k (4.6) allocated to each UE, no matter it is served by the MBS or the FAP, is dependent on their QoS requirement $\underline{u}$ and the CSI $\boldsymbol{\alpha}$. We assume the CSI $\boldsymbol{\alpha}$ is a function of the distance between the UEs and the BSs. Therefore, from an energy efficiency point of view, the MBS would like to compensate the FAP for hybrid access of K MUEs if they are nearer to the FAP than the MBS. In the following, we define the utility U_M of the MBS as the two-tier network global energy efficiency, i.e., the ratio between the total throughput and the sum power consumption for all UEs in the system to support their QoS requirements when hybrid access is adopted.

$$U_M = \frac{\eta(M+N)\underline{u}}{\left(\sum_{j\in\mathcal{N}-\mathcal{K}} p_j + \sum_{j\in\mathcal{M}+\mathcal{K}} p_j\right)}, \tag{5.33}$$

where $\mathcal{N}-\mathcal{K}$ is the set of MUEs served by the MBS, $\mathcal{M}+\mathcal{K}$ is the set of FUEs and acceptable MUEs served by the FAP in the hybrid access mode. η is the equivalent revenue per unit of energy efficiency.

From (4.6), it can be interpreted that the energy consumption part $EC = \sum_{j \in \mathcal{N}-\mathcal{K}} p_j + \sum_{j \in \mathcal{M}+\mathcal{K}} p_j$ is an decreasing function of the CSI α_j. For identical rate requirement $\underline{u}$ and fixed number of UEs $M + N$, the numerator of U_M (5.33) is a constant. Thus the objective of the MBS is to minimize the total power consumption of the whole two-tier networks. If the MBS wants to motivate the FAP to serve the MUEs, which are near the FAP but farther from the MBS, then it has to pay.

The MBS is able to determine how many and which are the K out-served MUEs it would like the nearby FAP to serve by solving

$$K_M^* = \max_{0 \leq K_M \leq N} U_M. \tag{5.34}$$

The more compensation c_K is paid to the FAP, the larger K will be. However in practice, due to Corollary 5.2 the total number of UEs in the FAP is restricted. Otherwise the QoS requirement cannot be reached. The MBS can control this in the hybrid access by choosing the proper compensation price κ in c_K.

5.2.1.2 Utility of FAP in Femtocell

The FAP can help the system operator to utilize the expensive wireless spectrum more thoroughly and spend the power more efficiently by adopting the hybrid access to serve the nearby MUEs. However, the FAP is responsible to select the number of acceptable MUEs so that its own utility U_F is maximized. Since the utility of the M subscribed FUEs is diminished with the increment of K. The utility U_F of the FAP is a tradeoff between the rate based utility v_F of its own subscribed M FUEs and the compensation c_K paid by the MBS for serving the K MUEs. We define $U_F = v_F + c_K - F$.

From (5.10), in the femtocell $\underline{u} = \log \frac{K+M}{\lambda(K+M-1)}$. The utility v_F of the registered FUEs is a M-fold rate function

$$\begin{aligned} v_F &= M \cdot \underline{u} \\ &= M \log \frac{M+K}{\lambda(M+K-1)}. \end{aligned} \tag{5.35}$$

It is intuitive that the first term v_F of U_F is a decreasing function of the number of accepted MUEs K. Therefore, in order to construct a concave utility function with respect to K, the compensation function c_K is defined as follows.

5.2.1.3 Compensation Function

The main idea of this section is to motivate the hybrid access of the femtocell network so that the MBS is able to satisfy the QoS requirement $\underline{u}$ of all the MUEs and FUEs with minimum power consumption. Since the power allocation p_k to each UE is a function of the CSI α_k, which depends on the distance between the UE k and the corresponding MBS or the FAP, we propose the compensation function c_K paid by the MBS to the FAP for serving K MUEs as

$$c_K = \left(\kappa + \frac{\kappa K}{K+M} - \frac{K}{M}\right)\sum_{k=1}^{K}\frac{1}{\alpha_k}, \tag{5.36}$$

where κ is the compensation price determined by the MBS. $\sum_{k=1}^{K}\frac{1}{\alpha_k}$ illustrates the power allocation of the UEs as an inverse function of the chennels. c_K in (5.36) is conducted to be a concave function with respect to K.

5.11 Remark. The compensation function c_K indicates the physical layer power consumption for the FAP to serve the K nearby MUEs with M FUEs because p_k in (4.6) is an inverse function of α. Since c_K is usually applied on the higher layers (e.g. application layer), the compensation framework provides a simple manner to reflect the physical layer energy consumption to the higher layer revenue of the networks. The compensation price κ is introduced such that the MBS can influence the choice of the FAP in the acceptable number K of MUEs in order to enhance the global energy efficiency.

5.2.2 Hybrid Access Protocol between Macro- and Femtocell

Similar to Sec. 5.1, we model the hybrid access protocol as a Stackelberg game, where the MBS acts as a leader and the FAP acts as a follower. The strategies of the MBS and the FAP are the compensation price κ and the optimal number K_F^* of acceptable MUEs, respectively. By backward induction, the MBS first predicts the strategy K_F^* of the FAP and then determines the compensation price κ to force $K_F^* = K_M^*$ so that the global energy efficiency is maximized in the two-tier macro-femtocell networks.

The MBS and the FAP are capable to sense the change of the wireless environment such as the CSI α_k and therefore adjust their strategies. The MBS and the FAP interact in the energy-aware hybrid access as follows.

- **Optimal Compensation Price κ Selection for MBS**

  In order to minimize the energy consumption in its utility U_M, the MBS optimizes K_M^* MUEs which are nearer to the FAP. By predicting the strategy of the FAP, the MBS chooses the optimal compensation price κ^* so that the FAP automatically accepts $K_M^* = K_F^*$ MUEs.

- **Utility Optimization of FAP with Given κ**

  The simple FAP maximizes its own utility U_F by selecting the K_F^* nearby MUEs with the compensation function c_K, in which the compensation price κ is determined by the MBS. As a result, this optimized K_F^* coincides with the the number K_M^*. This is performed by backward induction [23, pp.68], which starts to solve for the optimal choice of the FAP, and then computes backward the optimal choice of the MBS in order to fulfill the QoS requiement $\underline{u}$ with the minimum total power consumption.

We apply the backward induction in the following analysis.

5.2.2.1 Utility Optimization of FAP with Given κ

Given the compensation function c_K in (5.36) and v_F in (5.35), the utility U_F at the FAP is

$$U_F = M \log \frac{K+M}{\lambda(K+M-1)} - F + \left(\kappa + \frac{\kappa K}{K+M} - \frac{K}{M}\right) \sum_{k=1}^{K} \frac{1}{\alpha_k}. \tag{5.37}$$

The FAP optimizes K in order to maximize U_F, i.e.,

$$K_F^* := \arg \max_{0 \le K \le N} U_F. \tag{5.38}$$

5.12 Proposition. *Given the compensation term c_K in (5.36) paid by the MBS to the FAP for hybrid access, the FAP maximizes its utility U_F in (5.37) by accepting K_F^* MUEs (solving (5.38)). K_F^* can be solved numerically and its mathematical approximation $\hat{K}_F^*$ is*

$$\hat{K}_F^* = \left\lfloor M\left(\sqrt{\kappa - \frac{1}{\sum_{k=1}^{K} \frac{1}{\alpha_k}}} - 1\right)\right\rceil^+. \tag{5.39}$$

Proof. Please refer to Proof 5.3.3. □

5.13 Remark. For energy aware compensation framework, the FAP will accept $K_F^* > 0$ MUEs in hybrid access if the compensation price κ provided by the MBS satisfies

$$\kappa > 1 + \frac{1}{\sum_{j=1}^{K} \frac{1}{\alpha_j}}. \tag{5.40}$$

5.2.2.2 Utility Optimization of MBS of the Compensation Price

Substitute the power allocation p_k (4.6) and the QoS requirement $\underline{u}$ into the utility function U_M of the MBS. For identical rate requirement $\underline{u}$, we have

$$U_M = \frac{\eta(M+N)\underline{u}}{\left(\sum_{j \in \mathcal{N}-\mathcal{K}} \frac{B_{N-K}}{\alpha_j} + \sum_{j \in \mathcal{M}+\mathcal{K}} \frac{B_{M+K}}{\alpha_j}\right)(1 - 2^{-\underline{u}})}. \tag{5.41}$$

The MBS will obtain the optimal number K_M^* of MUEs by numerical search to maximize its utility U_M. The result is provided in Sec. 5.2.3. Since the CSI α_k is dependent on the distance between the UE k and the corresponding MBS or the FAP, K_M^* changes through time due to the UEs' mobility. After obtaining the K_M^*, the MBS will determine the compensation price κ

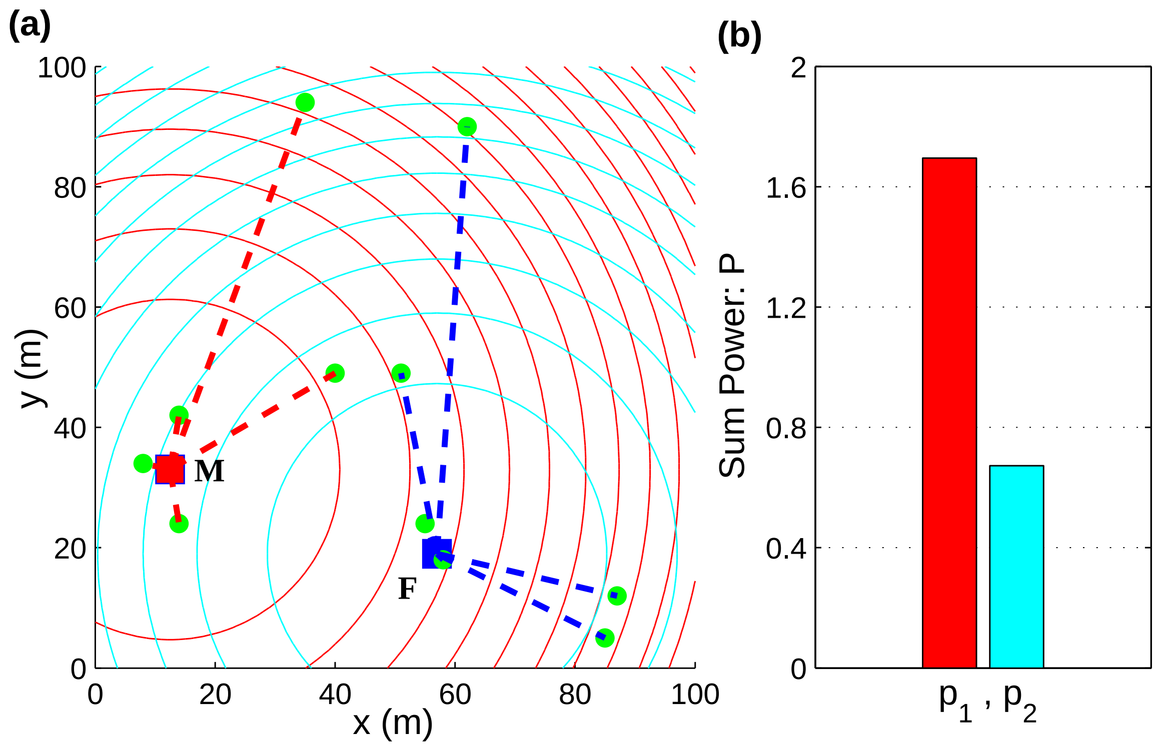

Figure 5.7: Sum power versus CSI as a function of the distance d_k.

so that the FAP will automatically accept $K_F^* = K_M^*$ MUEs in the hybrid access. The following proposition provides the optimum strategy of the MBS.

5.14 Proposition. *The FAP accepts $K_F^* = K_M^*$ MUEs in the hybrid access if the MBS provides the compensation price as*

$$\kappa^* = \frac{K+M}{D(K+M-1)} + \frac{(K+M)^2}{M^2}. \tag{5.42}$$

Proof. We obtain (5.42) by solving $\frac{\partial U_F}{\partial K} = 0$ (5.51) for κ as a function of K. □

5.2.3 Numerical Results

In this section, numerous simulations are conducted in order to evaluate the compensation framework to motivated hybrid access in the macro-femtocell networks. For all UEs, the distance d_k between the UE k and the MBS or the FAP has been randomly generated in the interval $[0, 100]$ meters. The CSI is generated as realizations of d_k^{-2} so the power decay factor is of 2. The total number of the MUEs in Fig. 5.7 is $N = 11$. The system load factor is $\lambda = 1.01$.

In the left part of Fig. 5.7, the green points are the positions of the N MUEs. The red point is the position of the MBS denoted as 'M' and the blue point is the position of the FAP denoted as 'F'. The points connected to the MBS with dashed lines in red are those MUEs nearer to the

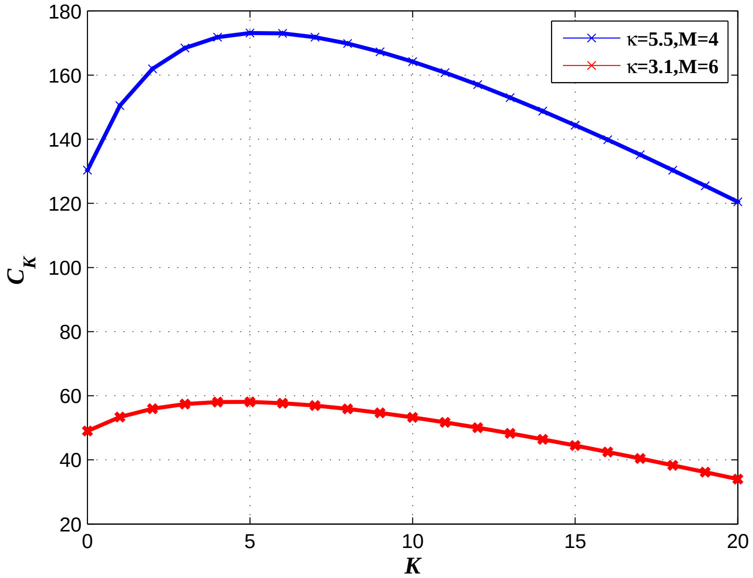

Figure 5.8: Compensation function with respect to K for energy aware compensation framework.

MBS and similarly, those points connected to the FAP with dashed lines in blue are relatively nearby the FAP. With this comparison, the MBS would like to assign $K_M^* = 6$ MUEs to the FAP in order to minimize the total power consumption, which is shown in the right part of Fig. 5.7. P_1 shows the sum power for the MBS to serve all the N MUEs by itself and P_2 shows the sum power allocated by the MBS to serve $N - K$ MUEs plus the sum power allocated by the FAP to serve K nearby MUEs. It is clear that when the CSI is a function of the distance d_k between the UEs and BSs and the power allocation to each UE is inversely proportional to the CSI, then by adopting hybrid access in the macro-femtocell network, the total power consumption is much lower. From the simulations, more than 50% of the energy in the physical layer is saved. We will use this numerical result $K_M^* = 6$ in the following simulations.

Fig. 5.8 shows the compensation function c_K with respect to the number K of accepted MUEs in the femtocell for different compensation price κ and MUEs M. It is increasing with K at the beginning since the more K the FAP serves, the more compensation it should receive. However, due to Corollary 5.2, only limited number of UEs can be served in a single cell in order to achieve the QoS requirement $\underline{u}$ of each UE. Since the FAP is a simple device who only cares about its utility U_F, the MBS guarantees this restriction by smartly making the compensation c_K concave but not monotonically increasing with the number K.

Fig. 5.9 and 5.10 show the utility function U_F of the FAP with respect to the number of K MUEs and M FUEs for different compensation prices κ, respectively. U_F is a concave function of K and the numerical result of the optimal acceptable K_F^* is given in the figure.

Fig. 5.11 and 5.12 show the optimal number of acceptable MUEs K_F^* to maximize the utility function U_F of the FAP versus the compensation price κ and the number of registered FUEs

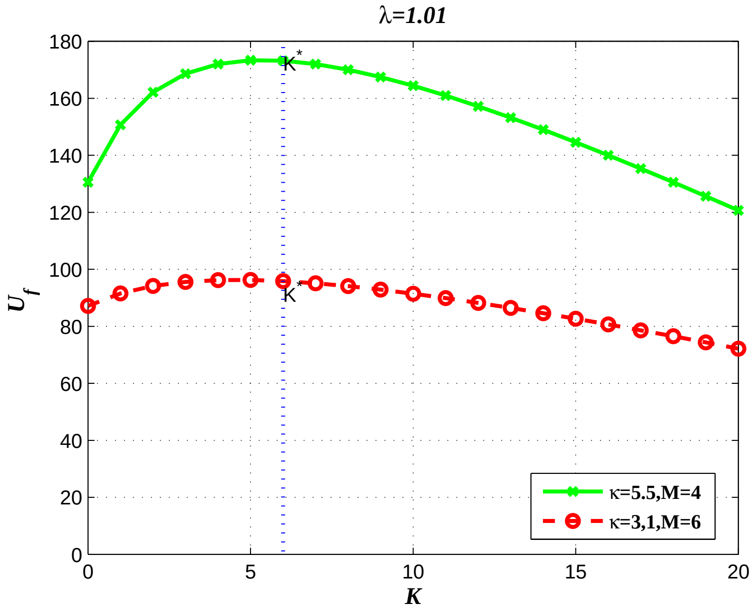

Figure 5.9: Utility of the FAP U_F as a function of number K of acceptable MUEs.

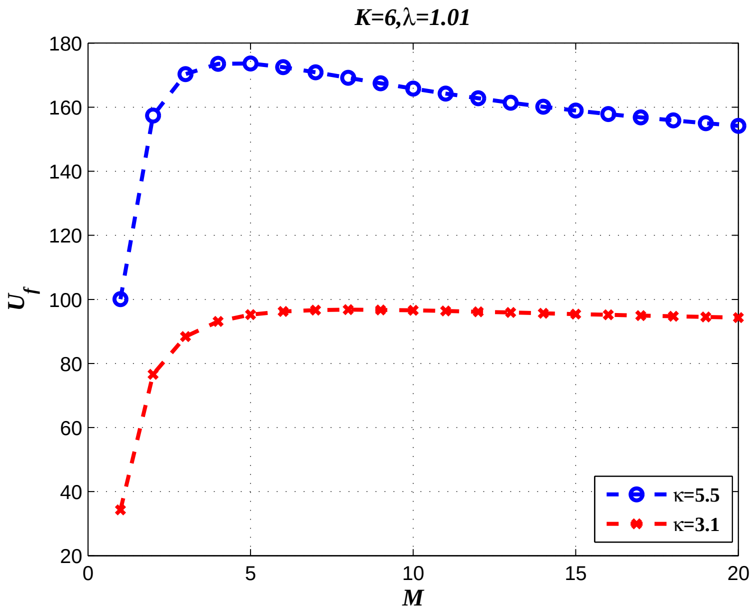

Figure 5.10: Utility of the FAP U_F as a function of number M of FUEs.

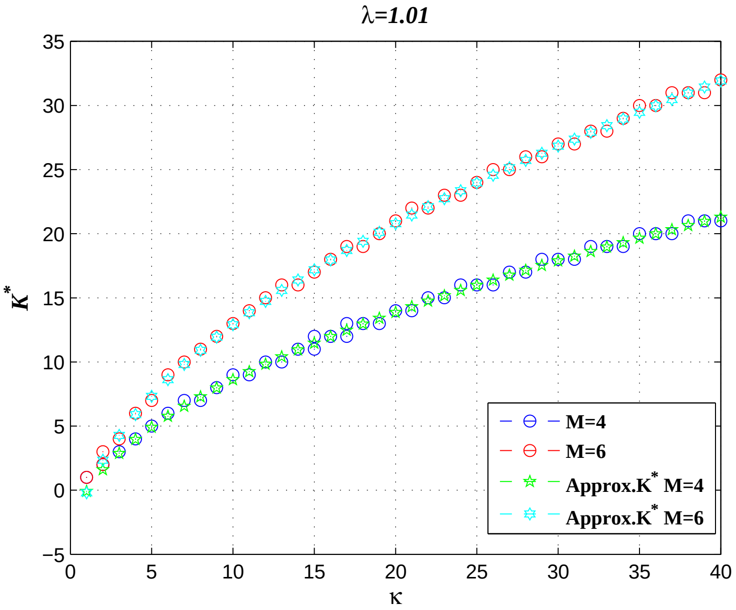

Figure 5.11: Optimal number of acceptable MUEs K^* vs. compensation price κ.

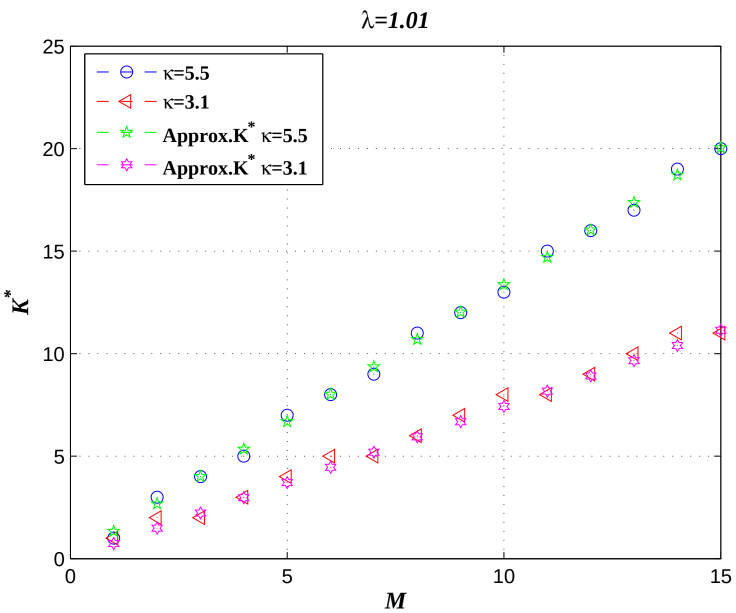

Figure 5.12: Optimal number of acceptable MUEs K^* vs. the number of FUEs M.

M. Note that the star points are the approximate results calculated in (5.39). It indicates that for different couples of parameters even when M and K are not large integers, $\hat{K}_F^*$ is quite accurate and simple to be implemented.

5.3 Proofs

5.3.1 Proof of Proposition 5.8

Proof. In order to find the optimal number of acceptable MUEs K, the FAP checks the first derivative of (5.23) with respect to K

$$\frac{\partial U_F}{\partial K} = \frac{M}{\lambda} \frac{-1}{(K+M-1)^2} + \frac{\kappa\gamma M \lambda}{(K+M)^2} + \kappa\gamma(1-\lambda). \tag{5.43}$$

To solve $\frac{\partial U_F}{\partial K} = 0$ in (5.43) is difficult since there are the 4th, 3rd order of K.

For the upper bound, we approximate the term $K+M-1$ to $K+M$. For large K and M this is naturally true, but we will show with simulation results that even for small value of K and M, this approximation is quite accurate and thereby simplifies the problem significantly.

Set $K+M=x$. After the transformation, $\frac{\partial U_F}{\partial K} = 0$ becomes

$$\begin{aligned}
\frac{M}{\lambda x^2} &= \frac{\kappa\gamma M\lambda}{x^2} + \kappa\gamma(1-\lambda) \\
(K+M)^2 &= \frac{M - \kappa\gamma M\lambda^2}{\kappa\gamma\lambda(1-\lambda)} \\
\bar{K}^* &= \sqrt{\frac{M - \kappa\gamma M\lambda^2}{\kappa\gamma\lambda(1-\lambda)}} - M.
\end{aligned}$$

The lower bound of the optimal number of MUEs served by the FAP is obtained by solving

$$\begin{aligned}
\frac{\partial \bar{U}_F}{\partial K} &= \frac{M}{\lambda} \frac{-1}{(K+M-1)^2} + \kappa\gamma(1-\lambda) + \frac{\kappa\gamma\lambda(M-1)}{(K+M-1)^2} \\
&= \frac{\kappa\gamma\lambda(M-1) - \frac{M}{\lambda}}{(K+M-1)^2} + \kappa\gamma(1-\lambda) = 0.
\end{aligned} \tag{5.44}$$

Then we obtain

$$\frac{\kappa\gamma\lambda^2(M-1) - M}{\lambda\kappa\gamma(\lambda-1)} = (K+M-1)^2. \tag{5.45}$$

The lower bound $\underline{K}^*$ in (5.30) is proved.

Note that K should always be positive integers, we find the nearest integer of the approximation result. Therefore the number of accepted MUEs in the femtocell is

$$\left\lfloor \sqrt{\frac{\kappa\gamma(M-1)\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)}} - M + 1 \right\rceil^+ \leq K^* \leq \left\lfloor \sqrt{\frac{\kappa\gamma M\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)}} - M \right\rceil^+$$

. □

5.3.2 Proof of Lemma 5.9

Proof. In order to ensure the utility function of the FAP U_F to be concave, the compensation price κ should fulfill

$$\begin{aligned} \frac{\partial^2 U_F}{\partial K^2} &= \frac{M}{\lambda}\frac{2}{(K+M-1)^3} - \frac{2\kappa\gamma M\lambda}{(K+M)^3} < 0 \\ \kappa\gamma\lambda^2 &> \frac{(K+M)^3}{(K+M-1)^3} \\ \kappa &> \frac{(K+M)^3}{(K+M-1)^3}\frac{1}{\gamma\lambda^2}. \end{aligned} \tag{5.46}$$

In order to ensure the optimal number K^* of accepted MUEs in the Femtocell to be positive, both the lower and the upper bound $\underline{K}^*$ and $\bar{K}^*$ should be positive.

For the upper bound of optimal number of accepted MUEs $\bar{K}^*$ to be positive values, from (5.29), it follows

$$\frac{M - \kappa\gamma M\lambda^2}{\kappa\gamma\lambda(1-\lambda)} > 0 \qquad \text{and} \qquad \frac{M - \kappa\gamma M\lambda^2}{\kappa\gamma\lambda(1-\lambda)} > M^2. \tag{5.47}$$

We obtain $\kappa > \max\left[\frac{1}{\gamma\lambda^2}, \frac{1}{\gamma\lambda(M(1-\lambda)+\lambda)}\right]$. Since $\lambda > 1$, $\lambda > \lambda + M(1-\lambda)$. Then to ensure a positive $\bar{K}^*$, the compensation price should fulfill

$$\kappa > \frac{1}{\gamma\lambda(M(1-\lambda)+\lambda)}. \tag{5.48}$$

For the lower bound of optimal number of accepted MUEs $\underline{K}^*$ to be positive values, from (5.30), it follows

$$\frac{\kappa\gamma(M-1)\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)} > 0 \qquad \text{and} \qquad \frac{\kappa\gamma(M-1)\lambda^2 - M}{\kappa\gamma\lambda(\lambda-1)} > M - 1. \tag{5.49}$$

We obtain $\kappa > \max\left[\frac{M}{M-1}\frac{1}{\gamma\lambda^2}, \frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))}\right]$. Since $\lambda > \lambda - (M-1)(\lambda-1)$, to ensure a positive $\underline{K}^*$, the compensation price should satisfy

$$\kappa > \frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))}. \tag{5.50}$$

Together with the conditions in (5.46), (5.48), (5.50), we have

$$\kappa > \max\Big[\frac{(K+M)^3}{(K+M-1)^3}\frac{1}{\gamma\lambda^2}, \frac{1}{\gamma\lambda(M(1-\lambda)+\lambda)}, \frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))}\Big].$$

Since $\frac{x}{x-1}$ is a decreasing function with respect to x, $\frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))} > \frac{(K+M)^3}{(K+M-1)^3}\frac{1}{\gamma\lambda^2}$. Therefore, in order to guarantee a positive K^* of the optimal number of accepted MUEs in the femtocell, the compensation price κ determined by the MBS is restricted with $\kappa > \max\Big[\frac{M}{M-1}\frac{1}{\gamma\lambda(\lambda-(M-1)(\lambda-1))}, \frac{1}{\gamma\lambda(\lambda-M(\lambda-1))}\Big]$, which depends on the number of FUEs registered in the femtocell M and the system load factor λ. □

5.3.3 Proof of Proposition 5.12

Proof. The first derivative of (5.37) is

$$\frac{\partial U_F}{\partial K} = \frac{-M}{(K+M)(K+M-1)} + \sum_{k=1}^{K}\frac{1}{\alpha_k}\left(\frac{\kappa M}{(K+M)^2} - \frac{1}{M}\right). \tag{5.51}$$

Mathematically solving $\frac{\partial U_F}{\partial K} = 0$ in (5.51) is difficult because of the 3rd order of K. We approximate the term $K+M-1$ to $K+M$. For large K and M this is naturally true, but we will show with simulation results in Sec. 5.2.3 that even for small values of K and M, this approximation is quite accurate and thereby simplifies the problem significantly.

Since $\sum_{k=1}^{K}\frac{1}{\alpha_k}$ is independent of κ and M, we set $\sum_{k=1}^{K}\frac{1}{\alpha_k} = D$. After the transformation and approximation, $\frac{\partial U_F}{\partial K} = 0$ becomes

$$\begin{aligned} D\left(\frac{\kappa M}{(K+M)^2} - \frac{1}{M}\right) &= \frac{M}{(K+M)^2} \\ (K+M)^2 &= M^2\left(\kappa - \frac{1}{D}\right). \end{aligned}$$

Note that K should always be positive integers. Therefore the mathematically calculated optimal number of accepted MUEs in the femtocell is $\hat{K}_F^* = \left\lfloor M\left(\sqrt{\kappa - \frac{1}{\sum_{k=1}^{K}\frac{1}{\alpha_k}}} - 1\right)\right\rceil^+$. □

5.4 Summary

For the two-tier macro-femtocell wireless networks, we propose two compensation frameworks to motivate the hybrid access. The utility functions of the FAP in femtocell and the MBS in macrocell are analyzed, respectively. The compensation function is provided by the MBS to encourage the FAP for hybrid access to accept the MUEs nearby. The Stackelberg game is formulated where the MBS plays as the leader and the FAP plays as the follower.

Firstly, the compensation framework based on the universal non-linear power pricing (Chapter 4) in order to fulfill the QoS requirement of each UE is discussed. The compensation framework with the universal power pricing provides the insight between the physical layer power cost to the upper layer revenue. The power allocation and the universal nonlinear prices obtained in Chapter 4 are applied in the compensation framework.

Secondly, in order to fulfill each UE's SINR-based QoS requirement with the minimum system sum power, we proposed an energy aware compensation framework. The MBS maximizes the global energy efficiency of all the UEs in the system. And the FAP maximizes its utility with the given compensation paid by the MBS.

The MBS predicts the best response of the FAP and chooses the compensation price. The closed form solution of the optimal number of acceptable MUEs is obtained. The optimal compensation price is calculated at the MBS as its strategy. Simulation results show that the utilities of both the FAP at the femtocell and the MBS at the macrocell are maximized with the proposed compensation frameworks, which result in a win-win solution.

6 Pricing for Distributed Resource Allocation in MAC Under QoS Requirements

In the previous chapters, the centralized resource allocation is studied using the frameworks of linear and nonlinear pricing. For the uplink transmission, it is convenient to allocate the resource such as power centrally since the BS obtains all the information about the transmitters. By the centralized pricing mechanism, the QoS requirements of all the users in the system can be guaranteed. However, there are situations where no centralized control is possible. The power should be allocated by each user themselves. How to ensure the QoS requirement of each user with distributed power allocation under the circumstances of interference coupling is interesting.

In this chapter, the distributed power allocation is investigated in the analytical setting of game theory for the general MAC system with and without SIC, respectively. The noncooperative game is formulated. The outcome of the game is the unique NE power allocation. If each self-optimizing user in the game aims at maximizing its own rate, then transmitting at the full power is their best strategy. However, this will cause high interference to other users and waste energy. For the mobile users, the battery life is an important problem. Saving energy for the long-term run is as well of interest to each user in the wireless system. Besides, the objective of each user in our system is not to pursue maximum rate but to fulfill its rate requirement. Therefore, transmitting with full power in order to achieve higher rate is not necessarily the best strategy of each user.

The individual price on the transmit power is introduced into the utility function of each user. The pricing performs as the trade-off between maximizing the rate and minimizing the transmit power and therefore limiting the interference to other users. The individual prices are carefully designed to ensure the existence, uniqueness and convergence of the NE power allocation and as a result to guarantee the rate requirement of each user at the NE point.

In the following, the noncooperative game is discussed firstly without the malicious users. Later on, the malicious behavior is analyzed and the strategy-proof pricing to counter the user misbehavior is proposed.

6.1 System Preliminaries

Consider the general MAC with K transmitters and one receiver as the BS. The uplink transmission system works as follows. We assume the system guarantees the rate requirement $\underline{u}_i$ of each self-optimizing user by providing the individual prices β_i. The transmit power p_i is allocated by each user i in a distributed fashion. Due to the interference coupling, the noncooperative game is formulated among the K users in the system. Each user as a player in the game maximizes its own utility u_i as a function of the price β_i and the transmit power $\boldsymbol{p}$. The pure strategy set of each user is their transmitting power with single user power constraint $p_i < p_i^{max}$.

The noncooperative game in normal form $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ is described by the set of players $i \in \mathcal{K}$, where $\mathcal{K}$ is a finite set $\mathcal{K} = \{1, 2, \ldots, K\}$ with the strategy profile of transmit power $\boldsymbol{p}$. Their strategy space is a compact and convex set denoted by $\mathcal{P} = [0, p_1^{max}] \times [0, p_2^{max}] \times \cdots \times [0, p_K^{max}]$. The utility function is the set $\mathcal{U} = \{u_1(p_1, p_{-1}), u_2(p_2, p_{-2}), \ldots,$
$u_K(p_K, p_{-K})\}$. The pricing controls the interference caused by each user and therefore leads the NE point of the noncooperative game to the desired region guaranteeing the rate requirement $\underline{u}_i$ of each user i.

The users play the BRD to reach the NE power allocation. The individual prices $\boldsymbol{\beta}$ are designed such that the feasible rate requirement of each user can be achieved at the NE point of the non-cooperative game with minimum power allocation.

6.1 Definition. The strategy profile of transmit power $\boldsymbol{p}^*$ is said to be the *NE power allocation* for $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ if and only if no unilateral deviation in strategy by any single player is profitable for that player, i.e.,

$$\begin{aligned} u_i(p_i^*, p_{-i}^*) \quad &\geq \quad u_i(p_i, p_{-i}^*), \qquad \forall i, i \in [1, \ldots, K], \\ 0 < \quad p_i \quad &\leq p_i^{max}, \end{aligned} \tag{6.1}$$

where $p_{-i} = [p_1, \cdots, p_{i-1}, p_{i+1}, \cdots, p_K]$ denotes the transmit power of all the other users except user i.

At the NE power allocation, no user can improve its own utility by changing its power level individually given the choices of others.

6.2 Noncooperative Game for MAC without SIC

In this section, the distributed power allocation for the general MAC system without SIC is discussed. The noncooperative game is formulated.

6.2.1 System Operation with Truthful Agents

The noncooperative game of the MAC system can be formulated as an economic model, where the consumers are the users. The trading good is the power. The producer provides the individual prices β_i to each consumer i. Since each user has a rate requirement $\underline{u}_i$ to be guaranteed and the interferences are coupled among all the users, the demand in power of each user is dependent on others. The BS is responsible to tune the prices such that the pricing enforces the NE power allocation to meet the rate requirement of each user in the system with minimum power.

There are various possibilities for pricing policies on transmit power, among which linear pricing is the easiest to apply. However, for the general MAC system without SIC, the linear pricing cannot implement a universal pricing mechanism [12]. In order to better illustrate the properties of the model, we introduce the normalized distributed pricing term $\beta_i(p_{-i})$ as a function of the individual price β_i and the demand of all the other users $I_i(p_{-i})$, i.e.,

$$\beta_i(p_{-i}) = \frac{\beta_i}{I_i(p_{-i})}. \tag{6.2}$$

6.2 Definition. $I_i(p_{-i})$ is a function denoting the demand on power $\boldsymbol{p}$ for all the other users except i.

The normalized pricing term denotes the quality of the good (power). If the interference from other users is high, then the price of the power for user i should be lower in order to guarantee its rate requirement. The utility function of each self-interested user is based on its achievable rate $r_i(p_i, p_{-i})$ and the normalized pricing term as follows.

$$u_i(p_i, p_{-i}) = r_i(p_i, p_{-i}) - \beta_i(p_{-i})p_i. \tag{6.3}$$

When there is single link or $I_i(p_{-i})$ is a constant, the utility function is $u_i(p_i, p_{-i}) = r_i(p_i, p_{-i}) - \beta_i p_i$. In the multiuser case, the interference obviously influences the quality of the good (resource) that user i buys. In order to express the quality loss due to interference, the higher interference, the lower the pricing term, and thus the more power consumed. Therefore, the pricing term $\beta_i(p_{-i})$ is normalized by the noise plus interference caused by all the other users. Let the normalized noise plus interference to user i caused by all the other users be $I_i(p_{-i}) = 1 + \sum_{k \neq i} \alpha_k p_k$. The utility of user i with normalized pricing term is

$$\begin{aligned} u_i(p_i, p_{-i}) &= r_i(p_i, p_{-i}) - \frac{\beta_i}{I_i(p_{-i})} p_i \\ &= \log\left(1 + \frac{\alpha_i p_i}{I_i(p_{-i})}\right) - \frac{\beta_i}{I_i(p_{-i})} p_i. \end{aligned} \tag{6.4}$$

Each user plays its BRD by maximizing its own utility function $u_i(p_i, p_{-i})$, i.e., each rational self-optimizing user chooses its power level as the BR to the power chosen by other users.

6.3 Definition. *Best response power allocation* is the strategy which produces the most favorable outcome for a player, taking other players' strategies as given [23]. In our scenario,

$$u_i(p_i^{BR}, p_{-i}) \geq u_i(p_i, p_{-i}) \qquad \forall i, i \in [1, \ldots, K]. \tag{6.5}$$

The game BRD for user i can be expressed as the K coupled problems $\forall i = 1, \ldots, K$,

$$\max_{0 \leq p_i \leq p_i^{max}} u_i(p_i, p_{-i}) = r_i(p_i, p_{-i}) - \frac{\beta_i}{I_i(p_{-i})} p_i \qquad s.t. \qquad r_i(p_i, p_{-i}) \geq \underline{u}_i \tag{6.6}$$

A basic result from game theory is that each fixed point of the BRD is an NE point, although in general, convergence of the BRD is not guaranteed, nor is the existence of the fixed point.

In the following section, the BR power of each user i is obtained in closed form.

6.2.1.1 Best Response Power Allocation

If the prices $\beta_i = 0$, transmitting with full power p_i^{max} is the BR of each user. Due to the pricing term with positive $\beta_i > 0$, we can conclude the users' BR of transmit power as follows.

6.4 Proposition. *For all $i = 1, \ldots, K$, define $\underline{p}_i(p_{-i})$ as*

$$\underline{p}_i(p_{-i}) = \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(1 + \sum_{k \neq i} \alpha_k p_k\right). \tag{6.7}$$

The i-th user's best-response is given by $p_i^{BR} = \max(0, \min(\underline{p}_i(p_{-i}), p_i^{max}))$. Moreover, the noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ always admits an NE $\{p_i^{BR}\}_{i=1}^{K}$.

Proof. Please refer to Proof 6.5.1. □

Each user plays its BR strategy on the transmit power by taking the other users' BR power into consideration. In the following section, the existence, convergence and uniqueness of the NE power allocation of the game is investigated.

6.2.1.2 Nash Equilibrium Power Allocation

The noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ always admits at least one NE power allocation $\{p_i^{NE}\}_{i=1}^{K}$. In this part, we figure out the NE point and show that it is unique.

6.5 Proposition. *The Nash equilibrium power allocation of each user i in the noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ for the general MAC system without SIC is $p_i^{NE} = \max(0, \min(\underline{p}_i^{NE}, p_i^{max}))$. With given individual prices β_i,*

$$\underline{p}_i^{NE} = \frac{\alpha_i - \beta_i}{\alpha_i^2} \cdot \frac{1}{\sum_{j=1}^{K} \frac{\beta_j}{\alpha_j} - K + 1}. \tag{6.8}$$

The noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ always admits this unique NE point.

Proof. Please refer to Proof 6.5.2. □

In order to ensure the positive power allocation and therefore to guarantee the rate requirement of each user, the following conditions regarding the number of users in the wireless system, the individual prices and the channel states should be fulfilled.

6.6 Corollary. *In the general K-user MAC system without SIC, the rate requirement of each user i is achieved by the NE power allocation if and only if*

$$K - 1 < \sum_{i=1}^{K} \frac{\beta_i}{\alpha_i} < K. \tag{6.9}$$

Proof. In order to ensure the rate requirement of each user, the system guarantees $\underline{p}_i^{NE} > 0$ in (6.8) by providing the prices $\boldsymbol{\beta}$. From (6.7), $\beta_i < \alpha_i$. Therefore, the right part of the inequality is proved. The left part of the inequality is obtained by ensuring $\frac{1}{\sum_{j=1}^{K} \frac{\beta_j}{\alpha_j} - K + 1} > 0$ in (6.8). □

The existence and uniqueness of the NE power allocation for the general MAC system without SIC is proved. In the numerical simulation, the convergence rate of the NE is shown. We will observe that the proposed noncooperative game converges very fast.

By definition, the best-response correspondence (BRC) $BR(\boldsymbol{p}) = \{BR_k(p_{-k})\}_{k=1}^{K}$ is a standard function if, it satisfies the following three properties [10]. 1) Positivity: $BR_k(p_{-k}) \geq 0$ for all $p_{-k} \geq 0, k = 1, \ldots, K$. 2) Monotonicity: $BR_k(p_{-k}^{(1)}) \geq BR_k(p_{-k}^{(2)})$ for all $p_{-k}^{(1)} \geq p_{-k}^{(2)}$, $k = 1, \ldots, K$. 3) Scalability: $\lambda BR_k(p_{-k}) > BR_k(\lambda p_{-k})$ for all $p_{-k} \geq 0, \lambda > 1, k = 1, \ldots, K$. Now, the following proposition holds.

6.7 Proposition. *The non-cooperative game $\mathcal{G}(\mathcal{K}, \mathcal{S}, \mathcal{U})$ admits a unique NE, and its BRD is guaranteed to converge to the unique NE.*

Proof. The key concept of the proof is to realize that the BRC of the noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{S}, \mathcal{U})$ is a standard function. From Corollary 6.6, $\underline{p}_i(p_{-i})$ in (6.7) is positive for all $p_{-i} \geq 0$.

Since $\left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right) > 0$, $\underline{p}_i(p_{-i})$ is monotonically increasing with p_{-i}. The equality in the property of monotonicity holds if $p_i^{BR} = p_i^{max}$ or $p_i^{BR} = 0$.

Since $\lambda > 1$, it holds that $\lambda\left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(1 + \sum_{k \neq i} \alpha_k p_k\right) = \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(\lambda + \lambda \sum_{k \neq i} \alpha_k p_k\right) > \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(1 + \sum_{k \neq i} \alpha_k \lambda p_k\right) = \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(1 + \lambda \sum_{k \neq i} \alpha_k p_k\right)$.

Therefore, the BRC in Proposition 6.4 is a standard function which satisfies the properties of positivity, monotonicity and scalability.

It is shown in [10] that the fixed point $\boldsymbol{p} = BR(\boldsymbol{p})$ is unique for a standard function. Therefore, standard games, are known to admit a unique NE and to have a BRD that converges to the NE, provided an NE exists [2]. □

6.2.1.3 Pricing for QoS Requirements

The objective of pricing in the proposed noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ is to implicitly enforce the NE power allocation to the desired point. The NE power allocation is *efficient* if the rate requirement of each user is guaranteed with minimum power. The prices $\boldsymbol{\beta}$ are chosen to ensure that the efficient NE is the outcome of the game.

As shown in [97], the power allocation is solved as a function of the rate requirement $\underline{\boldsymbol{u}}$ of each user to achieve the SINR-based QoS requirements. Recall (4.6) in Chapter 4 that

$$p_i^U = \frac{B_K}{\alpha_i} \cdot \frac{2^{\underline{u}_i} - 1}{2^{\underline{u}_i}}, \tag{6.10}$$

where $B_K = \frac{1}{\sum_{j=1}^{K} \frac{1}{2^{\underline{u}_j}} - K + 1}$ is a constant for given $\underline{u}_j, j = 1, \cdots, K$. This power allocation is done centrally at the system optimizer, which could be the BS for the general MAC system. With the properly designed universal pricing term, the power allocation in (6.10) is solved such that the rate requirement $\underline{\boldsymbol{u}}$ is guaranteed for all the users.

For the noncooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$, the individual price β_i is designed by the BS such that the rate requirement $\underline{u}_i$ of each user i is achieved at the NE transmit power p_i^{NE}. For the problem at hand, in order to determine the individual prices, $\underline{p}_i^{NE}$ should be equal to p_i^U. Therefore, we solve the universal individual prices for the distributed power allocation in MAC without SIC as follows.

6.8 Lemma. *In the K-user non-cooperative game $\mathcal{G}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ of the general MAC system without SIC, the rate requirement $\underline{u}_i$ of each user i is achieved with the NE power allocation p_i^{NE} if the individual price is*

$$\beta_i = \frac{\alpha_i}{2^{\underline{u}_i}}. \tag{6.11}$$

Proof. Solve the equation $\underline{p}_i^{NE} = \frac{\alpha_i - \beta_i}{\alpha_i^2} \cdot \frac{1}{\sum_{j=1}^{K} \frac{\beta_j}{\alpha_j} - K + 1} = p_i^U = \frac{B_K}{\alpha_i} \cdot \frac{2^{\underline{u}_i} - 1}{2^{\underline{u}_i}}$ for β_i. □

6.9 Remark. The region in (6.9) is equivalent to the feasible utility region in Corollary 1 in [75] (Corollary 4.3), if the individual prices β_i are given in (6.11).

The price β_i is only dependent on the individual CSI α_i and the rate requirement of each user $\underline{u}_i$. Therefore, it is the local information of each user i. The users can update its individual prices when its CSI and rate requirement change.

6.10 Remark. The closed form individual price β_i allows the distributed implementation of the proposed noncooperative game. The prices acting as a control signal can be broadcasted by the BS to all the transmitters before the game is played.

From the power allocation in (6.10), the sum power consumption in the MAC system is $P_{sum}(\alpha_1, \ldots, \alpha_K) = \sum_{i=1}^{K} \frac{B_K}{\alpha_i} \cdot \frac{2^{\underline{u}_i} - 1}{2^{\underline{u}_i}}$. If we consider the special case of identical rate requirements $\underline{u}_i = \underline{u}$, $i \in [1, \ldots, K]$, the following Lemma is provided.

6.11 Lemma. *Given the identical rate requirement $\underline{u}_i = \underline{u}, i \in [1, \ldots, K]$, the sum power consumption for the general MAC without SIC is $P_{sum}(\alpha_1, \ldots, \alpha_K) = B_K \cdot \frac{2^{\underline{u}} - 1}{2^{\underline{u}}} \cdot \sum_{i=1}^{K} \frac{1}{\alpha_i}$. $P_{sum}(\alpha_1, \ldots, \alpha_K)$ is Schur-convex in the CSI $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_K]$ of all users, i.e.,*

$$P_{sum}(1, 0, \ldots, 0) \;\; \geq \;\; P_{sum}(\alpha_1, \ldots, \alpha_K) \geq P_{sum}\left(\frac{1}{K}, \ldots, \frac{1}{K}\right), \tag{6.12}$$

for all $\alpha_i \geq 0, \sum_{i=1}^{K} \alpha_i = 1$.

Proof. $P_{sum}(\alpha_1, \ldots, \alpha_K)$ is a symmetric function because its value is the same for any permutation of its K variables $\boldsymbol{\alpha}$, i.e.,

$$P_{sum}(\alpha_1, \alpha_2, \ldots, \alpha_K) = P_{sum}(\alpha_2, \alpha_1, \ldots, \alpha_K) = \cdots = P_{sum}(\alpha_1, \ldots, \alpha_K, \alpha_{K-1}).$$

$P_{sum}(\alpha_1, \ldots, \alpha_K)$ is Schur-convex because it is symmetric and convex. □

As described in Fig. 4.8 in [98], Lemma 6.11 shows that in the perspective of energy efficiency, all users distributed equally around the BS is the best scenario.

6.2.1.4 Algorithm of Noncooperative Game

The algorithm of the proposed noncooperative game for the general MAC without SIC where the transmit power is allocated in a distributed manner is provided in Algorithm 1.

Algorithm 1 Noncooperative game for MAC without SIC

Input:

Input K; $(\underline{u}_1, \ldots, \underline{u}_K)$; $(\alpha_1, \ldots, \alpha_K)$; $(\beta_1, \ldots, \beta_K)$; n; ϵ: required accuracy

Initialize:

$P_0 = (p_1^0, \ldots, p_K^0)$; $p_i^{-1} = 0$

while $| p_i^n - p_i^{n-1} | \geq \epsilon$ **do**

  for $i = 1 : 1 : K$ **do**

    $P_n = (p_1^n, \ldots, p_K^n)$;

    $p_i^n = \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right)\left(1 + \sum_{k \neq i} \alpha_k p_k^{n-1}\right)$

    $n = n + 1$

  end for

end while

return

NE power $P_n = (p_1^n, \ldots, p_K^n)$

With the provided individual price β_i, each user can achieve its rate requirement $\underline{u}_i$ at the NE transmit power when playing the BRD in the noncooperative game.

The problem when there exist malicious users is analyzed in the next section.

6.2.2 Malicious Behavior for MAC without SIC

From the game theoretic point of view, the users have incentives to hide their private types. These types include the private information, such as the CSI, or its own utility preferences. For the noncooperative game, the users are more likely to conceal their true utility functions to each other in order to overtake the other users when performing the BRD. In this section, we investigate the user misbehavior where the malicious users try to enhance its own utility

Table 6.1: Private type of user behavior

User behavior	V_i
Malicious users	$0 < V_i \leq 1$
Selfish users	$V_i = 0$
Altruistic users	$-1 \leq V_i < 0$

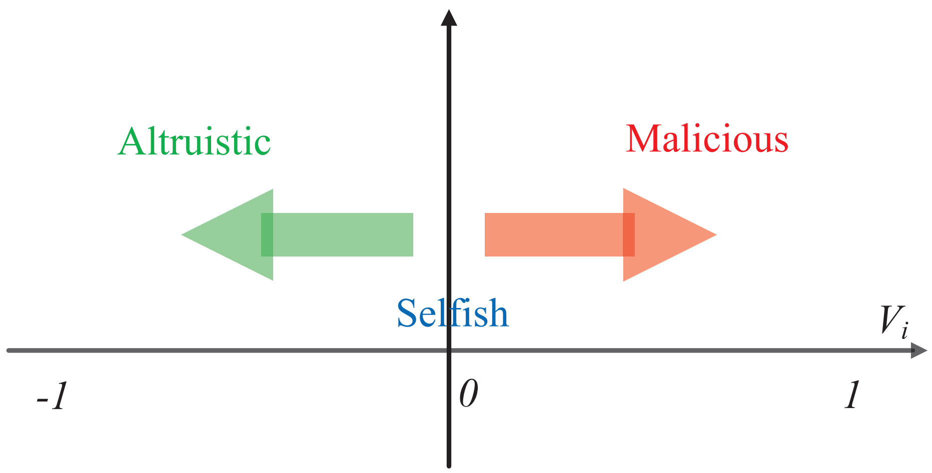

Figure 6.1: Private type of user behavior

by harming the other users. The private type determines the utility function of each user and is independent of each other.

We define V_i to denote the private type [99] of user behavior in the system. See Table 6.1. As shown in Fig. 6.1, the private type V_i of each user i is a continuous normalized value between $[-1, 1]$, which denotes the extent of its behavior. For example, if user i's private type is $V_i = 1$, then it is an extreme malicious user and if $V_i = -1$, then it is an extreme altruistic user.

The utility function of each user i with the private type V_i is denoted as $u_i(p_i, p_{-i}, V_i)$. Since each user i in the noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ has the individual rate requirement $\underline{u}_i$ to be achieved besides maximizing its utility function $u_i(p_i, p_{-i}, V_i)$, altruistic users who benefit the other users' utilities are not concerned in the current model. Later on, we focus on considering the malicious behavior with private types V_i.

The utility function of user i with type V_i for MAC without SIC is defined as

$$u_i(p_i, p_{-i}, V_i) = r_i(p_i, p_{-i}, V_i) - \frac{\beta_i}{I_i(p_{-i})} p_i + \frac{V_i \alpha_i p_i}{I_i(p_{-i})}, \tag{6.13}$$

where the third term reflects the interference to all the other users. For malicious users, they benefit from harming all the other users.

In the following, the noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ is played for the general MAC without SIC where malicious behavior exists.

6.2.2.1 Best Response Power Allocation with Malicious Users

Follow a similar procedure as in Section 6.2.1, by maximizing the utility function $u_i(p_i, p_{-i}, V_i)$, we obtain the BR and the NE power allocation of each user i with private type V_i for MAC without SIC.

6.12 Lemma. *For all users $i = 1, \ldots, K$ with private type V_i and utility $u_i(p_i, p_{-i}, V_i)$ in (6.13), define $\underline{p}_i(V_i)$ as*

$$\underline{p}_i(V_i) = \left(\frac{1}{\tilde{\beta}_i(V_i)} - \frac{1}{\alpha_i}\right)\Big(1 + \sum_{k \neq i} \alpha_k p_k(V_k)\Big). \tag{6.14}$$

Here $\tilde{\beta}_i(V_i) = \beta_i - V_i \alpha_i$ is the individual price with type V_i. The i-th user's best-response power allocation with type V_i is given by $p_i^{BR}(V_i) = \max(0, \min(\underline{p}_i(V_i), p_i^{max}))$.

Proof. Please refer to Proof 6.5.3. □

Define the BR power allocation with V_i of malicious users as $p_{i,m}^{BR}(V_i)$ and selfish users as $p_{i,s}^{BR}(V_i)$, respectively. We observe that the BR power allocation of the malicious user is higher than that if all users are regular, i.e., $p_{i,m}^{BR}(V_i) > p_i^{BR}$. Because $\tilde{\beta}_i(V_i) = \beta_i - V_i\alpha_i < \beta_i$ for positive V_i. For selfish users, although its own private type $V_i = 0$, $p_{i,s}^{BR}(V_i)$ is higher than it should be to achieve the rate requirement due to the increment of transmit power of other existing malicious users, i.e., $p_{i,s}^{BR}(V_i) > p_i^{BR}$. If there is no malicious users in the system, the BR transmit power in the proposed noncooperative game with the private type $\boldsymbol{V}$ remains the same as in Sec. 6.2.1. If $V_i = 0$ for all $i, i \in [1, \ldots, K]$, $p_i^{BR}(V_i) = p_i^{BR}$.

6.13 Remark. Notice that the BRD of $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the MAC without SIC when considering the malicious behavior of users is not restricted to single malicious user. The number of the malicious users can be arbitrary integers. The BR transmit power of each user i is independent of the private types of other users. So the users do not require information exchange about the private types of each other to perform the BRD of the game. The property that the proposed noncooperative game is applicable for arbitrary number of malicious users also holds for the NE power calculation in the next subsection.

6.2.2.2 Nash Equilibrium Power Allocation with Malicious Users

In this part, we analyse the NE power allocation of the noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ with private type V_i. From (6.8), we can conclude the following result.

6.14 Proposition. *The Nash equilibrium power allocation of each user i in the noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the general MAC system without SIC and with private type V_i is $p_i^{NE}(V_i) = \max(0, \min(\underline{p}_i^{NE}(V_i), p_i^{max}))$. Given the individual prices $\tilde{\beta}_i(V_i)$ with type V_i,*

$$\underline{p}_i^{NE}(V_i) = \frac{\alpha_i - \tilde{\beta}_i(V_i)}{\alpha_i^2} \cdot \frac{1}{\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j} - K + 1}. \tag{6.15}$$

The noncooperative game always admits this unique NE point.

Proof. The proof follows the same steps as in the Proof 6.5.2 by replacing the individual price β_i with $\tilde{\beta}_i(V_i)$. □

This NE power is achieved when there are arbitrary number of malicious users. The difference in the number of malicious users implies in $\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j}$.

From Proposition 6.14, we observe that the NE power $\underline{p}_i^{NE}(V_i)$ is a function of types $\boldsymbol{V} = [V_1, \ldots, V_K]$ of all the users in the system. However, given the values of the types $\boldsymbol{V}$, $\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j}$ can be considered as a constant. $\underline{p}_i^{NE}(V_i)$ can be seen as a function of its own type V_i and CSI α_i under the assumption that the type values remain constant for a long period of time.

6.15 Remark. Define $p_{i,s}^{NE}(V_i)$ as the NE transmit power for the selfish users and $p_{i,m}^{NE}(V_i)$ as the NE transmit power for the malicious users, respectively. The NE power of user i when there are malicious users in the system is higher than that when there are no malicious users, no matter user i itself is malicious or selfish. Comparing with p_i^{NE} in (6.8), for malicious users, due to the private type $0 < V_i \leq 1$, both parts $\frac{\alpha_i - \tilde{\beta}_i(V_i)}{\alpha_i^2}$ and $\frac{1}{\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j} - K + 1}$ in (6.15) become larger. Therefore, $p_{i,m}^{NE}(V_i) > p_i^{NE}$. For selfish users, $\frac{1}{\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j} - K + 1}$ is larger since there exist malicious users in the system. Therefore, $p_{i,s}^{NE}(V_i) > p_i^{NE}$ as well.

This observation is important because the system power consumption is much higher when there are malicious users. In order to understand the influence of the malicious behaviour on the resulting NE power and the rate of both the selfish and malicious users comprehensively, we have the following Proposition.

6.16 Proposition. *With the individual price $\beta_i = \frac{\alpha_i}{2^{\underline{u}_i}}$, the NE power allocation $p_i^{NE}(V_i)$ in (6.15) of each user i in the noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the general MAC system without SIC and with private type V_i is higher than or equal to p_i^U in (4.6). Denote $\underline{p}_i^{NE}(V_i, V_{-i}.\underline{\boldsymbol{u}})$ as a function of the rate requirement $\underline{u}_i$, $i = [1, \ldots, K]$,*

$$\underline{p}_i^{NE}(V_i, V_{-i}.\underline{\boldsymbol{u}}) = \frac{1 + V_i - 2^{-\underline{u}_i}}{\alpha_i} \cdot \frac{1}{\sum_{j=1}^{K}(2^{-\underline{u}_j} - V_j) - K + 1}. \tag{6.16}$$

Given the type value $\boldsymbol{V}$ of all the users,

$$\underline{p}_i^{NE}(V_i, V_{-i}, \underline{\boldsymbol{u}}) = \frac{1 + V_i - 2^{-\underline{u}_i}}{\alpha_i} \cdot B_K(\boldsymbol{V}), \tag{6.17}$$

where $B_K(\boldsymbol{V}) = \frac{1}{\sum_{j=1}^{K}(2^{-\underline{u}_j} - V_j) - K + 1}$.

The resulting rate $r_i(V_i)$ of user i is

- $r_i(V_i) = \underline{u}_i$, *for selfish users with $V_i = 0$*
- $r_i(V_i) > \underline{u}_i$, *for malicious users with $0 < V_i \leq 1$.*

Proof. Please refer to Proof 6.5.4. □

When there are malicious users in the MAC system without SIC, the feasible region for the individual prices $\boldsymbol{\beta}$ is different due to the values of user private types $\boldsymbol{V}$.

6.17 Corollary. *In the general MAC system without SIC, when there exist malicious users with private types $\boldsymbol{V}$, the rate requirement of each user i is achieved by the NE power allocation if and only if*

$$K - 1 + \sum_{j=1}^{K} V_j < \sum_{j=1}^{K} \frac{\beta_j}{\alpha_j} < K + \sum_{j=1}^{K} V_j. \tag{6.18}$$

Proof. The proof follows the same step as in Corollary 6.6 to ensure the positive NE power in (6.15). $\sum_{j=1}^{K} \frac{\tilde{\beta}_j(V_j)}{\alpha_j} - K + 1 > 0$ proves the left part of the inequality. And $\frac{\alpha_i - \beta_i + V_i\alpha_i}{\alpha_i^2} > 0$ proves the right part of the inequality for positive α_i. □

For the uplink transmission, when the achievable rate $r_i(V_i)$ of user i is obtained by the BS, the private type V_i of each user i can be detected.

6.18 Lemma. *Given the achievable rate $r_i(V_i)$ of each user $i \in [1, \ldots, K]$, the private type V_i is obtained as*

$$V_i = 2^{-\underline{u}_i} - 2^{-r_i(V_i)}, \tag{6.19}$$

where the achievable rate of each user i in the general MAC without SIC is

$$r_i(V_i) = \log\left(\frac{1}{2^{-\underline{u}_i} - V_i}\right). \tag{6.20}$$

Proof. Please refer to Proof 6.5.5 □

6.19 Remark. The achievable rate of each user is only dependent on its own private type V_i and the rate requirement $\underline{u}_i$ in the proposed noncooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the MAC system without SIC when users misbehavior is considered. Therefore, no collusion can be formed in the system.

If $V_i = 0$, then $r_i(V_i) = \underline{u}_i$ for selfish users. Otherwise if $0 < V_i \leq 1$, then $r_i(V_i) > \underline{u}_i$ for malicious users. The selfish users can achieve its rate requirement but the malicious users can achieve better rates. The selfish users compensate the higher interference from malicious users by increasing its transmit power as well. The system is responsible to detect the malicious users by means of Lemma 6.18 and investigate the mechanism to counter the user misbehavior.

The number of the malicious users M and the total users K, the private type V_i and the rate requirement $\underline{u}_i$ are mutually restricted to ensure the positive NE power allocation $p_i^{NE}(V_i)$, and therefore to ensure the positive achievable rate $r_i(V_i)$.

6.20 Lemma. *In the general K-user MAC system without SIC, the rate requirement $\underline{u}_i$ of each user i can be achieved if and only if the following conditions are fulfilled $\forall j, j \in [1, \ldots, K]$.*

$$0 \leq \sum_{j=1}^{K} V_j < \sum_{j=1}^{K} 2^{-\underline{u}_j} - K + 1 \qquad \text{and} \qquad 0 \leq V_j < 2^{-\underline{u}_i} \tag{6.21}$$

Proof. Since $2^{-\underline{u}_j} < 1$ and $0 \leq V_i \leq 1$, the first term in (6.16) is positive. In order to achieve the rate requirement $\underline{u}_i$, positive power allocation must be ensured. Thus the second term in (6.16) should be positive as well. With $\tilde{\beta}_i(V_i) = \beta_i - V_i\alpha_i$, $0 \leq \sum_{j=1}^{K} V_j < \sum_{j=1}^{K} 2^{-\underline{u}_j} - K + 1$ is obtained. Since the feasible region of the rate requirement is given in Corollary 1 in [75] as $K - 1 < \sum_{j=1}^{K} 2^{-\underline{u}_j} < K$, $\sum_{j=1}^{K} V_j < 1$ is satisfied.

The single type constraint in Lemma 6.20 is to ensure the positive rate $r_i(V_i)$ in (6.20). Thus $\frac{1}{2^{-\underline{u}_i} - V_i} > 1$. With $2^{-\underline{u}_i} < 1$, (6.21) is proved. □

6.21 Remark. Note that if the user types $\boldsymbol{V}$ do not fulfill Lemma 6.20, then the NE power allocation $p_i^{NE}(V_i, V_{-i})$ and the achievable rate of each user i is negative no matter it is selfish or malicious. Thereby, the utility requirements $\underline{\boldsymbol{u}}$ are not feasible. Then the rates of all users cannot be guaranteed and the misbehaviour is immediately detected by the receiver.

Lemma 6.18 provides the BS the opportunity to capture the misbehavior and the type values of the malicious users. Since the uplink transmission is considered, the BS is able to obtain the rate $r_i(V_i)$ of all the users. If the rate achieved by user i is higher than its rate requirement $\underline{u}_i$, then the BS detects the malicious user i and applies the punishment strategy on it with the strategy-proof price β_i^M. The following section gives the details.

6.2.3 Strategy-Proof Pricing

In this section, we design the strategy-proof prices in order to counter the malicious behavior analysed in Section 6.2.2. If the types of the malicious users are detected, then the following mechanism can be adopted.

Denote β_i^M as the trigger price applied on the malicious user i whenever it is detected by the system. In order to counter the malicious behavior, the price given to the malicious users β_i^M

should be tailored such that the BR power allocation of the malicious users are made smaller than if it is selfish. β_i^M can be considered as the punishment price. The following Proposition on cheat-proof pricing is obtained.

6.22 Proposition. *In the K-user non-cooperative game $\mathcal{G}^v(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ of the general MAC system without SIC, no user has an incentive to behave maliciously if the punishment price β_i^M is given as*

$$\beta_i^M \geq \beta_i + V_i \alpha_i. \tag{6.22}$$

Proof. With the individual price β_i, $p_{i,m}^{BR}(V_i) > p_i^{BR}(V_i)$. Therefore, the punishment price β_i^M should be introduced such that the BR power allocation of malicious users $p_{i,m}^{BR}(\beta_i^M)$ is smaller than the BR power allocation of the selfish users, i.e.,

$$\left(\frac{1}{\beta_i^M - V_i\alpha_i} - \frac{1}{\alpha_i}\right) I_i(p_{-i}) \leq \left(\frac{1}{\beta_i} - \frac{1}{\alpha_i}\right) I_i(p_{-i}). \tag{6.23}$$

Since $I_i(p_{-i}) > 0$ and $\alpha_i > 0$, (6.23) becomes $\frac{1}{\beta_i^M - V_i\alpha_i} \leq \frac{1}{\beta_i}$. Therefore, (6.22) is proved. ☐

The punishment price β_i^M can be seen as the original individual price β_i plus an additional price $V_i\alpha_i$ which is proportional to the private type of users.

Whenever the malicious behavior is detected by means of Lemma 6.18, the punishment price is applied on the malicious user. This is the rule of the proposed game and all rational players are fully aware of the rule before the game is played. By maximizing its own utility function $u_i(p_i, p_{-i}, V_i)$ in (6.13), no user will have incentives to harm the other users.

From Lemma 6.18, the private type V_i of each user i is detected at the BS from the achievable rate $r_i(V_i)$ and the rate requirement $\underline{u}_i$. By observing the user misbehavior, the BS is able to punish the targeted malicious user with the trigger price β_i^M in (6.22). Otherwise, the BS can take the default value $V_i = 1$ for malicious users in the punishment price. Since the individual utility $u_i(p_i, p_{-i}, V_i)$ is a linear function of the private type V_i of each user i, the optimal private V_i for malicious users is the maximum value that fulfills the restrictions in Lemma 6.20.

6.2.4 Strategy-Proof Algorithm for MAC without SIC

If there exist malicious users in the general MAC system without SIC, the noncooperative game works as follows. The Input values of the individual prices become $\tilde{\beta}_i(V_i)$ with the private type V_i of users. If the misbehavior is detected, the strategy-proof price $\beta_i^M = \beta_i + V_i\alpha_i$ is adopted to the malicious user i from then on.

The strategy-proof algorithm for MAC without SIC is shown in Algorithm 2. The system operation with all truthful agents is a special case of Algorithm 2.

Algorithm 2 Noncooperative game for MAC without SIC with private type V_i and trigger strategy in (6.22)

Input:

Input K; $(\underline{u}_1, \ldots, \underline{u}_K)$; $(\alpha_1, \ldots, \alpha_K)$; $(\tilde{\beta}_1(V_1), \ldots, \tilde{\beta}_K(V_K))$; ϵ: Required accuracy; n

Initialize:

$P_0 = (p_1^0, \ldots, p_K^0)$; $p_i^{-1} = 0$

while $| p_i^n - p_i^{n-1} | \geq \epsilon$ **do**
  for $i = 1 : 1 : K$ **do**
    $P_n = (p_1^n, \ldots, p_K^n)$;
    $p_i^n = \left(\frac{1}{\tilde{\beta}_i(V_i)} - \frac{1}{\alpha_i}\right)\left(1 + \sum_{k \neq i} \alpha_k p_k^{n-1}\right)$
    if $r_i(V_i) > \underline{u}_i$ **then**
      $V_i = 2^{-\underline{u}_i} - 2^{-r_i(V_i)}$
      $\tilde{\beta}_i(V_i) = \beta_i + V_i \alpha_i$
    end if
    $n = n + 1$
  end for
end while
return

NE power $P_n = (p_1^n, \ldots, p_K^n)$;

6.3 Numerical Results

In this section, we present some numerical results of our proposed distributed power allocation framework with pricing in the general MAC system without SIC under individual QoS requirement $\underline{u}_i$.

Define the channel gains $\alpha_i =| h_i |^2 \sim \chi_n^2$ with diversity order n. Fig. 6.2 shows the system average sum NE power $\sum_{i=1}^{K} p_i^{NE}$ with different diversity orders n for different numbers of users in the MAC. The rate requirement is set as identical $\underline{u}_i = 0.05$.

Fig. 6.3 demonstrates the convergence rate of the BRD using the chosen price β_i in (6.11) for the 2-user MAC. It is shown that the BRD converges very fast. Results of different sets of parameters are shown. The convergence points of the power allocation are the same as the NE power $\underline{p}_i^{NE}$ in (6.8), where $\underline{p}_i^{NE} = p_i^U$ in (4.6).

Fig. 6.4 shows the Price of Malice (PoM) [100] of the proposed model. The PoM captures the ratio between the NE in a purely selfish system and the worst NE with M malicious players. Formally, PoM in our case is

$$PoM(M) = \frac{P_{sum}^{NE}(0)}{P_{sum}^{NE}(M)}, \tag{6.24}$$

where $P_{sum}^{NE}(M)$ denotes the sum power allocation at the NE when there are M malicious users. $P_{sum}^{NE}(M) = \sum_{i=1}^{K} p_i^{NE}(V_i)$ in which M users are with $V_i > 0$ and $K - M$ selfish users are with $V_i = 0$.

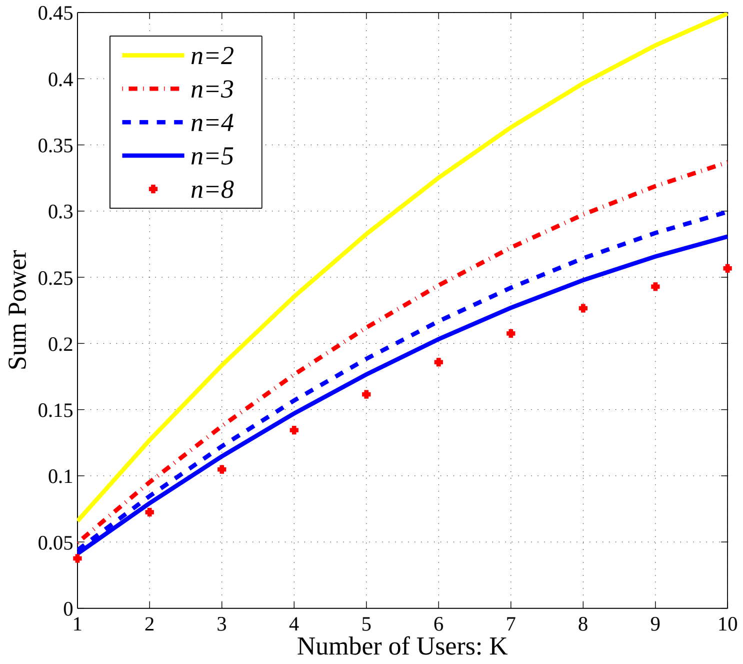

Figure 6.2: Average sum power required to fulfill the QoS requirement for different number of total users

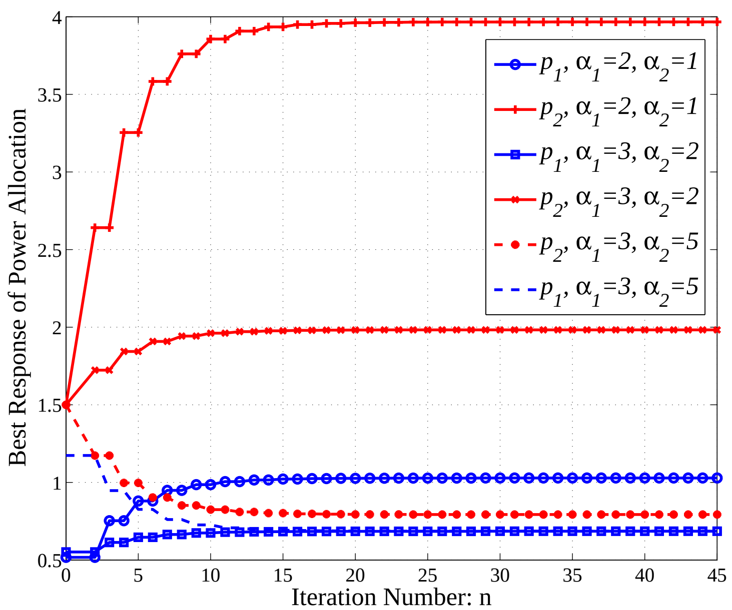

Figure 6.3: Convergence of the BR dynamics for the noncooperative game in MAC without SIC

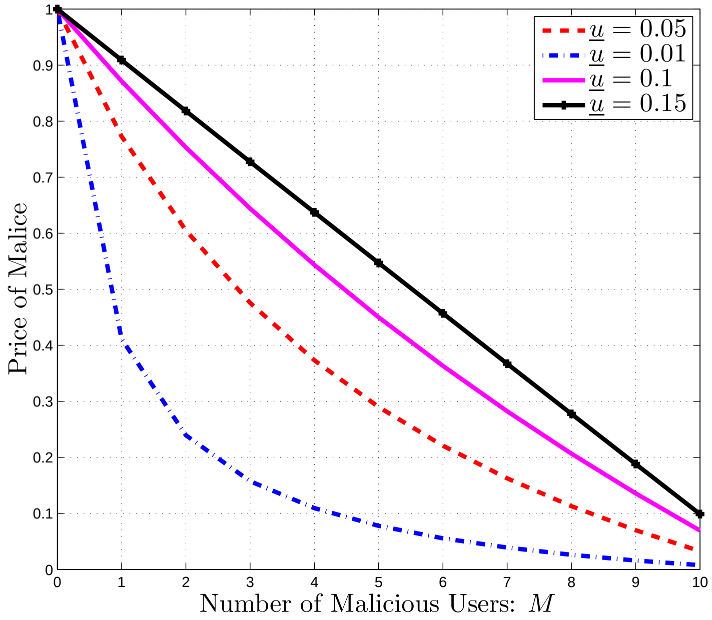

Figure 6.4: Price of Malice vs. number of malicious users

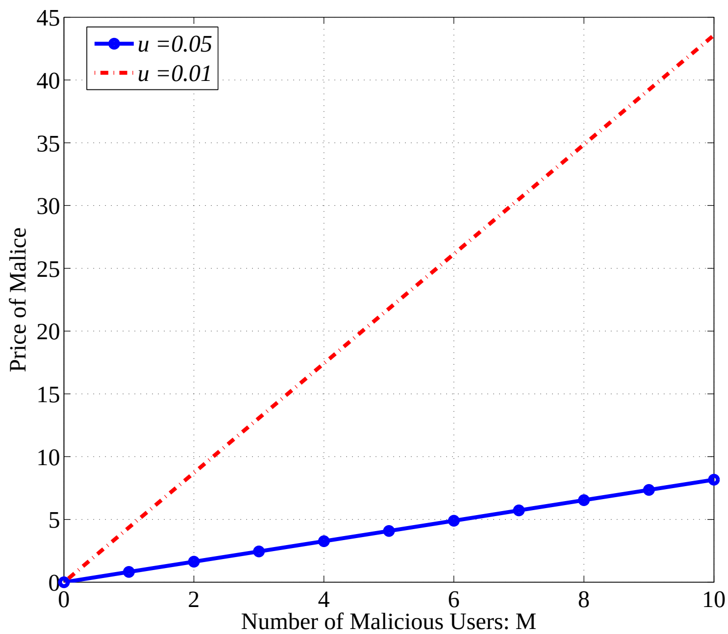

Figure 6.5: Price of Malice in the criterion of sum utility difference vs. number of malicious users

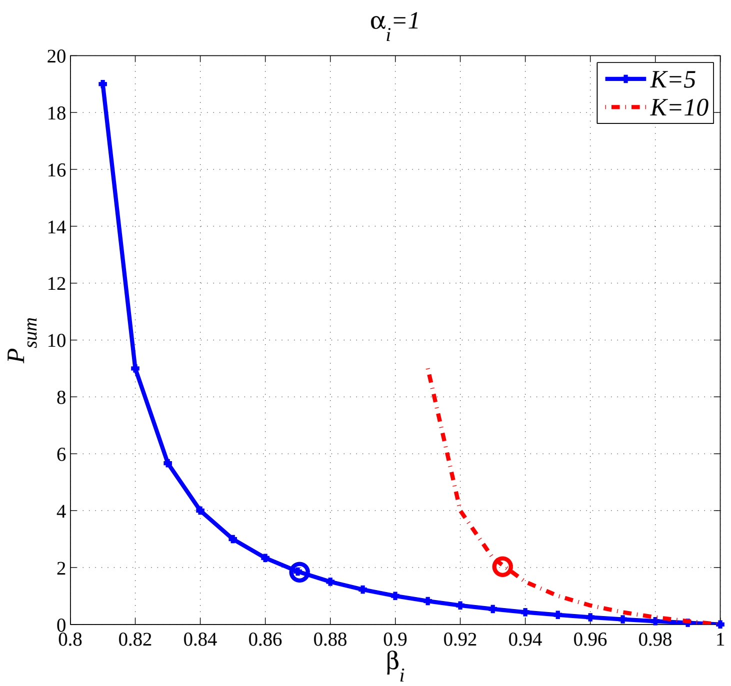

Figure 6.6: Sum NE power for K users as a function of individual price

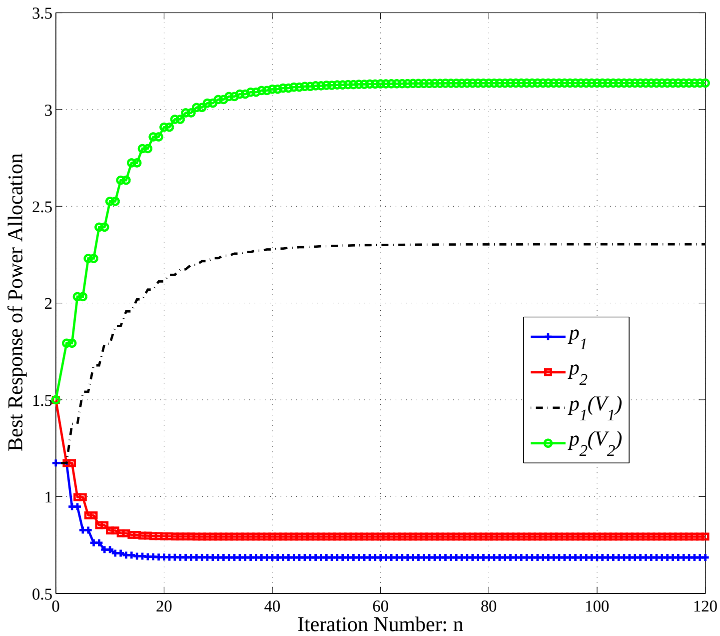

Figure 6.7: Comparison of BR transmit power with and without malicious user for the 2-user MAC without SIC

We apply the $PoM(M)$ to evaluate how much the sum power consumption of the whole K-user MAC system loses when there exist M malicious users. In the simulation, the total number of users in the system is $K = 10$. Different sets of rate requirements of each user $\underline{u}_i$ are performed. The channel gain is set to be $\alpha_i = 1$. The private type of the M malicious user i is $V_i = 0.06$, while $V_j = 0$ for the $K - M$ selfish users. When there is no malicious user in the system, $PoM(M)$ is one and it is strictly decreasing with the number of malicious users. It is observed that the PoM quickly drops from one if one or two malicious users are added. For some QoS requirements, the $PoM(M)$ decreases more than 20% when there is one malicious user, which indicates the importance of the counter mechanism.

If we define the PoM in a different way as $PoM_u(M) = \frac{\sum_{i=1}^{K} u_i(p_i,p_{-i},V_i) - \sum_{i=1}^{K} u_i(p_i,p_{-i})}{\sum_{i=1}^{K} u_i(p_i,p_{-i})}$ [99], then Fig. 6.5 shows the curves for $K = 10$ users with different rate requirements $\underline{u}$. The CSI $\boldsymbol{\alpha}$ and the individual prices $\boldsymbol{\beta}$ as well as the private types $\boldsymbol{V}$ are set to be identical. It is shown that the more malicious users in the MAC system, the higher the difference between the sum utilities of the system with and without malicious users. Since $PoM_u(M)$ is positively correlated to $2^{-\underline{u}}$, the impact of malicious users is larger if the rate requirement $\underline{u}$ is smaller. $PoM_u(M)$ is almost linearly dependent on the number of malicious users.

In Fig. 6.6, the relation between the proposed prices $\boldsymbol{\beta}$ and the resulting NE transmit power as a summation $P_{sum}^{NE} = \sum_{j=1}^{K} p_j^{NE}$ is shown for different total numbers of users. In the simulation, the individual prices are restricted to the region in Corollary 6.6 for different K. That is the reason why the starting points of β_i are different. In order to show the influence on the resulting NE power of price choices, identical CSI and prices for all users are assumed. It is intuitive to see that the higher the individual prices $\boldsymbol{\beta}$, the lower the NE transmit power p_i^{NE} of each user. From Lemma 6.8, to ensure the rate requirement of each user the individual price β_i is related to $\underline{u}_i$ and the CSI α_i. Therefore, β_i in (6.11) provides the best individual price to lead the NE transmit power of the noncooperative game to the desired point with the minimum power consumption. Due to the identical CSI $\alpha_i = 1$, for all $i, i \in [1, \ldots, K]$, the curves in Fig. 6.6 show exactly the individual prices to ensure different rate requirement of each user and the resulting sum NE power. The points in the figure show $\beta = \frac{\alpha}{2^{\underline{u}}}$ as an example, where $\underline{u} = 0.2$ for $K = 5$ and $\underline{u} = 0.1$, $K = 10$, respectively.

Fig. 6.7 compares the BRD transmit power of the proposed noncooperative game for the 2-user MAC without SIC when there is no malicious user and when user 2 is malicious. We observe that both the power of the selfish user 1 and the malicious user 2 become larger compared to the BRD transmit power without malicious user. It shows the importance to detect and prevent the misbehavior of users when they allocate their power distributively.

6.4 Distributed Power Allocation for MAC with SIC

In this section, we extend the pricing for distributed resource allocation to the general MAC with SIC. Without loss of generality, we assume the SIC is performed at the receiver with the

SIC decoding order as $[K \to \cdots \to 1]$ for the K transmitters. In the following, this decoding order is fixed if without specification. The operation for MAC with SIC is denoted as $.^{SIC}$.

The linear pricing, which is linear in both the prices $\boldsymbol{\beta}$ and the power $\boldsymbol{p}$ is adopted for the distributed power allocation in the general MAC with SIC. Linear pricing is a universal pricing for interference functions in MAC with SIC. Linear pricing for MAC with SIC is a simple and more efficient pricing scheme. Given the non-linear pricing for the general MAC without SIC, the whole picture of distributed power allocation in MAC under QoS requirement of each user is provided with the linear pricing analysed in this section.

6.4.1 System Operation with Truthful Agents

Different from the characterization for the MAC system without SIC, the utility function of each user for MAC with SIC is based on the achievable rate $r_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$ and the linear pricing term $\beta_i^{SIC} p_i^{SIC}$ as follows.

$$u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}) \quad = \quad r_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}) - \beta_i^{SIC} p_i^{SIC} \tag{6.25}$$

The noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ is played among the K users. The utility function of each user i is $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$. Their strategy space is the transmit power $p_i^{SIC} \in [0, p_i^{max}]$. In the following, the BRD and NE power of the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ are analyzed.

The BRD of this noncooperative game can be expressed as the K coupled problems

$$\max_{0<p_i^{SIC}<p_i^{max}} u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}) \quad s.t. \quad r_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}) \geq \underline{u}_i \qquad \forall i = 1, \ldots, K. \tag{6.26}$$

Each user maximizes its own utility function $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$ and then plays the BRD in the noncooperative game.

6.4.1.1 Best Response Power Allocation for MAC with SIC

The BR power allocation for the noncooperative game of MAC with SIC decoding order $[K \to \cdots \to 1]$ is concluded as follows.

6.23 Proposition. *For all $i = 1, \ldots, K$, define $\underline{p}_i^{SIC}$ as*

$$\underline{p}_i^{SIC}(p_{-i}^{SIC}) = \frac{1}{\beta_i^{SIC}} - \frac{1}{\alpha_i}\left(1 + \sum_{k=1}^{i-1} \alpha_k p_k^{SIC}\right). \tag{6.27}$$

The i-th user's best-response for the general MAC system with SIC decoding order $[K \to \cdots \to 1]$ is given by $p_{i,SIC}^{BR} = \max(0, \min(\underline{p}_i^{SIC}, p_i^{max}))$. Moreover, the noncooperative game $\mathcal{G}^{SIC}$ always admits an NE $\{p_{i,SIC}^{BR}\}_{i=1}^{K}$.

Proof. Please refer to Proof 6.5.6. □

6.4.1.2 Nash Equilibrium Power Allocation for MAC with SIC

In this part, we figure out the unique NE point of the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ for the general MAC with SIC.

6.24 Proposition. *The Nash equilibrium power allocation of each user i in the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ for the general MAC system with SIC decoding order $[K \to \cdots \to 1]$ is $p_{i,SIC}^{NE} = \max(0, \min(\underline{p}_{i,SIC}^{NE}, p_i^{max}))$. Given individual prices $\boldsymbol{\beta}^{SIC}$ from the BS,*

$$\underline{p}_{i,SIC}^{NE} = \frac{1}{\beta_i^{SIC}} - \frac{\alpha_{i-1}}{\alpha_i} \frac{1}{\beta_{i-1}^{SIC}}, \tag{6.28}$$

where $p_1^{SIC} = \frac{1}{\beta_1^{SIC}} - \frac{1}{\alpha_1}$. The noncooperative game $\mathcal{G}^{SIC}$ always admits this unique NE point.

Proof. Please refer to Proof 6.5.7. □

6.4.1.3 Pricing for MAC with SIC under QoS Requirements

The BS of the uplink transmission provides the individual price β_i to each user and leads the NE point of the noncooperative game to guarantee the rate requirement of each user with minimum power.

The minimum power to achieve the QoS requirement $\underline{u}_i$ in the general MAC with SIC decoding order $[K \to \cdots \to 1]$ is shown in [97] as a function of $\underline{\boldsymbol{u}}$. Recall (4.14) as

$$p_{i,SIC}^{U} = \frac{2^{\underline{u}_i} - 1}{\alpha_i} \prod_{j=1}^{i-1} 2^{\underline{u}_j}. \tag{6.29}$$

In order to achieve the QoS requirement $\underline{u}_i$, the NE power allocation of the game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ should be set equal to the power $p_{i,SIC}^{U}$ in (6.29). This could be managed by providing a set of properly designed prices $\boldsymbol{\beta}^{SIC}$. Thereby, the individual price β_i^{SIC} of the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ for the general MAC with SIC is set as follows.

6.25 Lemma. *In the K-user non-cooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U})$ of the general MAC system with SIC decoding order $[K \to \cdots \to 1]$, the rate requirement $\underline{u}_i$ of each user i is achieved with the NE power allocation $p_{i,SIC}^{NE}$ if the individual price β_i^{SIC} is*

$$\beta_i^{SIC} = \alpha_i \cdot 2^{-\sum_{j=1}^{i} \underline{u}_j}. \tag{6.30}$$

Condition $\frac{\beta_i^{SIC}}{\beta_{i-1}^{SIC}} < \frac{\alpha_i}{\alpha_{i-1}}$ ensures the positive NE power $\underline{p}_{i,SIC}^{NE}$ in (6.28).

Proof. Solve the equation $\underline{p}_{i,SIC}^{NE} = \frac{1}{\beta_i^{SIC}} - \frac{\alpha_{i-1}}{\alpha_i} \frac{1}{\beta_{i-1}^{SIC}} = p_{i,SIC}^{U} = \frac{2^{\underline{u}_i}-1}{\alpha_i} \prod_{j=1}^{i-1} 2^{\underline{u}_j}$ for β_i using the forward substitution.

The NE power in (6.28) $\underline{p}_{i,SIC}^{NE} = \frac{1}{\beta_i^{SIC}} - \frac{\alpha_{i-1}}{\alpha_i}\frac{1}{\beta_{i-1}^{SIC}} > 0$ proves the condition $\frac{\beta_i^{SIC}}{\beta_{i-1}^{SIC}} < \frac{\alpha_i}{\alpha_{i-1}}$. □

In the noncooperative game proposed for MAC with SIC, the last decoded user's strategy on transmit power is fixed in order to meet its rate requirement due to total interference cancelation. From the game theoretical point of view, it is a dominant strategy. Then by backward induction, the best strategy of the users decoded earlier will be fixed. The NE point of this game is quickly reached. However the game still needs to be played because the best response power allocation of the users are dependent on the strategies made by those users who are decoded later than them. Here the analysis of user misbehavior comes into play.

6.4.2 Malicious Behavior for MAC with SIC

If there exist malicious users in the MAC system with SIC as mentioned in Sec. 6.2.2, the private type V_i still applies. We follow the same procedure as in Sec. 6.2.2 in this section.

We assume for the general MAC with SIC, the utility function of each user with the private type V_i is as follows.

$$u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}, V_i) \quad = \quad r_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}) - \beta_i^{SIC} p_i^{SIC} + V_i \alpha_i p_i^{SIC}, \tag{6.31}$$

where the third term denotes the influence to the users who are decoded later than the user i. Since the interference caused by the malicious user i is only due to its own power allocation, it is simplified as the linear term to keep consistent with the linear pricing. The higher the term $V_i \alpha_i p_i^{SIC}$, the more interference to the other users.

6.4.2.1 Private Type Best Response Power for MAC with SIC

Follow a similar procedure as in Section 6.4.1, we obtain the distributed BR power allocation of each user with private types V_i and NE point with malicious users in the system.

6.26 Lemma. *For all $i = 1, \ldots, K$ with type V_i in the general MAC with SIC decoding order $[K \to \cdots \to 1]$, define $\underline{p}_i^{SIC}(V_i)$ as*

$$\underline{p}_i^{SIC}(V_i) = \frac{1}{\tilde{\beta}_i^{SIC}} - \frac{1}{\alpha_i}\left(1 + \sum_{k=1}^{i-1} \alpha_k p_k^{SIC}(V_k)\right). \tag{6.32}$$

Here $\tilde{\beta}_i^{SIC}(V_i) = \beta_i^{SIC} - V_i \alpha_i$ is the individual price with type V_i. The i-th user's best-response with type V_i is given by $p_{i,SIC}^{BR}(V_i) = \max(0, \min(\underline{p}_i^{SIC}(V_i), p_i^{max}))$.

Proof. Solve $\underline{p}_i^{SIC}(V_i)$ for the first derivative $\frac{\partial u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}, V_i)}{\partial p_i^{SIC}(V_i)} = 0$ from (6.31).

$$\frac{\partial u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}, V_i)}{\partial p_i^{SIC}(V_i)} = \frac{\alpha_i}{1 + \sum_{j=1}^{i} \alpha_j p_j^{SIC}} - \beta_i + V_i \alpha_i = 0$$

provides the result in (6.32).

The second derivative with respect to $p_i^{SIC}(V_i)$ is

$$\frac{\partial^2 u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}, V_i)}{\partial^2 p_i^{SIC}(V_i)} = \frac{-\alpha_i^2}{(1+\sum_{j=1}^{i}\alpha_j p_j^{SIC})^2} < 0. \tag{6.33}$$

Therefore, $\underline{p}_i^{SIC}(V_i)$ in (6.32) is the global optimum. □

If there is no malicious user in the system, the result in Lemma 6.26 is exactly $p_{i,SIC}^{BR}$ in (6.27) when $V_i = 0$ for all $i, i \in [1, \ldots, K]$.

6.4.2.2 NE Power Allocation with Malicious Users for MAC with SIC

The K users in the system play the BRD in the proposed noncooperative game and their NE point is derived as follows.

6.27 Proposition. *The NE power allocation of each user i in the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the general MAC system with SIC decoding order $[K \to \cdots \to 1]$ and private type V_i is $p_{i,SIC}^{NE}(V_i) = \max(0, \min(\underline{p}_{i,SIC}^{NE}(V_i), p_i^{max}))$. Given the individual prices $\tilde{\beta}_i^{SIC}(V_i)$ with type V_i,*

$$\underline{p}_{i,SIC}^{NE}(V_i) = \frac{1}{\tilde{\beta}_i^{SIC}(V_i)} - \frac{\alpha_{i-1}}{\alpha_i}\frac{1}{\tilde{\beta}_{i-1}^{SIC}(V_i)}. \tag{6.34}$$

The noncooperative game always admits this unique NE point.

Proof. The proof follows the same steps as in Proof 6.5.7 by replacing the individual price β_i^{SIC} with $\tilde{\beta}_i^{SIC}(V_i)$. □

Given the individual price $\beta_i^{SIC} = \alpha_i \cdot 2^{-\sum_{j=1}^{i}\underline{u}_j}$, the NE power in (6.34) can be expressed as a function of the rate requirement $\underline{\boldsymbol{u}}$ and the private types $\boldsymbol{V}$.

6.28 Proposition. *With the individual price $\beta_i^{SIC} = \alpha_i \cdot 2^{-\sum_{j=1}^{i}\underline{u}_j}$, the Nash equilibrium power allocation $p_{i,SIC}^{NE}(V_i)$ of each user i in the noncooperative game $\mathcal{G}^{SIC}(\mathcal{K}, \mathcal{P}, \mathcal{U}^v)$ for the general MAC with SIC decoding order $[K \to \cdots \to 1]$ and private type V_i is higher than or equal to $p_{i,SIC}^{U}$ in (6.29).*

$$\underline{p}_{i,SIC}^{NE}(V_i, \underline{\boldsymbol{u}}) = \frac{1}{\alpha_i}\Big(\frac{1}{\prod_{j=1}^{i} 2^{-\underline{u}_j} - V_i} - \frac{1}{\prod_{j=1}^{i-1} 2^{-\underline{u}_j} - V_{i-1}}\Big), \tag{6.35}$$

$$\textit{where} \quad \underline{p}_{1,SIC}^{NE}(V_1, \underline{\boldsymbol{u}}) = \frac{1}{\alpha_1}\left(\frac{1}{2^{-\underline{u}_1} - V_1} - 1\right). \tag{6.36}$$

Proof. Insert $\tilde{\beta}_i^{SIC}(V_i) = \beta_i^{SIC} - V_i\alpha_i$ with $\beta_i^{SIC} = \alpha_i \cdot 2^{-\sum_{j=1}^{i}\underline{u}_j}$ into (6.34), then (6.35) is proved. If all the users are selfish, $\underline{p}_{i,SIC}^{NE}(V_i, V_{-i}) = p_{i,SIC}^{U}$, which is the minimum power allocation in order to achieve the rate requirement $\underline{u}_i$ of each user i.

From (6.32), for malicious users with private type $0 < V_i \leq 1$, the transmit power is larger than that of a selfish user. □

For the uplink transmission, by comparing with the rate requirement of each user, the achievable rate serves to detect the user misbehavior. The achievable rate $r_i^{SIC}(\boldsymbol{V})$ is obtained given the rate requirements $\underline{\boldsymbol{u}}$ and the private types $\boldsymbol{V}$ of user i and all the users decoded later than i.

6.29 Lemma. *Given the private types $\boldsymbol{V}$ of the users, the rate achieved for each user i in the general MAC with SIC decoding order $[K \rightarrow \cdots \rightarrow 1]$ is*

$$r_i^{SIC}(\boldsymbol{V}) = \log\left(\frac{\prod_{j=1}^{i-1} 2^{-\underline{u}_j} - V_{i-1}}{\prod_{j=1}^{i} 2^{-\underline{u}_j} - V_i}\right), \qquad \textit{where} \quad r_1^{SIC}(\boldsymbol{V}) = \log\left(\frac{1}{2^{-\underline{u}_1} - V_1}\right). \tag{6.37}$$

Proof. Insert the result of NE power with the malicious users in (6.35) into the rate $r_i^{SIC}(\boldsymbol{V})$. If the SIC decoding order is $[K \rightarrow \cdots \rightarrow 1]$ without generality, the rate of user 1 is

$$r_1^{SIC}(\boldsymbol{V}) = \log\left(1 + \alpha_1 p_{1,SIC}^{NE}(V_1, V_{-1})\right) = \log\left(\frac{1}{2^{-\underline{u}_1} - V_1}\right). \tag{6.38}$$

For the users $i > 1$,

$$r_i^{SIC}(\boldsymbol{V}) = \log\left(\frac{1 + \sum_{k=1}^{i}\left(\frac{1}{\prod_{j=1}^{k} 2^{-\underline{u}_j} - V_k} - \frac{1}{\prod_{j=1}^{k-1} 2^{-\underline{u}_j} - V_{k-1}}\right)}{1 + \sum_{k=1}^{i-1}\left(\frac{1}{\prod_{j=1}^{k} 2^{-\underline{u}_j} - V_k} - \frac{1}{\prod_{j=1}^{k-1} 2^{-\underline{u}_j} - V_{k-1}}\right)}\right). \tag{6.39}$$

Eliminate the same items step by step in the numerator and denominator, respectively. Then we obtain $r_i^{SIC}(\boldsymbol{V}) = \log\left(\frac{\frac{1}{\prod_{j=1}^{i} 2^{-\underline{u}_j} - V_i}}{\frac{1}{\prod_{j=1}^{i-1} 2^{-\underline{u}_j} - V_{i-1}}}\right)$ and $r_i^{SIC}(\boldsymbol{V})$ in (6.37) is proved. □

The extent of users' malice is restricted by the rate requirements $\underline{\boldsymbol{u}}$. Otherwise no user can achieve its rate requirement and the malicious users cannot benefit by the misbehavior.

6.30 Lemma. *In the general MAC system with SIC decoding order $[K \rightarrow \cdots \rightarrow 1]$, the rate requirement $\underline{u}_i$ of each user i can be achieved if and only if the following conditions of the user private type V_i, the total number of users K and the rate requirement $\underline{u}_i$ are fulfilled.*

$$\prod_{j=1}^{i-1} 2^{-\underline{u}_j}(1 - 2^{-\underline{u}_i}) \quad > \quad V_{i-1}^{SIC} - V_i^{SIC}, \tag{6.40}$$

$$2^{\underline{u}_i} V_i \quad \geq \quad V_{i-1}, \tag{6.41}$$

$$0 \leq V_i^{SIC} \quad < \quad \prod_{j=1}^{i} 2^{-\underline{u}_j}. \tag{6.42}$$

Proof. The rate requirement of each user is only achieved with positive transmit power. Therefore, (6.40) is proved by ensuring (6.35) to be positive.

As shown in (6.37), the achievable rate is a function of the rate requirements $\underline{\boldsymbol{u}}$ and the type value $\boldsymbol{V}$. The actual rate $r_i^{SIC}(\boldsymbol{V})$ is higher than or equal to $\underline{u}_i$ if and only if $\frac{\prod_{j=1}^{i-1} 2^{-\underline{u}_j} - V_{i-1}}{\prod_{j=1}^{i} 2^{-\underline{u}_j} - V_i} \geq 2^{\underline{u}_i}$. Therefore, condition (6.41) is proved.

The third condition is due to the positive rate in (6.37). $\underline{u}_i > 0, 0 < 2^{-\underline{u}_i} < 1$, therefore, $\prod_{j=1}^{i} 2^{-\underline{u}_j} < 1$. □

Given the expression of the achievable rate $r_i^{SIC}(\boldsymbol{V})$ as a function of the private types of the users, the type values can be calculated by the BS.

6.31 Lemma. *In the general MAC with SIC decoding order $[K \to \cdots \to 1]$, the private types $\boldsymbol{V}$ of the users are obtained by the BS given the achievable rate $r_i^{SIC}(\boldsymbol{V})$ and the rate requirement $\underline{u}_i$.*

$$V_i^{SIC} = \prod_{j=1}^{i} 2^{-\underline{u}_j} - \prod_{j=1}^{i} 2^{-r_j^{SIC}(\boldsymbol{V})}, \qquad i \in [1, \dots, K]. \tag{6.43}$$

Proof. From (6.37), we obtain

$$V_i = \frac{2^{r_i^{SIC}(\boldsymbol{V})} \prod_{j=1}^{i} 2^{-\underline{u}_j} - \prod_{j=1}^{i-1} 2^{-\underline{u}_j} + V_{i-1}}{2^{r_i^{SIC}(\boldsymbol{V})}}. \tag{6.44}$$

The proof is given by the forward induction. For the last decoded user $i = 1$, its private type is $V_1^{SIC} = 2^{-\underline{u}_1} - 2^{-r_1^{SIC}(\boldsymbol{V})}$. Insert V_1^{SIC} into V_2^{SIC} and calculate the type values forwardly and so on, (6.43) is proved. □

Similar to Sec. 6.2.3, when the user misbehavior is detected, the strategy-proof pricing for MAC with SIC is applied on that user with $\beta_{i,M}^{SIC} = \beta_i^{SIC} + V_i\alpha_i$. By maximizing the individual utility function $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC}, V_i)$, no user will have incentives to harm the other users and therefore, the rate requirements of all users in the system are guaranteed.

Figure 6.8 compares the regions of individual prices for 2-user MAC with and without SIC and malicious user, respectively. The colors are changed due to the transparent effect of the overlapping regions. The CSI of the two users are set to be $\alpha_1 = 1$ and $\alpha_2 = 2$. For the case of MAC with user misbehavior, user 2 is assumed to be malicious with private type $V_2 = 0.1$. User 1 is selfish with private type $V_1 = 0$. According to Lemma 6.8 and Remark 6.9, we understand that the region of individual prices in Corollary 6.6 corresponds to the region of feasible QoS requirements in Corollary 4.3 of Chapter 4. In other words, for every point $\underline{u}_i$ in the feasible rate region, there exists an individual price β_i or β_i^{SIC} such that $\underline{u}_i$ can be achieved by the proposed noncooperative game for MAC without and with SIC, respectively.

The feasible QoS regions for MAC with and without SIC are illustrated in Fig. 4.3 and 4.4 in Chapter 4. The rate region for MAC with SIC is larger than that without SIC. Therefore in Fig. 6.8, the region of individual prices for MAC with SIC is larger as well. The right lower

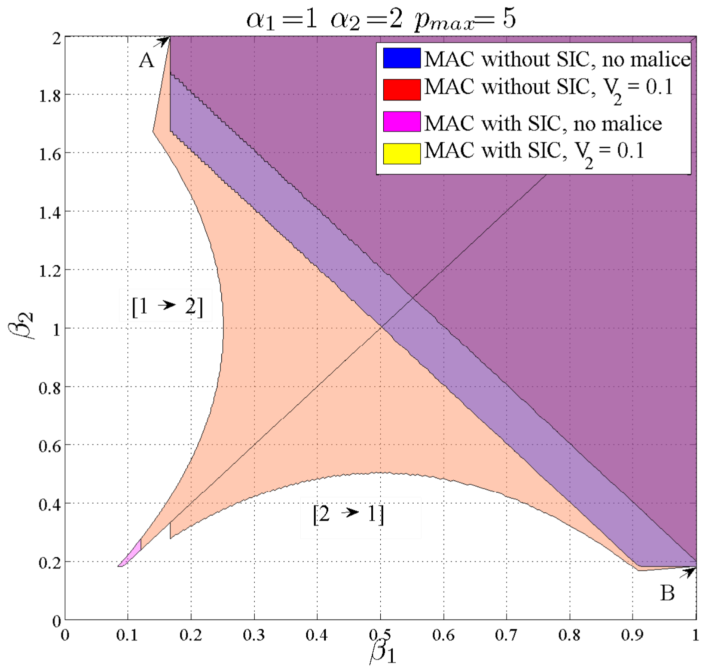

Figure 6.8: Regions of individual prices for MAC with and without SIC and malicious user.

part denotes the SIC decoding order $[2 \to 1]$ and the left upper part denotes the SIC decoding order $[1 \to 2]$. Due to different CSIs, the regions of the two decoding orders are not symmetric.

The regions of prices for MAC without SIC are from Corollary 6.6 and 6.17. The regions of prices for MAC with SIC are from Lemma 6.25 for feasible QoS requirements $\underline{\boldsymbol{u}}$. The region of MAC with SIC and malicious user is restricted by $\frac{\tilde{\beta}_i^{SIC}}{\tilde{\beta}_{i-1}^{SIC}} < \frac{\alpha_i}{\alpha_{i-1}}$, where $\tilde{\beta}_i^{SIC} = \beta_i^{SIC} - V_i\alpha_i$. It is shown that the regions with malicious user is smaller than that without malicious user, which implies that the rate region is declined due to user misbehavior. The regions converge to the point A and B because of the single user power constraint p_{max}.

6.5 Proofs

6.5.1 Proof of Proposition 6.4

Proof. Solve the first derivative of $u_i(p_i, p_{-i})$ to be zero with respect to p_i.

$$\begin{aligned} \frac{\partial u_i(p_i, p_{-i})}{\partial p_i} &= \frac{\alpha_i}{1 + \sum_{k \neq i} \alpha_k p_k + \alpha_i p_i} - \frac{\beta_i}{1 + \sum_{k \neq i} \alpha_k p_k} \\ &= 0. \end{aligned} \tag{6.45}$$

The positive result $\underline{p}_i(p_{-i})$ is achieved in (6.7) if $\beta_i < \alpha_i$. Otherwise it is set to zero to avoid negative power.

The second derivative of $u_i(p_i, p_{-i})$ with respect to p_i is

$$\frac{\partial^2 u_i(p_i, p_{-i})}{\partial p_i^2} = \frac{-\alpha_i^2}{(1 + \sum_{k \neq i} \alpha_k p_k + \alpha_i p_i)^2} < 0. \tag{6.46}$$

Therefore, $\underline{p}_i(p_{-i})$ in (6.7) is the global maximum.

By observing that the strategy set of each user is a compact and convex set, $u_i(p_i, p_{-i})$ is a continuous function with respect to the powers of all users, and concave with respect to p_i, which implies the existence of at least one NE. □

6.5.2 Proof of Proposition 6.5

Proof. In order to determine the NE power allocation $\underline{p}_i^{NE}$, we find the fixed point by jointly solving the set of utility maximization problems in (6.6). We formulate it as linear equations $\boldsymbol{A} + \boldsymbol{D} \cdot \underline{\boldsymbol{p}} = \underline{\boldsymbol{p}}$. Therefore, $\underline{\boldsymbol{p}}$ is solved by

$$\underline{\boldsymbol{p}} = (\boldsymbol{I} - \boldsymbol{D})^{-1} \cdot \boldsymbol{A}, \tag{6.47}$$

where the matrix $\boldsymbol{D}$ is formulated as

$$\boldsymbol{D} = \begin{bmatrix} 0 & A_1\alpha_2 & \ldots & A_1\alpha_K \\ A_2\alpha_1 & 0 & \ldots & A_2\alpha_K \\ \vdots & \vdots & \ddots & \vdots \\ A_K\alpha_1 & A_K\alpha_2 & \ldots & 0 \end{bmatrix}, \tag{6.48}$$

where $A_i = \frac{1}{\beta_i} - \frac{1}{\alpha_i}$.

Using the Cramer's rule, $\underline{\boldsymbol{p}} = \frac{\det(\boldsymbol{B}^i)}{\det(\boldsymbol{B})}$, where $\boldsymbol{B} = \boldsymbol{I} - \boldsymbol{D}$. The matrix $\boldsymbol{B}^i$ is the matrix of $\boldsymbol{B}$ where the ith column is replaced by the vector $\boldsymbol{A}$.

$$\boldsymbol{B} = \begin{bmatrix} 1 & -A_1\alpha_2 & \ldots & -A_1\alpha_K \\ -A_2\alpha_1 & 1 & \ldots & -A_2\alpha_K \\ \vdots & \vdots & \ddots & \vdots \\ -A_K\alpha_1 & -A_K\alpha_2 & \ldots & 1 \end{bmatrix}. \tag{6.49}$$

Now we solve $\det(\boldsymbol{B}^i)$ and $\det(\boldsymbol{B})$.

$$\begin{aligned}
&\det(\boldsymbol{B}^i)\\
=\;& \prod_{i=1}^{K} A_i \cdot \prod_{j\neq i} \alpha_j \cdot \det \begin{bmatrix} 1 & -1 & \dots & -1 \\ 1 & \frac{1}{A_2\alpha_2} & \dots & -1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & -1 & \dots & \frac{1}{A_K\alpha_K} \end{bmatrix}\\
=\;& \prod_{i=1}^{K} A_i \cdot \prod_{j\neq i} \alpha_j \cdot \det \begin{bmatrix} 1 & 0 & \dots & 0 \\ 1 & \frac{1+A_2\alpha_2}{A_2\alpha_2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & \frac{1+A_K\alpha_K}{A_K\alpha_K} \end{bmatrix}\\
=\;& \prod_{i=1}^{K} A_i \cdot \prod_{j\neq i} \alpha_j \left(1 + \frac{1}{A_j\alpha_j}\right).
\end{aligned} \tag{6.50}$$

$$\begin{aligned}
\det(\boldsymbol{B}) &= \prod_{i=1}^{K} A_i\alpha_i(-1)^K \cdot \det \begin{bmatrix} \frac{-1}{A_1\alpha_1} & 1 & \dots & 1 \\ 1 & \frac{-1}{A_2\alpha_2} & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & \frac{-1}{A_K\alpha_K} \end{bmatrix}\\
&= \prod_{i=1}^{K} A_i\alpha_i \cdot \det \begin{bmatrix} C & \frac{1+A_1\alpha_1}{A_1\alpha_1} & \dots & \frac{1+A_1\alpha_1}{A_1\alpha_1} \\ 0 & \frac{1+A_2\alpha_2}{A_2\alpha_2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{1+A_K\alpha_K}{A_K\alpha_K} \end{bmatrix}\\
&= \prod_{j}(1 + A_j\alpha_j)\left(1 - \sum_{j=1}^{K} \frac{A_j\alpha_j}{1 + A_j\alpha_j}\right),
\end{aligned} \tag{6.51}$$

where $C = \frac{1}{A_1\alpha_1} - \frac{1+A_1\alpha_1}{A_1\alpha_1} \cdot \sum_{j\neq 1} \frac{A_j\alpha_j}{1+A_j\alpha_j}$. Therefore, the NE power $\underline{p}_i = \frac{\det(\boldsymbol{B}^i)}{\det(\boldsymbol{B})}$ is

$$\underline{p}_i = \frac{A_i}{1 + A_i\alpha_i} \cdot \frac{1}{1 - \sum_{j=1}^{K} \frac{A_j\alpha_j}{1+A_j\alpha_j}}. \tag{6.52}$$

Insert $A_i = \frac{1}{\beta_i} - \frac{1}{\alpha_i}$, The proposition is proved. □

6.5.3 Proof of Lemma 6.12

Proof. Solve $\underline{p}_i(V_i)$ for the first derivative $\frac{\partial u_i(p_i, p_{-i}, V_i)}{\partial \underline{p}_i} = 0$ from (6.13).

$$\begin{aligned} \frac{u_i(p_i, p_{-i}, V_i)}{\underline{p}_i} &= \frac{\alpha_i}{\alpha_i p_i + I_i(p_{-i})} - \frac{\beta_i}{I_i(p_{-i})} + \frac{V_i \alpha_i}{I_i(p_{-i})} \\ &= 0. \end{aligned} \tag{6.53}$$

We obtain

$$\alpha_i p_i + I_i(p_{-i}) = \frac{\alpha_i I_i(p_{-i})}{\beta_i - V_i \alpha_i}.$$

Therefore (6.14) is proved.

The second derivative of $u_i(p_i, p_{-i}, V_i)$ with respect to p_i is

$$\frac{\partial^2 u_i(p_i, p_{-i}, V_i)}{\partial \underline{p}_i^2} = \frac{-\alpha_i^2}{(\alpha_i p_i + I_i(p_{-i}))^2} < 0. \tag{6.54}$$

Therefore, the global optimum of the utility function with private type V_i in (6.13) is guaranteed. $p_i^{BR}(V_i) = \max(0, \min(\underline{p}_i(V_i), p_i^{max}))$ ensures the positive transmit power to achieve the rate requirement of each user under single user power constraint p_i^{max}. □

6.5.4 Proof of Proposition 6.16

Proof. Insert $\tilde{\beta}_i(V_i) = \beta_i - V_i \alpha_i$ with $\beta_i = \frac{\alpha_i}{2^{\underline{u}_i}}$ into (6.15), then (6.16) is proved. It can be observed that the second term in (6.16) is a constant for all the users with the given type V_j and it is larger if there exists at least one user with $V_i > 0$. If all the users are selfish, $\underline{p}_i^{NE}(V_i, V_{-i}) = p_i^U$, which is the minimum power allocation in order to achieve the rate requirement $\underline{u}_i$ of each user i.

Finally, we calculate the achievable rate of each user with $p_i^{NE}(V_i)$. The rate requirement $\underline{u}_i$ can be achieved for the selfish users with $V_i = 0$. Since the power allocation of malicious users is larger than that of selfish users, their actual rate is greater than their rate requirements. □

6.5.5 Proof of Lemma 6.18

Proof. Insert $\underline{p}_i^{NE}(V_i, V_{-i})$ in (6.17) into $r_i(V_i)$.

$$\begin{aligned} r_i(V_i) &= \log\left(1 + \frac{(1 + V_i - 2^{-\underline{u}_i}) B_K(\boldsymbol{V})}{1 + \sum_{j \neq i}(1 + V_j - 2^{\underline{u}_j}) B_K(\boldsymbol{V})}\right) \\ &= \log\left(1 + \frac{1 + V_i - 2^{-\underline{u}_i}}{2^{-\underline{u}_i} - V_i}\right) \\ &= \log\left(\frac{1}{2^{-\underline{u}_i} - V_i}\right). \end{aligned} \tag{6.55}$$

From the result of the achievable rate $r_i(V_i)$ in (6.20), V_i in (6.19) is obtained. □

6.5.6 Proof of Proposition 6.23

Proof. Solve the first derivative of $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$ to be zero with respect to p_i^{SIC}.

$$\frac{\partial u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})}{\partial p_i^{SIC}} = \frac{\alpha_i}{1 + \sum_{k=1}^{i-1} \alpha_k p_k^{SIC} + \alpha_i p_i^{SIC}} - \beta_i^{SIC} = 0. \tag{6.56}$$

The positive result $\underline{p}_i^{SIC}$ is achieved in (6.27) if $0 < \beta_i^{SIC} < \frac{\alpha_i}{1+\sum_{k=1}^{i-1} \alpha_k p_k^{SIC}}$. Otherwise it is set to zero to avoid negative power.

The second derivative of $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$ with respect to p_i^{SIC} is

$$\frac{\partial^2 u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})}{\partial p_{i,SIC}^2} = \frac{-\alpha_i^2}{(1 + \sum_{k=1}^{i} \alpha_k p_k^{SIC})^2} < 0.$$

Therefore $\underline{p}_i^{SIC}(p_{-i}^{SIC})$ in (6.27) is the global optimum of the utility function.

By observing that the strategy set of each user is a compact and convex set, $u_i^{SIC}(p_i^{SIC}, p_{-i}^{SIC})$ is a continuous function with respect to the power of all users, and concave with respect to p_i^{SIC}, which implies the existence of at least one NE. □

6.5.7 Proof of Proposition 6.24

Proof. The NE power allocation is obtained by jointly solving the set of utility maximization problem in (6.26). $\underline{\boldsymbol{p}}^{SIC}$ is solved by the linear equations

$$\boldsymbol{C} \cdot \underline{\boldsymbol{p}}^{SIC} = \boldsymbol{A}, \tag{6.57}$$

where $\boldsymbol{C}$ is a lower triangular matrix

$$\boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ \frac{\alpha_1}{\alpha_2} & 1 & 0 & \dots & 0 \\ \frac{\alpha_1}{\alpha_3} & \frac{\alpha_2}{\alpha_3} & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha_1}{\alpha_K} & \frac{\alpha_2}{\alpha_K} & \frac{\alpha_3}{\alpha_K} & \dots & 1 \end{bmatrix}, \tag{6.58}$$

and $A_i = \frac{1}{\beta_i^{SIC}} - \frac{1}{\alpha_i}$.

The matrix equation with lower triangular matrix is very easy to solve by an iterative process called forward substitution. Therefore, the NE power allocation is obtained in (6.28). □

6.6 Summary

In this chapter, we investigate the distributed power allocation by means of noncooperative game for the general MAC system with and without SIC, respectively. Each user in the game allocates its own power by maximizing its individual utility function. We propose the individual prices in the utility function such that the Shannon rate-based QoS requirement of each user is satisfied at the NE point power allocation. We provide the BRD power allocation, which converges rapidly to the NE point. The existence, uniqueness and convergence of the NE power allocation are proved. The different private types regarding the user behavior are analysed, especially the malicious behavior. The resulting power allocation and the achievable rates at the NE power allocation for all the users with the different individual types are observed. It is proved that with the presence of malicious users, the number of users satisfying the QoS requirement will be less compared to a all regular user network if the power allocation remains the same. The strategy-proof mechanism is designed with the punishment price to counter the malicious behavior, in which an additional price proportional to user types is introduced. The private types of users are detected by comparing the achievable rates and the QoS requirements. Numerical results illustrate the PoM and show that the BRD of the proposed noncooperative game converges rapidly to the unique NE point. With the punishment price, no self-optimizing user will have incentives to behave maliciously.

6.6.1 Comparison of Centralized and Distributed Pricing-based Resource Allocation

Comparing with the centralized power allocation investigated in Chapter 4, the resulting NE power allocation in the proposed noncooperative game achieves the same power as in the centralized algorithm. This is the minimum power allocation which ensures the QoS requirement of each user in the general MAC system. Therefore, the outcome of the proposed noncooperative game is led to the efficient point by introducing the individual prices into the user utility function.

The prices in the centralized allocation is independent of the user CSI. This is important for the central controller (system regulator) to provide the prices. Because by knowing the QoS requirements $\underline{\boldsymbol{u}}$ of the transmitters, which are the relatively long-term constants, the regulator needs not to update the prices as a control signal rapidly with the change of channel states. The regulator is released from updating the CSI of users and the prices of the centralized allocation are the long-term parameters. The regulator in this setting could be the higher layer devices such as the wireless vender and can locate far away from the transmitters. The stable pricing parameters also make possible the mapping between the physical layer resource allocation and the higher layer revenue.

The individual prices provided by the BS in the distributed allocation are dependent on the QoS requirements $\underline{\boldsymbol{u}}$ and each user's own CSI. For the BS in MAC, the CSI of all the users are acquired due to the uplink transmission. For each transmitters, its own CSI is the local information. Therefore, each user can allocate its transmit power with the local optimization.

By playing the proposed noncooperative game with the individual prices, the NE power allocation is achieved. No user will deviate unilaterally from the NE power allocation. Since the NE point is the same as the centralized power allocation, the rate requirements of all the users in the feasible rate region are guaranteed. From Definition 1.11, both the pricing framework of the centralized and distributed resource allocation are universal pricing.

For the uplink transmission where single receiver exists, the centralized power allocation is a proper mechanism. Since the prices are independent of CSI, the computational complexity is manageable, However, there are scenarios where the centralized control is not available. In that cases, the distributed power allocation is necessary. In our proposed noncooperative game, each user achieves the NE power allocation by local estimation of others. Due to the closed form results in both the centralized and distributed frameworks, the computational complexity of both frameworks are very low.

Moreover, the two frameworks discuss different user misbehavior and cheat-proof strategies. In the centralized allocation, the manipulation of the CSI is analyzed. The worst case study to ensure the QoS requirements of all the honest users and the RG to prevent malicious users from cheating are investigated. In the distributed allocation, since each self-interested user maximizes its own utility, the misrepresentation of the utility function is studied. The strategy-proof mechanism by adopting the punishment prices to the malicious users is presented. By anticipating the resulting payoff, no user in the MAC system will have incentives to behave maliciously.

7 Conclusions and Future Work

We investigate the resource allocation for the general MAC and BC under individual QoS requirements, particularly we focus on the uplink MAC scenario. The single-user decoding is assumed at the receivers, therefore interference is treated as noise. The quasi-static block flat-fading channels are statistically independent of each other. Due to the high demand in data rate and the scarcity of wireless resources such as power, it is important to allocate the resource in a socially optimal manner. The theory of microeconomics, typically game theory and mechanism design come into play.

Instead of maximizing the achievable rates, our problem deals with allocating the power efficiently to guarantee the QoS requirement of all the users in the wireless system. The Shannon rate is set to be the criterion of the QoS requirement. From the game theoretic point of view, revealing one's true private information or announcing one's exact preferences for utilities might not be the best interest of users. The designed system must be capable of monitoring and preventing the user misbehavior such that the power allocation ensures the rate requirement of each user.

Pricing on the physical layer resources is proposed in our system model. We investigate the universal pricing mechanism to allocate the power in the wireless system. A pricing mechanism is said to be universal pricing if for all the points in the feasible utility region, there exists a price such that the required utility is achieved by the price-based resource allocation. Both linear and nonlinear pricing frameworks are studied. Linear pricing in the current context refers to the pricing term which is linear in both the prices and power. Nonlinear pricing refers to the pricing term which is logarithmic in power and linear in the prices. The conditions for both linear and nonlinear pricing to be universal pricing are analyzed.

Typical multi-user communication systems include MAC and BC. For the general MAC system, we show that linear pricing is a universal pricing if SIC is applied at the receiver. The regulator is introduced into the system to provide the prices and weights (priority) to the system. The regulator is responsible to make sure the QoS requirement of each user is achieved by selecting the prices. The power of each user is allocated by the system optimizer. Being a simple device, the system optimizer allocates the power to each user by maximizing the UMP with the given prices and weights. The prices serve as the tradeoff between maximizing the sum rate and minimizing power. Therefore the UMP is the difference between the system weighted sum rate and the sum pricing term. We show that with the proposed prices, the power allocation is derived such that all users achieve their QoS requirements. The best SIC decoding order regarding to minimize the sum power consumption is provided. Based on the SIC decoding order, the cost terms are analyzed with regard to different orders of weights.

Due to the uplink-downlink duality, the linear pricing based power allocation for BC with DPC is analyzed as well. MAC without SIC is shown as a contrary example for the linear pricing to be the universal pricing mechanism.

There are scenarios where no SIC is applied at the receiver, for example the single BS is shared by several operators with different RANs. Nonlinear pricing is shown to be universal pricing for the MAC system without SIC. Besides guaranteeing the QoS requirements of all users by providing the prices and weights to the system optimizer, the regulator takes the responsibility in detecting and preventing the users from cheating their reported CSI. The optimal power is allocated by the system optimizer with the given prices. The prices are shown to be long-term values which are independent of the user CSI. Restricted by the total number of users in the system, the feasible rate region of the general MAC is characterized. The cost terms on power are analyzed with regard to different weights. It is possible for the selfish (malicious) users to manipulate the universal nonlinear pricing scheme by reporting the lower CSI instead of the true values for higher short-term utility. The users' best cheating strategy and the results on rates of all the users in the system are investigated. Derived from this, the repeated game is introduced to prevent users from cheating. In the RG, the trigger strategy with the suitable trigger price is applied to the cheated user whenever the misbehavior is detected. All the honest users are protected by the worst-case strategy. By anticipating the total payoff of the proposed RG, we show that no user will have incentives to cheat. Numerical results confirm that the long-term total payoff after cheating is made smaller than the honest total payoff leading to a stable incentive-compatible operation. The nonlinear pricing mechanism works as well for the general MAC with SIC.

The uplink transmission within the heterogeneous networks is exactly the same scenario as MAC. From the energy efficient point of view, the MBS in the macrocell is willing to motivate the hybrid access of femtocells, which the nearby MUEs can be served by the FAP instead of the MBS itself. Based on the universal nonlinear pricing framework for MAC without SIC, the power allocation to ensure the feasible QoS requirements of all users in the system is adopted into the heterogeneous networks. Since both the MBS and FAP are self-interested devices, two compensation frameworks are proposed to motivate the hybrid access. The Stackelberg game is formulated where the MBS serves as the leader with the compensation price as its strategy and the FAP serves as the follower with the accepted number of MUEs in the hybrid access as its strategy. The first compensation framework is based on the universal non-linear power pricing, which provides a good connection between the physical layer power cost to the upper layer revenue. Concerning the total power consumption of the whole two-tier macro-femtocell network, an energy aware compensation framework is discussed in the second model. The MBS determines the best compensation price by maximizing the global energy efficiency of all the UEs in the system. And the FAP chooses the optimal number of accepted MUEs in the hybrid access by maximizing its utility with the given compensation paid by the MBS. Numerous simulations are conducted showing that the proposed compensation frameworks result in a win-win solution. The utilities of both the FAP at the femtocell and the MBS at the macrocell are maximized with the given compensation frameworks.

For multi-user communication systems where there is single BS, centralized power allocation is appropriate. However, there are situations when central control is not possible. Here the distributed power allocation comes into play. Each user in the system allocates its own power by maximizing its utility function. The noncooperative game is applied to analyze the distributed power allocation for the general MAC with and without SIC, respectively. It is well known that the NE point of a noncooperative game might not be efficient. The individual prices are introduced to the utility functions of each user in the proposed noncooperative game such that the resulting NE power allocation achieves the QoS requirement of each user. We prove that the unique NE power allocation exists. The BRD is provided to converge rapidly to the unique NE point. The different private types regarding the user behavior are analysed, especially the malicious behavior. The resulting power allocation and the achievable rates at the NE point for all the users with the different individual types are observed. In order to counter the malicious behavior, the strategy-proof mechanism is designed with the punishment price, in which an additional price proportional to user types is introduced. The PoM, the convergence of BRD and the comparison of power allocation with and without malicious behavior are illustrated with numerical results. The regions of prices are shown for 2-user MAC with and without SIC and malicious user, respectively. The price region corresponds to the region of feasible QoS requirements. For every point in the feasible rate region, there exists an individual price such that the QoS requirement can be achieved by the proposed noncooperative game for MAC without and with SIC, respectively.

The universal pricing are successfully applied to resource allocation for the multi-user communication systems. By smart price selection and adaptation, the QoS requirement of each user in the system is guaranteed. The user misbehavior is analyzed, where for centralized resource allocation the malicious users cheat for their reported CSI and for distributed allocation the malicious users misrepresent their utility functions. Methods from game theory and mechanism design are utilized to prevent user misbehavior. By proposing the proper punishment prices, no user has incentives to behave maliciously. Furthermore, some potential future works are discussed in the following.

7.1 Future Works

In this thesis, we focus our scenario on the single cell of multi-user communication systems where single BS exists. The pricing framework could be implemented to multi-cell scenarios. Besides, the general MAC or BC can be extended to interference channels.

For the heterogeneous network, it is interesting to extend results from the single macro-femtocell cluster to multi-femtocells. The different femtocells competes for the nearby MUEs in order to maximize their revenue. The MBS is responsible to distribute different MUEs to separate FAPs in order to improve the energy efficiency of the whole two-tier system. Auction can be utilized to model such scenarios. Each FAP acting as the bidder bids for the quantity of acceptable MUEs. The MBS acting as the auctioneer decides the winner of the auction.

The universal pricing mechanism is adopted in this thesis in order to lead the power allocation to fulfill the QoS requirement of each user in the system. Other methods besides pricing could be interesting for the future works.

List of Publications

I **Fei Shen** and Eduard Jorswieck, "Universal Non-Linear Cheat-Proof Pricing Framework for Wireless Multiple Access Channels," Wireless Communications, IEEE Transactions on, vol.13, no.3, pp.1436-1448, March 2014.

II **Fei Shen** and Eduard Jorswieck, "Universal Linear Pricing for Multiple Access and Broadcast Channels under QoS Requirements," In Proceedings of the 5th International ICST Conference on Performance Evaluation Methodologies and Tools (VALUETOOLS '11), ICST , pp. 538-547, May, 2011.

III **Fei Shen** and Eduard Jorswieck, "Universal cheat-proof pricing for multiple access channels without SIC under QoS requirements," Communications (ICC), 2012 IEEE International Conference on, pp.3895-3899, 10-15 June 2012.

IV **Fei Shen** and Eduard Jorswieck, "User-centric Compensation Framework with Universal Pricing for Hybrid Femtocell Networks," Wireless Communications and Signal Processing (WCSP), 2012 IEEE International Conference on, pp.1-6, 25-27 Oct. 2012. 'Best Paper Award'

V **Fei Shen**, Ming Zhang and Eduard Jorswieck, "User-centric Energy Aware Compensation Framework for Hybrid Macro-Femtocell Networks," 2013 IEEE Global Communications Conference (Globecom), 09-13 Dec. 2013.

VI **Fei Shen**, Eduard Jorswieck, Anil Kumar Chorppath and Holger Boche, "Pricing for Distributed Resource Allocation in MAC without SIC under QoS Requirements with Malicious Users," Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt), 12th International Symposium on, pp. 557-562, May 2014.

VII **Fei Shen**, Eduard Jorswieck, Anil Kumar Chorppath and Holger Boche, "Pricing for Distributed Resource Allocation in MAC under QoS Requirements with Malicious Users," Wireless Communications, IEEE Transactions on, under review, 2014.

VIII Alessio Zappone, Zhijiat Chong, **Fei Shen** and Eduard Jorswieck, "Energy-Aware Competitive Resource allocation in Relay-Assisted Interference Channels," Wireless Communication Systems (ISWCS), 2012 International Symposium on, pp.1029 - 1033, 28-31 Aug. 2012.

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