Development of Efficient Resource Allocation Techniques for Cooperative Communication Networks using Game Theoretic Models

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by

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under the supervision of

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Declaration

I, **Amanjot Kaur Lamba**, hereby certify that the thesis entitled "**Development of Efficient Resource Allocation Techniques for Cooperative Communication Networks using Game Theoretic Models**", submitted to Thapar Institute of Engineering and Technology, Patiala, in partial fulfilment of the requirements for the degree of **Doctor of Philosophy** in **Electronics and Communication Engineering** is an authentic record of my independent and original research work carried out under the supervision of **Dr. Sanjay Sharma** and **Dr. Ravi Kumar**. I have cited the due references about any text/figure/table from where it has been taken.

The work presented in this thesis has not been used for the award of any degree/diploma or some other title from any institution.

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I hereby declare that the above statement made by the candidate is true to the best of my knowledge.

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.........to my family

Abstract

The ever growing need of wireless data services is swiftly saturating channel capacity of present wireless networks. This situation can be dealt with diversity provided by multiple-input multiple-output (MIMO) technology. However, its implementation becomes infeasible for the small size user nodes. Hence, the idea of cooperative communication, which is also regarded as a virtual MIMO, came into existence. With efficient resource allocation, the performance of cooperative systems can be further increased. This research work presents different game theoretic solutions to address the problem of resource allocation in various cooperative networks. Game theory is used to develop and design novel distributed algorithms and cooperation models which consider the tradeoff between the profit obtained through cooperation and the costs for cooperation.

First, a novel integrated scheme based on Stackelberg game (SG) and coalitional game (CG) for both disjoint and overlapping coalitions has been implemented in multi-relay environment. This scheme has paid dividend by ensuring an optimal solution, better throughput and fair distribution of payoffs among relay nodes. Simulation results have confirmed that the formation of coalitions has yielded comparable system throughput with respect to that of the centralized approach. The difference in system throughput obtained by overlapping coalitions and centralised approach comes out to be a meagre 0.05 Mbps in case of orthogonal multiple access (OMA) and 0.06 Mbps for non-orthogonal multiple access (NOMA). However, for disjont coalition scheme, it comes out to be 0.09 Mbps and 0.08 Mbps for OMA and NOMA, respectively. The significantly enhanced throughput of the OCG-SG approach as compared to the disjoint CG approach confirms the efficacy of this technique which seems to be more relevant to practical scenarios.

Additionally, there is a need to consider the possible uncertainties in the channel parameters known to a user owing to the random and dynamic nature of the wireless medium. A low-complexity robust SG has been presented to investigate the joint problem of relay selection and power allocation in multiple-relay device-to-device (D2D) systems in which the imperfect channel state information (CSI) is

considered. Optimality of the obtained solution in terms of power and price has been analytically established by proving the existence of the Stackelberg Equilibrium (SE) in the robust game. Effectiveness of the robust game theoretic solution against the nominal solution in terms of system throughput has been confirmed by the simulation results.

Further, a game theoretic solution has been developed based on auction theory for allocating power in downlink multi-user NOMA and hybrid NOMA-OMA networks. The convergence of these games to a unique Nash Equilibrium (NE) has been established mathematically. Simulation results have demonstrated that the average sum rate of users for the auction-based scheme for downlink hybrid NOMA-OMA networks improves by roughly 39.9% and 35.7% of the auction-based scheme for downlink NOMA networks for 3 and 4 pairs of users, respectively. This confirms that in addition to power allocation, user pairing significantly improves the performance of NOMA systems.

Building upon the above results, a novel cooperative NOMA scheme consisting of low-complexity joint user pairing and subchannel assignment with SG-based power allocation has been proposed. Closed-form expressions for the optimal price set up by the base station (BS) and the power allocated to all users have been derived. The proposed cooperative NOMA scheme yields 25.71% and 45.13% higher average sum rate of users than the random user pairing and fixed power allocation (RUP-FPA) cooperative NOMA scheme as well as the cooperative OMA scheme with $P_t/\sigma^2 = 20$ dB and 15 user pairs, respectively. Besides, simulation results have shown that the proposed cooperative NOMA scheme delivers superior performance than the existing NOMA schemes in terms of average sum rate of users, thus, confirming its effectiveness in improving the system performance.

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Amanjot Kaur Lamba

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List of Abbreviations

3GPP	Third Generation Partnership Project
5G	Fifth Generation
AF	Amplify-and-Forward
AWGN	Additive White Gaussian Noise
B3G	Beyond Third Generation
BS	Base Station
CG	Coalitional Game
CR	Cognitive Radio
CSI	Channel State Information
D2D	Device-to-Device
DD	Destination Device
DF	Decode-and-Forward
FDMA	Frequency Division Multiple Access
HD	Half-Duplex
LAN	Local Area Network
LHS	Left Hand Side
LTE-A	Long Term Evolution-Advanced
MBS	Macro Base Station
MIMO	Multiple-Input Multiple-Output
MRC	Maximal Ratio Combining
MUST	Multiuser Superposition Transmission
NE	Nash Equilibrium
NOMA	Non-Orthogonal Multiple Access
NTU	Non-Transferable Utility
OCG	Overlapping Coalitional Game
OFDM	Orthogonal Frequency-Division Multiplexing
OMA	Orthogonal Multiple Access
RD	Relay Device

RHS	Right Hand Side
RUP-FPA	Random User Pairing and Fixed Power Allocation
SB	Subband
SBS	Small Base Station
SD	Source Device
SE	Stackelberg Equilibrium
SER	Symbol Error Rate
SG	Stackelberg Game
SIC	Successive Interference Cancellation
SINR	Signal to Interference plus Noise Ratio
SNR	Signal to Noise Ratio
TDMA	Time Division Multiple Access
TU	Transferable Utility
QoS	Quality of Service

Chapter 1

Introduction

In the last few years, the tremendous growth in wireless communication has significantly burdened the current wireless network infrastructure to meet the demands of better throughput, more robustness and enhanced coverage. Such demands are, in fact, expected to grow stronger in the next generation wireless systems. Besides traditional voice transmission, wireless communication is playing a pivotal role in carrying more and more real time traffic, like games and videos. The real time traffic needs higher data rates for meeting quality of service (QoS) requirements. Since wireless channels are susceptible to interference, noise, and other impairments, transmitting reliable and high rate data over a wireless channel is quite challenging.

Being one of the fundamental aspects of wireless communication, the phenomenon of fading poses tough technical challenges in designing robust wireless networks [1]. Primarily, fading refers to the variations in time and frequency of the channel quality in a wireless medium. The fading effect can be classified into small-scale fading and large-scale fading [2]. The former occurs because of the constructive as well as destructive interference of the multipath components between the transmitter and receiver ends. On the contrary, the later is caused by the shadowing effects due to large objects like obstacles, hills, buildings etc. and signal attenuation as a function of distance. The initial stage of cell-site planning usually accounts for large-scale fading and mitigates its effect by careful power control. However, small-scale fading, also termed as multipath fading, is critical for designing any robust current or future wireless system.

One of the most promising solutions for dealing with multipath fading and improving the signal quality is spatial diversity. It offers diversity gain without any additional bandwidth or time resource [2]. It can be achieved through multiple-input multiple-output (MIMO) technology, where more than one antenna can be installed at both transmitter as well as receiver ends [3]. However, using MIMO in small size nodes is quite impractical and challenging to achieve [4]. Moreover, it costs more to overhaul the system. A MIMO-based system is expensive as compared to single antenna-based system because of its increased hardware and advanced software requirements. To tackle these issues, the idea of cooperative communication or cooperative diversity came into existence.

Cooperative communications allow single antenna nodes to gain some advantages of a MIMO system. The basic concept is that in a multi-user scenario, single antenna nodes share their antennas in such a way that they form a virtual MIMO system [5]. There are three ways of cooperation realization in the network nodes, namely user-assisted communication, relay-assisted communication and device-to-device (D2D) communication [6]. User-assisted communication allows the network nodes to hear-and-forward signals to other nodes, whereas there is a dedicated relay node that helps in exchange of information in relay-assisted communication. In D2D communication, user nodes forward signals without traversing the core network.

In general, multiple relays can aid the communication from a source to destination simultaneously. However, the reliability of such communications increases only if the network nodes stick to the rules of cooperation. In multi-user wireless systems, all users compete for limited resources, like time, bandwidth, and energy, thus can interfere with each other. The conflicting objectives of users make it highly unlikely for any user to gain more profit without harming other users. The possibility of exploiting interactions among wireless users has not been considered in traditional information-theoretic studies of the multi-user systems. Therefore, the results obtained from the information-theoretic perspectives might lead to unstable or even infeasible solutions for multi-user systems when the selfish nature of the users is considered. Indeed, it is logical to assume that each user competes to attain maximum possible benefit. This competition needs to be regulated and analyzed for improving the overall performance of multi-user systems.

Since game theory is a study of interaction among autonomous agents, it is quite helpful in modeling the autonomous and selfish behavior of the nodes [7]. It can be useful in the cases having conflict in interests of two or more entities. The behavior of entities in a conflicting situation can be expressed by a mathematical model, considering that their actions or decisions follow certain rules. Participants are assumed to act rationally, i.e., they take actions which are expected to generate the largest possible benefit, whilst considering the options of opponents as well as external circumstances.

Therefore, for multi-user systems, the problem of resource allocation can be investigated from a game theoretic perspective. Without coordination among users, the existence of stable outcomes can be analyzed. On the other hand, if there exists a voluntary cooperation among user nodes, extra benefits for all the user nodes can be gained and distributed among them optimally [8]. For both non-cooperative as well as cooperative scenarios, the efficiency of utilizing resources can be boosted and the system stability can be guaranteed.

1.1 Motivation

In recent years, cooperative communication has gained quite popularity in wireless networks. This transmission paradigm creates an efficient virtual MIMO system that exploits the broadcasting nature of the wireless medium. With cooperation among the nodes, a signal travels through various paths between the source and destination. Such multiple versions of the transmitted signal reaching the destination make the links robust to different wireless channel impairments. Further, single hop communication breaks into multi-hop communication [9] with cooperation among the nodes, which reduces the overall signal attenuation as well as transmission power at the nodes. Such fascinating aspects of cooperative communication have motivated to examine its role in yielding power efficient and reliable transmissions.

As wireless communications are always resource limited, a crucial challenge in implementing cooperative communication is how to allocate limited available resources among the various nodes of the network whilst providing QoS. Allocating resources efficiently can give a significant boost to the performance of cooperative networks. If resources are not allocated properly, QoS parameters like throughput, probability of error and received signal to noise ratio (SNR) get affected. Traditional algorithms for cooperative communication assume the existence of a centralized controller which takes the decisions for all the nodes in the network. This centralized entity needs the prior information of whole network to allocate resources among the available users.

These algorithms assume that the available nodes always cooperate for the benefits of the whole network. Moreover, such schemes are computationally expensive and involve high signaling overhead.

This lead to the need for distributed decision making that require only local measurements of channel state information (CSI), thereby, reducing the signaling overhead and computational costs. In distributed schemes, the nodes in wireless networks make decisions related to power, energy, packet forwarding etc. which are constrained by rules and different protocols and algorithms. In making such decisions, the nodes may try to optimize the whole network or work for their own profit [10]. The nodes can act maliciously for the networks and ruin their overall performance. In such cases, game theory is a viable option as game theoretic models support strategy spaces that take dynamic decision making of users into account [11].

As game theory is a powerful bag of tools that helps in modeling the rationality of relaying nodes in interactive decision making processes, it is an appropriate choice for analyzing cooperative communication. Firstly, the network nodes are autonomous and make decisions only in the favour of their own interests. Game theory gives sufficient theoretical tools for analyzing the network nodes' actions and then, allocate the resources to them accordingly. Secondly, game theory deals with distributed optimization, thereby relies on the local information only. This aids in designing distributed algorithms. Therefore, in this thesis, different game theoretic models are designed for various cooperative networks. Distributed resource allocation algorithms are proposed and their performance is examined to demonstrate their efficacy.

1.2 Cooperative Communication

Cooperative communication has been proposed for improving the channel capacity in wireless systems. It utilizes the broadcast nature of wireless transmission along with the spatially separated antennas on wireless nodes to achieve spatial diversity. Besides enhanced capacity, cooperative communication also contributes to high energy efficiency and extended coverage area. Due to the tremendous potential, it has garnered the interest of many researchers for studying its theoretical performance and

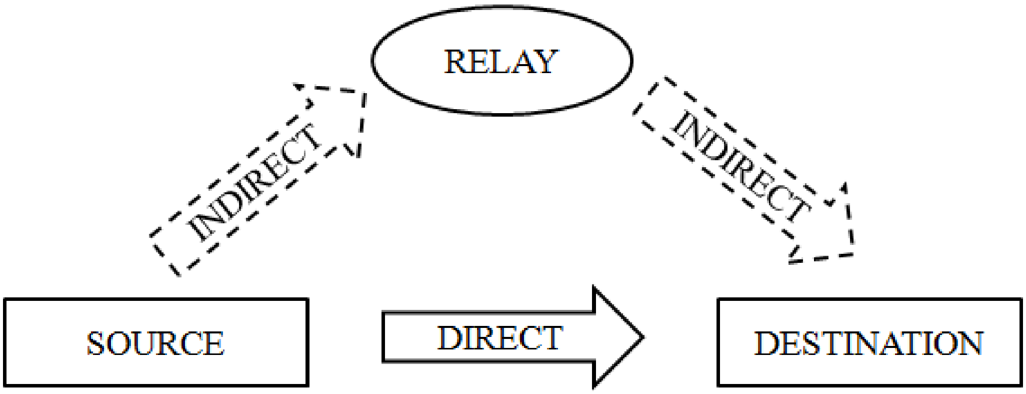


Figure 1.1: Basic model of cooperative communication.

practical implementation. The Long Term Evolution-Advanced (LTE-A) of Third Generation Partnership Project (3GPP) uses relays in mobile broadband access, which results in increased throughput and coverage extension cost-effectively.

1.2.1 Basic Idea

In wireless networks, signal transmitted by a source is broadcasted in every direction in such a way that the nearby nodes can overhear it. Relay listens this signal and further sends it to the intended destination as shown in Figure 1.1. Hence, the transmission in cooperative communication systems is accomplished in two phases:

- **Direct transmission phase:** The signal is transmitted from the source to destination via direct path in this phase. During this phase, relay, within the transmission range, overhears this transmitted signal.

- **Cooperative transmission phase:** The relay carries out certain protocol for the received signal which is then transmitted to the destination in cooperative transmission phase.

This results in two different uncorrelated independent transmissions of the original signal which are received at the destination. Hence, when combined, the resultant signal will never be in deep fade.

1.2.2 Elements of Cooperative Communication

Unlike non-cooperative systems, the three basic elements of cooperative communication model, namely source, relay, and destination, follow certain characteristics that are described below:

- **Source:** A source must be aware of the relay's presence. The signal that reaches relay in the first time slot must reach its intended destination in the subsequent time slot. Therefore, on receiving the signal in direct transmission, the destination must be aware of the fact that it will have to wait for the signal from the relay.

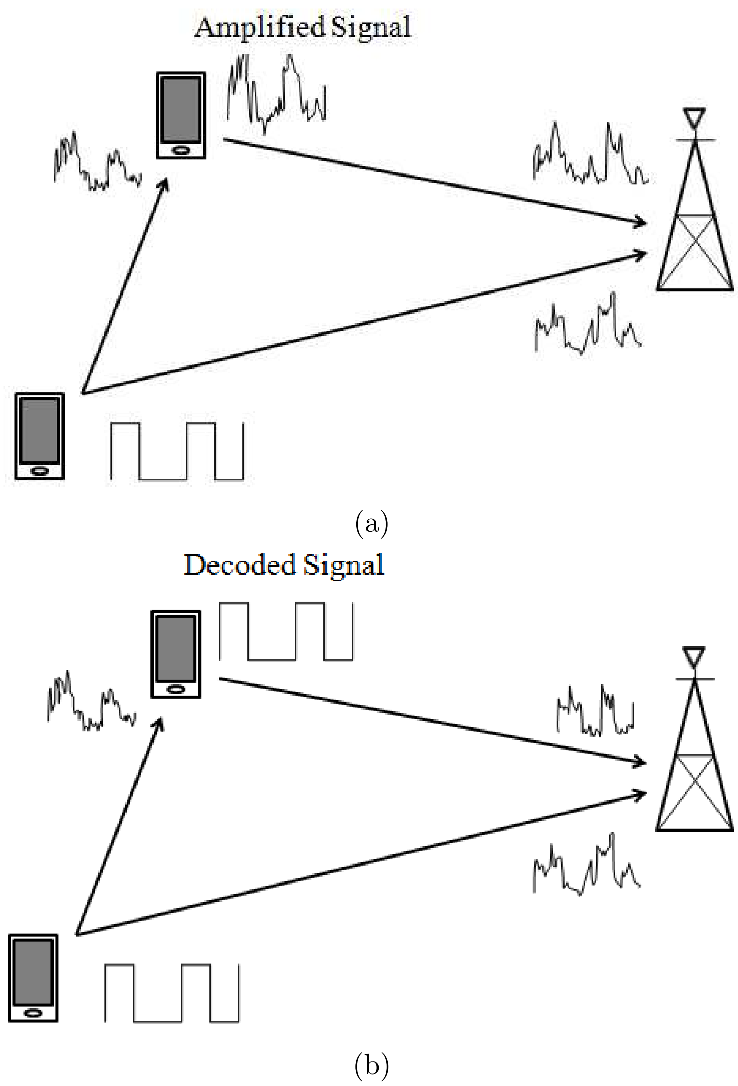


Figure 1.2: Different relaying protocols in cooperative communication: (a) AF protocol, (b) DF protocol. [5]

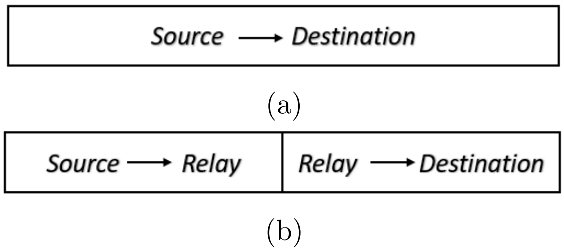


Figure 1.3: Example of time-division transmission for (a) direct communication, (b) multi-hop communication.

- **Relay:** The relay can employ several protocols, like amplify-and-forward (AF) and decode-and-forward (DF) [4], to process the received signal from the source. In AF protocol, it behaves like a repeater. It regenerates the received signal and retransmits it without decoding. On the other hand, in DF protocol, the relay transmits the received signal only after its decoding. Both AF and DF relaying protocols are visually described in Figure 1.2.

- **Destination:** In a cooperative communication system, signals from both the relay and source are received by the destination. The destination can use various combining techniques, like maximal ratio combining (MRC), fixed ratio combining and equal gain combining, to combine the signals received via different paths.

As the signal broadcasted by the source travels two different paths and is transmitted in two different time slots, both spatial and time diversity are exploited in cooperative diversity. An example of a cooperative relay network operating in time-division manner is shown in Figure 1.3.

1.2.3 Cooperative Communication System Model

A general cooperative communication system model consisting of a pair of source-destination (S-D) with a cooperating relay R is shown in Figure 1.4. In orthogonal multiple access (OMA) techniques, cooperation is modeled into two orthogonal phases, namely frequency division multiple access (FDMA) and time division multiple access (TDMA), so as to mitigate interference between the two phases.

Consider TDMA transmission in the system model. Suppose source S broadcasts a message x_s, then the signal received at both relay R and destination D, in the

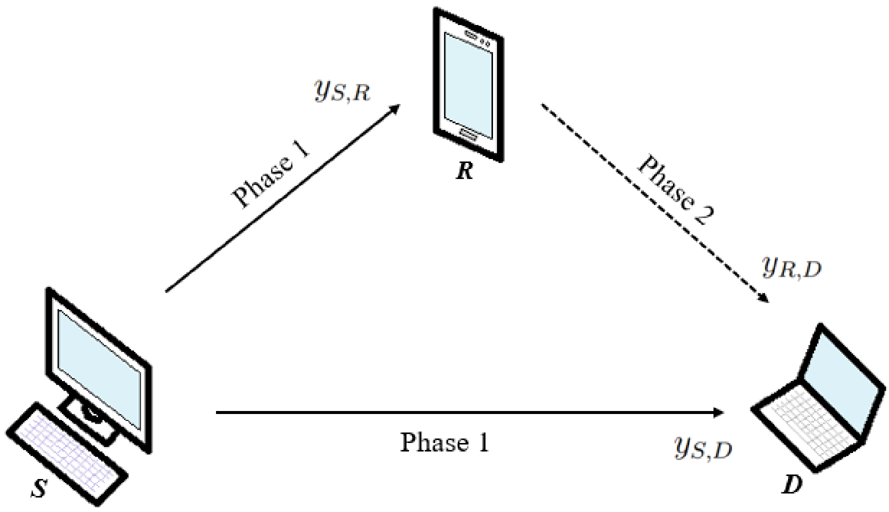


Figure 1.4: Cooperative communication system model.

phase 1, can be represented as

$$y_{S,R} = \sqrt{P_S} h_{S,R} x_S + \eta_{S,R} \tag{1.1}$$

and

$$y_{S,D} = \sqrt{P_S} h_{S,D} x_S + \eta_{S,D}, \tag{1.2}$$

respectively. Here, P_S is the transmit power at source S, $h_{S,R}$ and $h_{S,D}$ denote the respective $S \rightarrow R$ and $S \rightarrow D$ channel coefficients, whereas $\eta_{S,R}$ and $\eta_{S,D}$ represent the zero-mean additive white Gaussian noise (AWGN) samples having same noise power σ^2. Due to the direct transmission, SNR is

$$\Gamma_{S,D} = \frac{P_S \left|h_{S,D}\right|^2}{\sigma^2} \tag{1.3}$$

and the rate is given by

$$R_{S,D} = W \log_2 \left(1 + \Gamma_{S,D}\right), \tag{1.4}$$

where W denotes the bandwidth of the system.

In phase 2, the signal received at destination D due to the transmission by relay R can be expressed as

$$y_{R,D} = h_{R,D} f(y_{S,R}) + \eta_{R,D}. \tag{1.5}$$

Here, $h_{R,D}$ denotes the channel coefficient between relay R and destination D and $\eta_{R,D}$ signifies the zero-mean AWGN with σ^2 noise power. The function $f(.)$ depends on the processing implemented by relay R [12].

1.2.4 Cooperative Relaying Techniques

Different cooperative relaying techniques can be majorly classified into fixed relaying techniques as well as adaptive (or dynamic) relaying techniques. These techniques employ different types of processing by the relay terminals which are discussed in detail in this section.

(A) **Fixed Relaying** Fixed relaying deals with the deterministic division of channel resources between source and relaying nodes. The most popular and widely used techniques are fixed AF and DF relaying protocols.

- **AF relaying:** Centered on the principle of amplifying repeaters [13], AF protocol was formally introduced by Laneman *et al.* [14]. In fixed AF relaying, the scaled variant of the received signal is forwarded to the destination by a relay. The corresponding scaling factor is expressed as

$$\beta = \sqrt{\frac{P_R}{P_S \left|h_{S,R}\right|^2 + \sigma^2}}. \tag{1.6}$$

Hence, the signal received at destination D in the phase 2 is

$$\begin{aligned} y_{R,D} &= h_{R,D}\beta y_{S,R} + \eta_{R,D} \\ &= \frac{h_{R,D}\sqrt{P_R}\left(\sqrt{P_S}h_{S,R}x_S + \eta_{S,R}\right)}{\sqrt{P_S \left|h_{S,R}\right|^2 + \sigma^2}} + \eta_{R,D}, \end{aligned} \tag{1.7}$$

where $\eta_{R,D}$ is the received noise. The SNR of the relayed transmission is given by

$$\Gamma_{S,R,D} = \frac{P_S P_R \left|h_{S,R}\right|^2 \left|h_{R,D}\right|^2}{\sigma^2(P_S \left|h_{S,R}\right|^2 + P_R \left|h_{R,D}\right|^2 + \sigma^2)}. \tag{1.8}$$

Rate of the combined signal after MRC at destination D is

$$R_{S,R,D} = \frac{W}{2}\log_2\left(1 + \Gamma_{S,D} + \Gamma_{S,R,D}\right). \tag{1.9}$$

The rate is scaled by $\frac{1}{2}$ as the communication takes place over two slots.
Since the relay operation does not contain decoding and encoding, the AF strategy has lower demand on processing hardware than the DF scheme.

- **DF relaying:** DF scheme is mostly used in case of digital modulation in wireless communications which gives enough computing power for implementation. A relay decodes the signal received from the source and then forwards it to the intended destination after re-encoding. If an incorrect version of the signal is transmitted, then decoding at the destination becomes useless.
  Fixed DF relaying efficiently reduces the effects of additive noise at the relay as compared to AF relaying. However, it sometimes leads to the erroneously detected signals at the destination, thus diminishing the overall performance of the system.

Although fixed relaying can be easy implemented, but the system yields low spectral efficiency. Since half of the channel resources are allocated to the relaying node, it decreases the overall rate. Sometimes, high percentage of the packets could be decoded correctly by the destination in the direct transmission phase, leading to the wastage of relay's transmissions. To address these issues, adaptive relaying protocols are developed to enhance the system efficiency.

(B) **Adaptive Relaying**

Adaptive cooperation strategies include selective relaying and incremental relaying. Selection relaying decides whether to cooperate or not, based on the SNR between source, relay, and destination, whereas incremental relaying allows cooperation only on requirement. This improves the spectral efficiency of both fixed and selective relaying techniques [4].

- **Selective DF relaying:** In this scheme, signal received by a relay is firstly decoded and then transmitted to its intended destination, provided its SNR at the relay must exceed a given threshold. If the SNR falls below the threshold, the relay remains idle. Selective DF relaying outperforms fixed DF relaying, as the threshold overcomes its problem of forwarding each and every signal decoded by the relay even if some signals are incorrect [15]. The relay decodes the source's signal correctly if its SNR exceeds the threshold value. In such case, SNR of the MRC signal at destination is expressed as the summation of the received SNR from both relay and source.

- **Incremental relaying:** In this type of relaying, destination sends an acknowledgement to the relay over a feedback channel for informing that the message received from the source is deciphered correctly, thus, the relay is not required to retransmit the signal. This saves the spectrum, hence making the system spectral efficient. If the quality of signal at the destination is below threshold in direct transmission phase, then the signal is sent by relay as well. Both the signals that are received from relay and source are combined by the destination. This technique exhibits the best spectral efficiency as it is not necessary for the relay to always transmit. Cooperative transmission phase becomes opportunistic that depends on CSI of the source-destination link.

1.2.5 Applications

Some of the areas where cooperative communication finds its application have been discussed below (Figure 1.5).

- **Virtual antenna array:** Using MIMO technology enhances the diversity gain of wireless networks. However, it is quite unattractive for small network nodes due to their limited signal processing capability as well as hardware. In order to achieve diversity, user cooperation is employed through which wireless users create a virtual array by sharing their resources.

- **Wireless ad-hoc network:** In an ad-hoc network [17], distributed nodes self organize themselves to form a temporary functional network. Such networks are widely used in civilian as well as military communications.

- **Wireless sensor network:** Using cooperative relaying reduces the consumption of energy in sensor nodes and thus, increases the lifetime of sensor networks. Transmissions through weaker links need large amount of energy as compared to that of stronger links. Therefore, precise use of helping relay nodes in routing process leads to the selection of better communication links

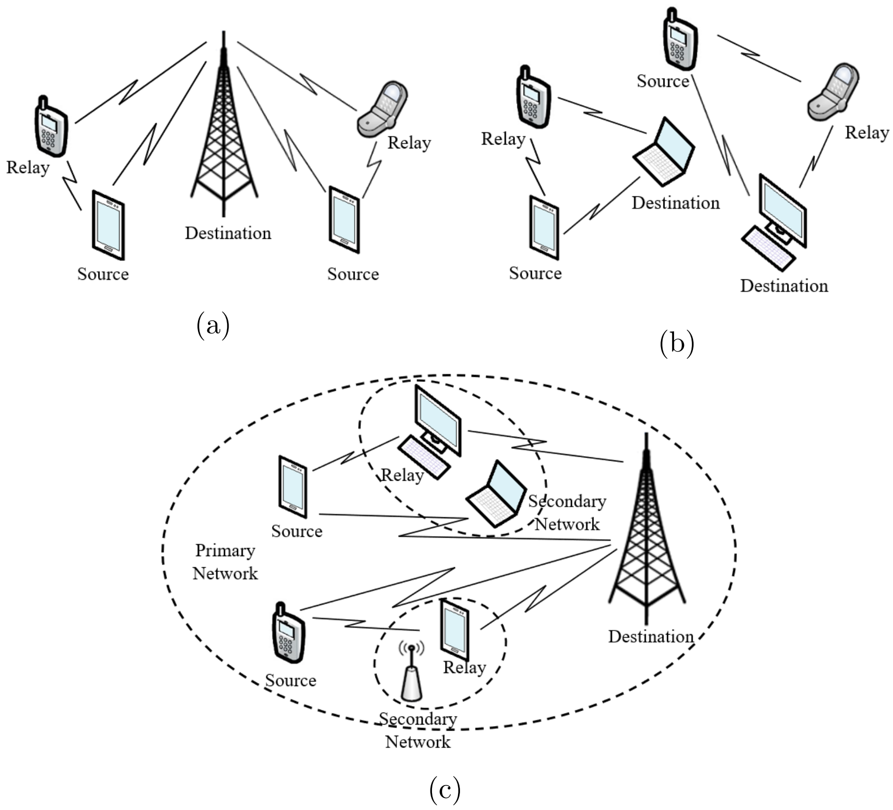


Figure 1.5: Networks where cooperation communication can be applied (a) cellular network, (b) ad-hoc network, (c) cognitive radio network. [16]

and saves battery power.

- **Cognitive radio (CR) network:** The concept of cooperation finds application in CR networks [18] for cooperative sensing. In CR systems, secondary users can utilize the limited resources of licensed primary users for which they are required to constantly sense the presence of primary users. With the help of spatially distributed nodes, probability of false alarm reduces and channel sensing reliability increases by sharing the information [5].

1.3 Need of Game Theory in Wireless Communication

In wireless networks, radio resources, like wireless channels, transmission power, are limited in nature. All the nodes which intend to transmit information should share these limited resources. Regulation of nodes sharing the same radio resources is critical to network performance. Further, the nodes can either compete or cooperate with each other to attain their objectives. Here, game theory proves to be a promising mathematical tool that helps in modeling as well as analyzing the resource allocation problems in wireless scenarios. Critical issues, such as power control, channel assignment, and cooperation enforcement among the networks nodes, can be addressed effectively with the help of game theory. Moreover, game theory can be used to analyze the behavior of nodes owing to its ability in comprehending their interactions with each other.

Further, in wireless networks, centralized controlling usually leads to huge overhead due to much information exchanges and coordination. Thus, distributed algorithms are necessary to make the networks more extensible. However, in the absence of centralized controller, rational nodes tend to optimize their own payoff without taking into account the overall performance of the network. In such cases, the existing centralized schemes are highly unsuitable, whereas game theory can provide distributed solutions for controlling the behavior of nodes owing to its solid theoretical foundations.

1.4 Game Theory in Wireless Communication

Game theory is a powerful bag of tools which is capable of analyzing the conflicting objectives of independent rational players and modeling their decision making interactions [19], [20]. Throughout the past decades, it has emerged as an indispensable mechanism to model strategic decision making problems in variety of disciplines like economics, philosophy, politics, and psychology [21]. This section gives a brief account of the basic concepts of game theory and outlines their usefulness in developing distributed algorithms to achieve efficient resource allocation in cooperative wireless networks.

There are three primary elements of a game model, namely a set of participants (or players), strategy space available to each participant and a set of payoffs corresponding to all combinations of participants' strategies. Particularly, in cooperative wireless networks, participants are the nodes present in the networks. They can be either source nodes which produce data or relaying nodes which forward information to designated destinations in the network. A set of strategies or actions may include decisions pertaining to data forwarding, power allocation, or channel assignment.

Table 1.1: Mapping of components. [16]

Elements of Game Theory	**Elements of Cooperative Communication**
Players	Source nodes Relaying nodes
Strategy	To cooperate or not Channel allocation Power control Price
Payoff/Utility	Revenue Data rate

In particular, source nodes can determine the amount of relaying nodes' resources required and in return, pay for their utilization. Similarly, relaying node can determine the price for sharing their resources in data forwarding. Payoffs may take various forms based on the system parameters, like power consumption, bandwidth utilization, transmission rate or lifetime. These payoffs are essential in designing distributed algorithms in order to facilitate the faithful participation of the selfish nodes in the game [10].

The mapping of the game components to the elements in cooperative communication is given in Table 1.1.

1.4.1 Non-Cooperative and Cooperative Games

Game theoretic framework can be classified into non-cooperative [22] and cooperative game theory [21]. In non-cooperative games, network nodes compete with each other and make decisions rationally so as to maximize their own payoff without considering its effect on the network performance. These games are suitable for modeling the competitive behavior of network nodes.

Since, in a non-cooperative game, no collaboration in the users exists, hence the existence of an equilibrium is the main concern. More specifically, Nash Equilibrium (NE), discovered by an American mathematician, John Nash in 1950 [23] is a key concept for determining a game's outcome in which multiple nodes make their decisions interactively and select their best strategy [19]. Further, the opted actions are such that no selfish node has any motive to autonomously change its strategy. Formally, let Q_i be the set of all feasible actions for node j, where $j = \{1, \ldots, N\}$

and N represents the total number of nodes. Let $q^* = (q_j^*, q_{-j}^*)$ be a strategy profile, i.e. a set containing single strategy for each node, where q_{-j}^* represents the $N-1$ possible actions of all the nodes except j. Let $u_j(q_j, q_{-j}^*)$ be node j's payoff which is defined as a function of the strategies. The strategy profile q^* is a NE if [19]

$$u_j\left(q_j^*, q_{-j}^*\right) \geq u_j\left(q_j, q_{-j}^*\right) \quad \forall\ q_j \in Q_j. \tag{1.10}$$

A game can have many NE if the game has more than two nodes with multiple element choices. A node might be indifferent in some strategies given the other nodes' choices. So if a node selects a different choice than the previous choice, the NE will be different. The strategy profile q^* is unique and called a strict NE if [19]

$$u_j\left(q_j^*, q_{-j}^*\right) > u_j\left(q_j, q_{-j}^*\right) \quad \forall\ q_j \in Q_j. \tag{1.11}$$

Besides establishing the existence of NE, it is desirable to analyze its uniqueness. Further, in the case of more than one equilibrium, it is essential to find those equilibria that are superior to others.

On the other hand, cooperation among the network nodes can be studied by using cooperative game theory. In cooperative games, communication among network nodes is allowed so that they can form binding commitments and the outcomes resulting from their different combinations can be analyzed.

Cooperative game theory typically comprises of two branches, namely Nash bargaining and coalitional game (CG) theory. A bargaining game provides network nodes with the opportunity of reaching a mutually profitable agreement. Nash bargaining solution is essential to cooperative game theory in the context that it establishes a unique Pareto optimality in the game [21]. An outcome of a game is defined as Pareto-optimal if there does not exist any outcome that makes atleast one node strictly better off and other nodes atleast well off [19]. In CGs, network nodes are allowed to form cooperative groups, usually referred to as coalitions, so as to improve their payoff. Coalitions are usually represented in terms of a characteristic function, which determines their outcomes on cooperation.

Since Stackelberg game (SG), auction mechanism and CGs are extensively employed in this thesis, their main principles are elaborated in the subsequent subsections.

1.4.2 Stackelberg Game

SG [19] is worth to mention particularly because it constructs a finite sequential game by introducing leaders and followers. In one-leader one-follower game, leader will choose first to maximize its payoff, so the original game converts into subgame where rational followers would make decision according to their observation of the strategy chosen by the leader. In multi-leader multi-follower SG, leaders often compete with each other and choose their actions by anticipating the followers' strategies. Here, leaders know the action set of all the followers. Given the leaders' decisions, the followers compete with each other.

As a non-cooperative game, there is a concept of equilibrium applied to SG which is named as Stackelberg Equilibrium (SE). The solution to get SE could be the same as tracking down the subgame perfect NE, since SG can be considered as a subgame peeled from original game. Observing the leader's action y, the follower responds with strategy $f(y) : y \to z$ which is optimal in regard to its expected payoff. A pair of strategies $(y, f(y))$ is said to be SE if [24]:

- The leader chooses its best-response strategy

  $$u_l(y, f(y)) \geq u_l(y', f(y')), \tag{1.12}$$

  for all leader's strategies y'.

- The follower chooses its best-response strategy

  $$u_f(y, f(y)) \geq u_f(y', z'), \tag{1.13}$$

  for all follower's strategies z'.

At the equilibrium, the leaders and followers do not deviate from their strategies as their revenues are maximum at this point.

1.4.3 Auction Theory

An auction is a process that is regulated by an auctioneer who wants to sell its resources or services by eliciting bids from potential buyers, usually referred to as bidders [25]. Specifically, for the resources placed out for auction, bidders place their bids and resources are, then, allocated to them according to the auction rules and the submitted bids. Primarily, in wireless networks, an auction model consists of [26]

- a set of potential buyers or bidders
- a set of possible resource allocations subject to constraints, if any
- a set of bidders' payments defined as a function of the bids

In many cases, an auction is precisely held since the seller wants to sell the resource but is unsure of its value. So by placing it out for auction, the bidders will determine its worth. Since the bidders do not know the value of the resource either, they will have their own independent private valuation of the resource, which can be different for each bidder. Each bidder wants to attain the resource and pay for it in such a way that it leaves them with the maximum possible profit. Hence, a bidder will never place a bid greater than its valuation of the resource. This mechanism can also be used to determine a "winner" who gets the resource and how much it should pay on the basis of the resource allocated to it [26].

1.4.4 Coalitional Games

Being a primary class of cooperative games, CGs are essentially employed in modeling formation of coalitions, allocation of resources and decision-making within the domain of game theory. The network nodes may form coalitions to accomplish a joint objective in addition to achieve their individual goals, provided that this cooperation benefits them. For T set of N network nodes, the coalition value, $w(L)$ measures the worth of a coalition $L \subseteq T$ in a CG defined by the pair (T, w). A coalition can be either represented in characteristic, partition, or graph form [27].
The characteristic form of a coalition was introduced by Von Neuman and Morgenstern [28]. In this, a coalition value, $w(L)$ solely depends on its coalition members

and not on the members in $T \setminus L$. If the total utility of a game, i.e. $w(T)$, can be divided among the coalition members in any manner, then the game is referred to as a CG with transferable utility (TU). The amount of utility obtained from the division of $w(T)$ by a node is termed as its payoff. On the contrary, there exists some scenarios where the distribution of total utility is restricted. Such games were introduced by Aumann and Peleg [29] and are often referred to as CGs with non-transferable utility (NTU) [21]. In NTU games, utility of each node in a coalition L depends on the joint actions of its members.

A game in partition form is one in which the value of a coalition $L \subseteq T$ is dependent on the other existing coalitions which are constituted by the members in $T \setminus L$ [30]. In these games, a coalition structure $\mathcal{L}$ can be defined as a collection of coalitions $\mathcal{L} = \{L_1, \ldots, L_l\}$, such that $\forall\ m \neq n$, $L_m \cap L_n = \phi$, and $\bigcup_{m=1}^{l} L_m = T$.

On the other hand, a game in graph form is one where the connections among the member nodes through a graph structure affect their coalition value [31]. In other words, the connectivity between the nodes within a coalition has a strong impact on the game's outcome.

A coalition structure is said to be stable when no node or coalition has a motive to deviate. In CGs, it is necessary to determine the stable coalition structures from all the possible ones which is a challenging combinatorial task. Furthermore, this task is often hindered by its high computational complexity and limited execution times. Hence, it is desirable to incentivize nodes to facilitate coalition formation whilst designing distributed algorithms and pose a good tradeoff between complexity and optimality.

1.5 Organisation of Thesis

The work in this thesis has been organized into seven chapters. The contents of all the chapters are briefly described below:

- **Chapter 1** presents the motivation for research, background theory of co-operative communication, cooperative communication system model, different cooperative relaying techniques and its applications. In addition to the need of game theory in wireless communication, it also discusses the concept of game theory and different games that are extensively used in wireless communication. Further, it presents the organisation of thesis.

- **Chapter 2** provides an exhaustive literature review on cooperative diversity in wireless networks and different resource allocation techniques in cooperative networks. Game theoretic resource allocation in cooperative wireless networks is also discussed. Further, limitations in the existing studies, problem formulation and research objectives are also presented.

- **Chapter 3** describes an incentives-based scheme to address power allocation issue in a single source, multiple-AF relay network. A game theoretic framework is provided for both disjoint as well as overlapping coalitions for finding a stable and optimal coalition set of relays.

- **Chapter 4** concentrates on the joint problem of relay selection and optimal power allocation in cooperative D2D communications under uncertainties in relaying channel conditions. A closed-form expression for the optimal power is obtained. Further, the SE is derived and its existence and uniqueness are demonstrated.

- **Chapter 5** presents auction-based power allocation schemes for both downlink cellular non-orthogonal multiple access (NOMA) and multi-user hybrid NOMA-OMA systems. The outcome of the games is investigated and their convergence to a unique NE is established mathematically.

- **Chapter 6** focuses on the problem of user pairing, subchannel assignment and power allocation in a downlink cooperative NOMA network. A joint user pairing and subchannel assignment algorithm is described that pairs a user having strong channel conditions with a user having weak channel conditions and assigns them a subchannel simultaneously. Closed-form expressions for optimal price as well as optimal power allocated to the users are also derived.

- **Chapter 7** provides the conclusions drawn from the research and outlines the possible extensions of this work in the future. The thesis concludes with the list of publications and references that were found useful throughout the course of research work.

1.6 Chapter Summary

This chapter presents the introduction and motivation for research. Through this chapter, the background theory of cooperative communication, cooperative communication system model, different cooperative relaying techniques and its applications have been explained. Need of game theory in wireless communication has been demonstrated. Further, the concept of game theory and various games are discussed in context with wireless cooperative communication. It has also presented the outline of thesis. In the next chapter, a comprehensive literature survey has been carried out so as to gain complete knowledge about the current scenario of cooperative diversity in wireless communication and different resource allocation techniques in cooperative networks.

Chapter 2

Research Background and Literature Survey

This chapter provides a comprehensive research background and literature survey on cooperative diversity and resource allocation techniques in cooperative networks followed by an extensive review on different game theoretic models for allocating resources in cooperative networks. After a brief introduction in this section, the first part of this chapter, i.e. Section 2.1, discusses the literature and current scenario on cooperative diversity. Section 2.2 presents the existing works in resource allocation in cooperative networks, highlighting specifically relay selection and power allocation. Section 2.3 discusses game theoretic resource allocation in cooperative networks. Limitations of the existing works are put forth in Section 2.4. The research problem is formulated in Section 2.5, whereas Section 2.6 provides the research objectives.

2.1 Cooperative Diversity in Wireless Networks

The concept of cooperation in a wireless scenario can be traced back to the pioneering work done by Van Der Meulen [32] in 1971. He first introduced the classical relay channel in which the underlying idea of cooperative diversity lies. Later, in 1979, lower and upper bounds on the channel capacity of a network having a single source-destination pair with one relay were derived by Cover and El Gamal in [33]. Authors [34] and [35] introduced the idea of user cooperation in 2003.

In 2004, cooperative diversity was formally introduced in [4]. Various protocols for half-duplex (HD) relays, namely AF and DF were analyzed along with their outage capacity to combat multipath fading in wireless networks. The authors proved that without physical arrays, the benefits of spacial diversity can be reaped by employing distributed antennas, though at the cost of additional receiver hardware and loss in spectral efficiency. In [5], Nosratinia *et al.* gave a nice introduction to this paradigm. They presented several signaling schemes for cooperative networks and discussed their realistic implications on the system design. Later, Ng and Goldsmith [36] presented a general analysis on the effect of CSI and power allocation on the performance of cooperative networks. Besides transmitter cooperation strategies, they paid attention to the receiver cooperation as well.

Recently, NOMA [37] has been proposed to enhance the spectral efficiency of fifth generation (5G) networks [38], [39]. For instance, a downlink version of NOMA, i.e. Multiuser Superposition Transmission (MUST), has been proposed for 3GPP LTE-A networks [40]. Unlike OMA, NOMA exploits power domain to serve multiple users in the same frequency and time resources [41], [42]. This is achieved by employing superposition coding at the transmitting ends with successive interference cancellation (SIC) at the receiving ends [43]. Owing to its potential benefits, NOMA is integrated with various existing wireless technologies, such as MIMO [44], beamforming [45], network coding [46], millimeter-wave communication [47] and cooperative communication [48], [49].

The application of cooperative relaying in NOMA is quite significant as it achieves spatial diversity even if the nodes are equipped with single antennas [50]. In [51] and [52], a dedicated relay was employed by the authors to aid transmission between the BS and NOMA users. User cooperation in NOMA networks was first introduced in [41] in 2015, where users with strong channel conditions were assumed to act as relays. Since SIC is used at the receiving ends in NOMA systems, users with stronger channel conditions decode the information intended for the users with weaker channel conditions. Therefore, the users with good channel conditions are recruited as relays to increase the reception reliability of the users with poor channel conditions. Further, Khan and Sohaib [53] proved that relay-cooperative NOMA yields significant performance gains as compared to that of non-cooperative NOMA.

Complexity is critical to the implementation of cooperative NOMA. Combining all the users to execute cooperative NOMA is quite unrealistic, as coordinating multiuser networks along with user cooperation will produce considerably large system overhead. To tackle these issues, Ding *et al.* [54] proposed a hybrid multiple access network incorporating user pairing/grouping to reduce the system complexity of cooperative NOMA. It was demonstrated that pairing user nodes with distinctive channel conditions results in a considerable increase in sum rate of the system.

2.2 Resource Allocation in Cooperative Networks

The overall performance of cooperative networks is largely dependent upon the resource allocation. Efficient resource allocation reduces battery consumption of the users and lessens the effect of interference in cooperative networks, thereby increasing their performance. The performance enhancement with cooperation can be evaluated in terms of increased throughput, better link reliability, extended coverage area, diversity gain, and balanced QoS of all the users.

Relay and power are the two fundamental resources in cooperative networks. With optimal resource allocation, relay and user cooperation can significantly improve the performance of the system. A crucial challenge in implementing cooperation in wireless networks is assignment of source-relay pairs before the cooperation begins.

2.2.1 Relay Selection

In general, relay selection can be categorized into single-relay selection and multiple-relay selection. Many researchers have investigated the performance of single-relay and multiple-relay cooperative networks. For example, Su *et al.* [55], [56] analyzed the symbol error rate (SER) performance of single-relay AF as well as DF cooperative networks under Rayleigh fading channels and derived both exact and asymptotic upper-bound expressions for the same. SER performance of multi-user single AF relay networks under Nakagami-m fading channels was analyzed by Yang *et al.* in [57]. On the other hand, Anghel and Kaveh studied the exact SER performance for multiple-relay AF cooperative networks in [58], whereas the exact as well as asymptotic performance of a multiple-relay DF cooperative network was analyzed in [59]. All the aforementioned techniques assume OMA technology.

The effect of relay selection on the performance of cooperative NOMA networks was investigated in [50], [60] and [61]. Further, Nomikos *et al.* in [62] proposed two relay selection strategies for NOMA and hybrid NOMA/OMA networks with multiple HD buffer-aided relays. It was shown that the opportunist relay selection can improve the system performance in terms of average sum rate and delay by efficient scheduling and prioritizing relay-destination links.

The most popularly used relay selection metrics are as follows:

- **Geographical location:** By this criterion, selection of relays is done according to their spatial distribution, assuming that their location is well known or can be estimated [63], [64]. However, this metric neglects the effects of fading and shadowing.

- **Average channel characteristics:** This metric selects relays according to the estimated values of average SNR or average channel characteristics. This method is recommended in case of static terminals. Since, the channels are prone to significant changes, it is not considered suitable for mobile terminals, like drones [65].

- **Instantaneous channel characteristics:** This metric was implemented by the numerous works like [66], [67]. By this metric, estimation of instantaneous channel characteristics is used to select relays. However, it suffers from the generation of huge overload due to the propagation of channel information between the terminals.

2.2.2 Power Allocation

Besides relay selection, allocation of power is another problem that could enhance the system performance with a proper solution. In 2003, Laneman and Wornell [68] studied the performance of an "all participate" AF network with uniform power distribution. This scheme obtained $(m+1)$ diversity order for m relays.

Later, the problem of power allocation in AF OMA networks was investigated in [69, 70, 71, 72, 73, 74, 75]. [70, 69, 71, 72, 73, 74] considered single-relay networks and proposed different solutions for optimal power allocation among the source and relaying nodes to minimize transmission power [69], maximize capacity [70], minimize sum-source-power [71], minimize outage probability [72], [73], or minimize probability of error [74]. In 2004, Hasna and Alouini [75] studied the optimal allocation of power over Rayleigh fading channels in multi-hop transmissions, where the relays were used to extend the coverage area. They showed that non-regenerative (AF) relay systems with optimal power allocation can outperform regenerative (DF) relay systems without power optimization.

Power allocation in DF OMA networks for a single user was studied in [76] in 2007, assuming that transmitters only possessed the knowledge of mean channel gains. Later, in 2010, the resource allocation problem in wireless multi-user DF relay networks was considered by Gong *et al.* in [77]. Authors in [78] investigated relay selection and power allocation in multiple-DF relay-assisted orthogonal frequency-division multiplexing (OFDM) CR networks aiming to maximize the instantaneous capacity of its transmission.

In recent years, the problem of optimal power allocation in NOMA AF relay networks has been discussed in [79] and [80]. Zhao *et al.* [79] addressed a sum rate optimization problem where the channel uncertainties were modeled by a worst-case model, whereas Gong *et al.* [80] addressed the power allocation problem at secondary users for overall system throughput maximization in a non-orthogonal AF cooperation-assisted NOMA network.

Further, in [81], Li *et al.* employed the Lagrange dual method and the Hungarian algorithm to address a joint problem of subcarrier pairing and power allocation for two-user downlink cooperative NOMA systems in a multi-carrier scenario. A power allocation strategy to optimize the worst-case energy efficiency of all users for a fixed relay assignment in multiple HD DF relay NOMA networks was proposed by Duan *et al.* [82] in 2020. In the same year, Dinh *et al.* [83] proposed a low-complexity framework for user pairing and power control in cooperative NOMA systems for maximizing the total achievable sum rate of the system while assuring a given QoS for all user nodes.

Moreover, several works have considered joint user/relay selection and power allocation in cooperative NOMA systems. For example, [84] proposed a relay selection and adaptive power allocation scheme and then, evaluated the outage performance of the system. In addition, [85] proposed a joint relay selection and power scheme to enhance the energy efficiency of the system.

However, all the aforementioned studies assume that all the nodes in a network are always helpful and cooperative with the other nodes. In such cases, game theory is a viable option as game theoretic models support strategy spaces while considering the dynamic decision making of the nodes.

2.3 Game Theoretic Resource Allocation Techniques in Cooperative Networks

Game theory is a powerful bag of tools that helps in constructing mathematical models involving conflict and cooperation among the rational decision-makers [21]. Since both conflict and cooperation coexist in a wireless scenario, both non-cooperative and cooperative game theoretic models have found wide applications in different wireless networks.

2.3.1 Non-Cooperative Game Theoretic Resource Allocation

One of the fundamental applications of game theoretic models in wireless communication is to model and analyze the problem of resource allocation [86]. Liang *et al.* in [87] addressed the problem of relay assignment in multiple-relay networks by modeling the available relays as rational players. Al-Tous *et al.* [88] proposed an AF cooperative scheme for jointly allocating power and bandwidth, aiming at maximization of sum rate in multi-user uplink networks.

To achieve better performance with lesser resources seems attractive to users as well as service providers [89]. However, when nodes do not belong to a same service provider, the problem of selfish node arises. Therefore, it is desirable to motivate such nodes to ensure cooperation. This motivation may be in terms of virtual payment [90], [91], reputation index [92], and exchange of resources [93]. A two-level SG proposed by Wang *et al.* in [94] modeled source and relays as buyer and sellers, respectively, for optimal power allocation in multi-user cooperative networks. Authors in [95, 96, 97] devised SG models for resource allocation in D2D communications, where BS acted as the leader and D2D pairs behaved as the followers. Huang *et al.* [98] used auction mechanism to allocate power among available relays for transmission rate maximization of the system. However, the authors in [90, 91, 92, 93, 94, 95, 96, 97, 98] considered OMA transmission in their work.

On the other hand, a subchannel and power allocation scheme based on matching game for a single-cell cooperative NOMA network was studied in [99]. Zhang *et al.* [99] considered an OFDM-AF relay that allocated power and spectrum resources to the source-destination pairs.

However, the aforementioned techniques neglect the fact that the relay nodes are capable of forming coalitions, to favour common interests and maximize the overall gains of their respective groups [100].

2.3.2 Cooperative Game Theoretic Resource Allocation

The fundamental branch of cooperative games demonstrates coalition formation [21] to strengthen the position of players in a game. Hence, CG theory is popularly used in modeling formation of coalitions by helping nodes in wireless networks. Saad *et al.* [101] developed a distributed merge-and-split algorithm for network nodes to form virtual MIMO clusters. In [102], the authors proposed a coalition-based scheme for selecting the best relays from the available relaying nodes and allocate optimal power to them for enhancing the system performance. Baidas and MacKenzie [103] proposed an altruistic coalitional model using a distributed merge-and-split algorithm allowing the relays to form groups in order to increase their achievable rate. Gao *et al.* [104] proposed a two-level decentralised approach based on CG for joint relay selection and resource allocation in network coding-assisted D2D communications. However, most of the existing research works based on CG model assume that the players form 'disjoint' coalitions; in other words, each player is allowed to join a single coalition which restricts its payoff [105].

To extract more gains from cooperation, it is necessary that the nodes should be allowed to form 'overlapping coalitions' and hence, receive payoffs from their respective multiple coalitions. Xiao *et al.* in [106] analyzed the spectrum sharing problem in D2D communications and proposed a Bayesian overlapping coalition formation game theoretic model for the same. In [107], the authors employed overlapping coalitional game (OCG) model for cooperative spectrum sensing in multichannel CR networks so as to achieve higher throughput in comparison with the respective disjoint CG model. Zhao *et al.* [108] proposed an overlapping coalition formation approach for joint spectrum resource allocation and relay selection in network coding-aided cooperative D2D communications.

There are several works in which authors integrated both non-cooperative and cooperative game theory to model their complex problems. For instance, an OCG-based double auction was used in [109] to address the problem of spectrum allocation along with economic efficiency. Further, a hierarchical framework employing OCG and SG was proposed by authors in [110] to jointly optimize the transmit power and sub-band (SB) allocation in heterogeneous networks. However, in [110], the cooperative unlicensed users form overlapping coalitions autonomously so as to maximize their payoff only.

2.4 Limitations of the Existing Studies

On the basis of the literature discussed, following limitations and research gaps have been identified in the existing studies.

- The existing methods studied in Section 2.2 ignore the fact that in reality, all user nodes may not be selfless. They wish to optimize their own profits while sharing their resources. Although some solutions exist for the selfish relay power allocation as discussed in Section 2.3, yet there is a sparsity of the literature that presents the joint source and relay power allocation solution to address the issue.

- Most of the current research on cooperative game theoretic solutions to resource allocation problem in cooperative networks is quite restricted to using standard CG models and analyze only limited aspects of cooperation.

- Most of the existing works ignore the fact that the dynamic nature of wireless networks may lead to uncertainty in the channel parameters known to a user. The literature lacks the game theoretic solution for resource allocation in cooperative networks under relaying channel uncertainties.

- Dense deployment of small cell networks leads to a higher number of nodes and heavy signaling overhead. The complexity of the existing algorithms increases many folds in such scenarios. The present state-of-the-art seems to treat this issue rather superficially. This necessitates further analysis for complexity reduction.

- In the recent years, NOMA has drawn great attention as a promising radio access technology for 5G and beyond networks. By multiplexing users in the power domain, NOMA can support several users simultaneously within the same time slot or frequency band. This, however, introduces severe interference among users. However, there is a dearth of literature investigating the effect of interference on cooperative NOMA networks.
- The research on cooperative NOMA is still in its infancy. Resource allocation in cooperative NOMA networks using game theoretic models has not been widely explored.

Based on the literature review and limitations of the existing works, formulated problem for this thesis is given in the next section.

2.5 Research Problem

Over the last couple of decades, the evolution of wireless communications from second generation to higher generation technologies has been swift, yet steady. The number of subscribers has increased from millions to billions in last few decades. Since more number of devices, with higher data rates are involved in communication in wireless medium, the effect of impairments needs to be addressed. Therefore, ingenious methodologies and techniques are required to combat the effects of environmental impairments on wireless networks. MIMO systems have proved to be a breakthrough in wireless communications but their use in small size nodes posed a challenge. In this context, cooperative communication has emerged as a novel paradigm which can exhibit high performance gains of the wireless systems. With optimal resource allocation, relay cooperation can significantly enhance the efficiency and efficacy of the communication systems. Despite that, implementing cooperation in large-scale networks encounters challenges like complexity, efficiency, fairness, and adequate modeling, among others.

Most of the existing cooperative systems assume the ideal cooperation, i.e. without any cost. These systems mostly focus on analyzing the benefits of cooperation, while giving less consideration to its impact on the networks' structure and the nodes' behavior. Thus, it is necessary to design cooperative algorithms that study the cost of cooperation and its effect on the overall structure and dynamics of the networks, besides reaping the numerous gains from its implementation.

With the selfish nature of wireless network nodes, it is challenging to derive practical and fair algorithms where the decision of not cooperating does not deteriorate the performance of any helping node. Further, use of distributed cooperative strategies with little to no dependency on centralized controllers is highly desirable. In this regard, game theory proves to be a highly suitable mathematical tool for analyzing the rational behavior and dynamic decision-making of the nodes in wireless systems. In addition, cooperative systems are viable only if the competitive nodes are willing to cooperate. Practically, relaying nodes may not help and share their power unless they are provided with some reimbursement. There is a need to stimulate cooperation among the nodes so as to improve the network performance.

While non-cooperative game theory provides analytical tools for studying competitive scenarios, cooperative game theory analyzes the behavior of rational nodes whenever they cooperate. In spite of the benefits of CG, it is quite challenging to find a stable and optimal coalition structure which is acceptable to all nodes of the system. Further, fair allocation of the aggregated utility among the members of a coalition is also challenging to achieve.

In addition, most of the studies proposed so far suppose that each node is completely aware of the transmission parameters of the other nodes which may not be practical owing to the random and dynamic nature of wireless environment. There is a need to consider the fact that information uncertainties are bound to happen and hence, they should be taken into account while investigating the various problems in wireless networks.

Recently, NOMA is viewed as a promising disruptive technology for future wireless networks. Due to enhanced system throughput and extended coverage area of cooperative wireless networks, NOMA has been paired with cooperative relaying to further enhance the performance of NOMA systems. However, both multi-user interference and complexity of the system increase with more users being multiplexed on the same subchannel, thereby, degrading the performance of individual users. Since the performance of NOMA systems is heavily influenced by resource allocation, there is a dire need to develop efficient resource allocation techniques to enhance the performance of such systems.

2.6 Research Objectives

Based on the aforementioned aspects, the research objectives for this research work are as follows:

- To propose a low complexity distributed algorithm for cooperative communication networks with fair resource allocation using game theoretic model.
- To formulate optimal power allocation solution for multi-relay system model considering the selfish behavior of nodes.
- To propose a stable coalitional framework in order to enhance the efficiency of the intermediary nodes and increase the system throughput.
- To formulate a game theoretical model for multi-relay networks with reduced interference.

2.7 Chapter Summary

An extensive literature survey has been carried out in this chapter to understand the current scenario of cooperative diversity and acquire knowledge of different resource allocation techniques in cooperative networks. Limitations in the existing studies have been highlighted and further, the problem for the thesis has been formulated. In addition, objectives for the current research work have been established. The next chapter presents a novel integrated game theoretic framework that involves incentives-based allocation of power among the cooperating relays.

Chapter 3

A Coalitional Game-based Integrated Framework for Optimal Power Allocation in Multiple-relay Cooperative Networks

Cooperative relaying has a prominent advantage of mitigating the effects of fading in a wireless network. Allocating resources efficiently can considerably enhance the performance of multi-relay systems affected by fading. In spite of that, a relay may refuse to cooperate unless given some incentive. To deal with this issue, this chapter presents a novel incentives-based game theoretic solution for optimal power allocation, where an SG is integrated with a CG. CG has been employed for modeling the cooperation among helping relays, whereas SG models the interactions between source and coalitions formed by relays. Besides considering the mutual benefits of source and relays, the proposed scheme has been formulated for disjoint as well as overlapping coalition set of relays. Simulations results confirm that the performance of proposed game theoretic solutions is comparable to that of the centralised scheme in terms of system throughput. Particularly, OCG approach yields better performance than the disjoint CG approach.

3.1 Introduction

Relay cooperation is viewed as a promising exemplar for data transmission in wireless networks with fading channels [4]. With optimal resource allocation, relay cooperation can significantly improve the performance of the system. To extract more gains from cooperation, it is necessary that the nodes should be allowed to form overlapping coalitions and hence, receive payoffs from their respective multiple coalitions. Initiating cooperation in wireless networks in the absence of a centralized controller is a dynamic process. Therefore, it is difficult but highly desirable to design distributed algorithms which can establish cooperation without depending on the centralized entity. In spite of the significant benefits of CGs, the primary challenge remains in the form of finding a stable coalition structure which is acceptable to all relays along with the source. Fair allocation of the aggregated utility among the members of a coalition is also challenging to achieve. This work addresses the above challenges by ensuring appropriate payoffs to the relays participating in the CG as well as maximizing the utility of the source.

In relay-aided networks, power is an important and scarce resource, which needs to be allocated optimally; while keeping in mind, the network throughput and energy efficiency [71]. However, practically, relay nodes may not cooperate and share their power unless provided with some reimbursement. This provided motivation to work on incentives-based optimal coalition selection and power allocation in multiple-relay cooperative environment.

In this chapter, an integrated game theoretic framework based on SG and CG has been formulated for both disjoint and overlapping coalitions. For analyzing the interactions between source and relays, SG is used in which the source is modeled as a buyer, while the relays are modeled as sellers. CG is used for modeling the cooperative conducts of the relays, which tend to form a stable and the best suitable coalitions structure. Allocating power optimally to the relays within the coalitions at optimal prices establishes SE of the game. This jointly maximizes the utilities of source and relays. The effectiveness of the proposed scheme is studied against the centralised scheme and cooperative scheme with non-overlapping coalitions. To the best of the author's knowledge, this is the first work to apply incentives-based OCG-SG integrated framework to deal with optimal power allocation in a multiple-relay wireless network with a single pair of source and destination, that considers the utilities of source and relays at once.

The main contributions of this work can be summed up as follows:

- A novel integrated scheme based on CG and SG is proposed for both disjoint and overlapping coalitions to optimally allocate power among available relays by the source.

- The OCG model is utilised to study the cooperative nature of relays in multiple coalitions, thereby enhancing their cooperative gains. The problem is formulated as an NTU game. Optimal allocation of power at optimal prices is done by considering the mutual benefits of the relays and source through the SG model.

- Fair distribution of payoffs to the relays is ensured.

- Two cases are considered, one in which relays within a coalition use orthogonal channels for transmission and one incorporating non-orthogonal transmission of signals by the relays in a time slot. No interference among relays belonging to same coalition is perceived due to the orthogonal transmission of signals. However, intra-coalition interference is considered when relays within a coalition employ NOMA for transmission.

- Attainment of a unique, stable, and satisfactory overlapping coalition structure.

The remaining chapter is organized as follows. Section 3.2 provides the system model for the proposed scheme. In Section 3.3, the problem is discussed and formulated. Sections 3.4 and 3.5 describe the centralised approach and disjoint coalition formation game approach for the stated problem, respectively. The detailed insight of the proposed OCG–SG framework is given in Section 3.6. The performance of the proposed game theoretic solutions is evaluated through simulation results in Section 3.7. Finally, Section 3.8 summarizes the chapter.

3.2 System Model

Consider a wireless network having a single pair of source-destination (S-D) and K AF relays R_k, $k \in \{1, 2, \ldots, K\}$, $K \geq 2$. Source S transmits its message to destination D over two phases. The model assumes that all the network channels are quasi-static. Source S can figure out the available relays by transmitting a signal and listening to the feedback of relays, if they wish to cooperate or not. The available relays form coalitions C_j, $j \in \{1, 2, \ldots M\}$, $M \leq K$, where M is the total number of coalitions formed. A coalition having a single relay is termed as singleton

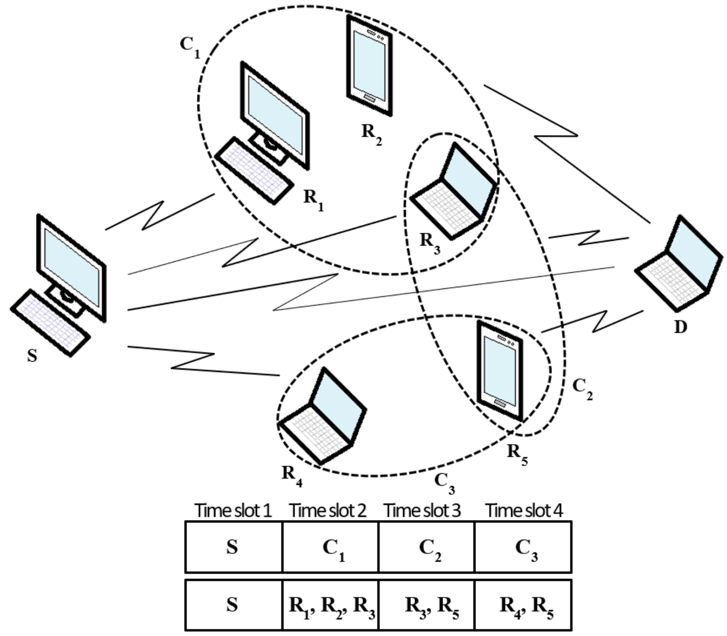


Figure 3.1: System model for a multi-relay network with $K = 5$ and $M = 3$.

coalition.

Further, TDMA transmission is considered in the system model. The first time slot is used by the source S to transmits its signal. The subsequent time slots are used by the different coalitions in a TDMA manner, which is one coalition per time slot, therefore, no interference is perceived from other coalitions during transmission [101]. An example of system model with overlapping coalitions for $K = 5$ and $M = 3$ is shown in Figure 3.1 in which coalitions $C_1 = \{R_1, R_2, R_3\}$, $C_2 = \{R_3, R_5\}$, and $C_3 = \{R_4, R_5\}$. R_3 and R_5 are part of two coalitions and hence, they use different time slots for each coalition for transmission.

(A) **Direct Transmission Phase:** In the first phase, source S broadcasts its data symbol x_S with unit energy. The signal received by destination D is given by

$$y_{S,D} = \sqrt{P_S G_{S,D}} x_S + \eta_{S,D}, \tag{3.1}$$

whereas the signal received by relay R_k, $R_k \in C_j$ is given by

$$y_{S,R_k} = \sqrt{P_S G_{S,R_k}} x_S + \eta_{S,R_k}, \tag{3.2}$$

where $G_{S,D}$ and G_{S,R_k} are the channel gains from source S to destination D and relay R_k, respectively, P_S denotes the transmit power of source S, and $\eta_{S,D}$ and η_{S,R_k} represent the zero-mean AWGN samples with N_0 noise power. The SNR due to the direct transmission is given by

$$\Gamma_{S,D} = \frac{P_S G_{S,D}}{N_0} \tag{3.3}$$

and the rate at destination D can be expressed as

$$R_{S,D} = W \log_2 \left(1 + \Gamma_{S,D}\right), \tag{3.4}$$

where W denotes the system bandwidth.

(B) **Cooperative Transmission Phase:** In this phase, relay R_k amplifies $y_{S,D}$ and transmits it to destination D. This signal received by destination D due to the transmission by relay R_k, $R_k \in C_j$, can be expressed as

$$y_{R_k,D} = \frac{\sqrt{P_k^j G_{R_k,D}} \left(\sqrt{P_S G_{S,R_k}} x_S + \eta_{S,R_k}\right)}{\sqrt{P_S G_{S,R_k} + N_0}} + \eta_{R_k,D}, \tag{3.5}$$

where $G_{R_k,D}$ denotes the channel gain between relay R_k and destination D, P_k^j represents the power transmitted by the relay R_k as a member of coalition C_j, and $\eta_{R_k,D}$ signifies the zero-mean AWGN having N_0 noise power. The SNR due to cooperative transmission is given by

$$\Gamma_{S,R_k,D} = \frac{P_S G_{S,R_k} P_k^j G_{R_k,D}}{N_0 (P_S G_{S,R_k} + P_k^j G_{R_k,D} + N_0)}. \tag{3.6}$$

After MRC of both the direct and relayed paths, the rate at destination D is

$$R_{S,R_k,D} = \frac{W}{2} \log_2 \left(1 + \Gamma_{S,D} + \Gamma_{S,R_k,D}\right). \tag{3.7}$$

For overlapping coalitions set $\mathcal{C} = \{C_1, C_2, \ldots, C_M\}$, the total system capacity can be written as

$$R_{S,R,D} = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{C_j \in \mathcal{C}} \sum_{R_k \in C_j} \Gamma_{S,R_k,D}\right), \tag{3.8}$$

where the weight, $\gamma_L = \frac{1}{(M+1)}$ reflects the total number of time slots used for the transmission. Here, the relays within a coalition use orthogonal channels for transmission in the same time slot to avoid intra-coalition interference. Orthogonal transmission by relays is considered throughout the chapter unless specifically mentioned.

On the other hand, when all the relays in coalition $C_j \in \mathcal{C}$ transmit simultaneously, the NOMA signal received at destination D can be expressed as

$$y_{C_j,D} = \sum_{R_k \in C_j} \frac{\sqrt{P_k^j G_{R_k,D}}\left(\sqrt{P_S G_{S,R_k}} x_S + \eta_{S,R_k}\right)}{\sqrt{P_S G_{S,R_k} + N_0}} + \eta_{C_j,D}, \tag{3.9}$$

where $\eta_{C_j,D}$ is the zero-mean AWGN sample with N_0 noise power. The receiver at destination D uses SIC to decode the received NOMA signal. The signal with the highest strength is decoded first by treating the rest of the signal as interference and then, removed it from the combined signal by the receiver. This process continues till all the relayed signals are decoded. For relay R_k, $R_k \in C_j$, the SNR of the relayed signal is given by

$$\Gamma_{S,R_k,D} = \frac{P_k^j X_k}{P_k + Y_k + Y_k \sum_{i=k+1}^{|C_j|} \frac{X_i P_i^j}{Y_i}}, \tag{3.10}$$

where $X_k = \frac{P_S G_{S,R_k}}{N_0}$, $Y_k = \frac{P_S G_{S,R_k} + N_0}{G_{R_k,D}}$ and $|.|$ represents the set cardinality, provided the relays within the coalition are sorted in the ascending order of their signal strengths, i.e. their equivalent channel gains which are given by $\frac{X_l}{Y_l}$, $\forall\ R_l \in C_j$.
The total capacity achieved by the NOMA-based system can be expressed as

$$R_{S,R,D} = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{C_j \in \mathcal{C}} \sum_{R_k \in C_j} \Gamma_{S,R_k,D}\right). \tag{3.11}$$

3.3 Problem Formulation

The structure of the proposed game is depicted in Figure 3.2. To model the interactions among relay nodes, OCG is employed in which each relay node acts as a player. Relay nodes behave selfishly and try to obtain a high utility even if their strategies

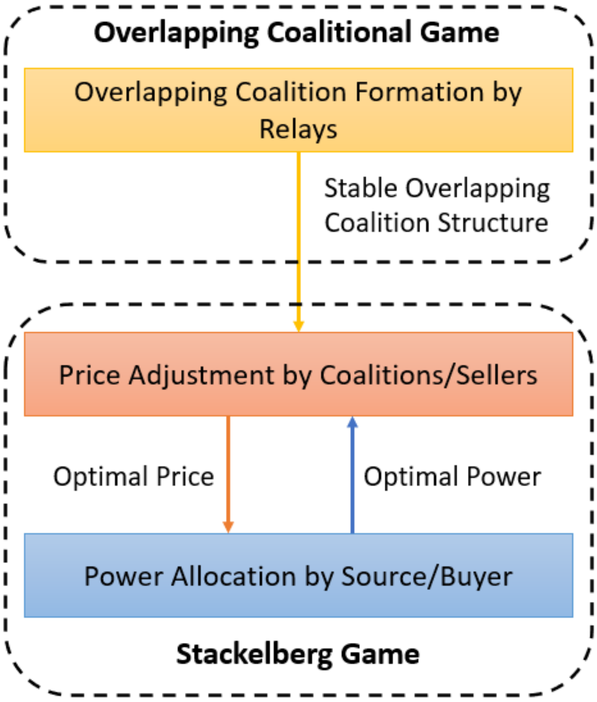


Figure 3.2: The proposed game framework.

degrade the others' utility. Therefore, determining a stable and optimal overlapping coalition structure is a problem. Furthermore, SG is employed for analyzing the interactions between source and coalitions formed by relays. This game disseminates power among relays in each coalition at optimal prices. It is formulated as below.

(A) **Source/Buyer:** If a is the gain per unit of the total achievable rate $R_{S,R,D}$ of source S, then for a fixed overlapping coalitional structure, its utility function is given by

$$U_S = aR_{S,R,D} - \sum_{C_j \in \mathfrak{C}} p_{C_j} P_{C_j}, \tag{3.12}$$

. Here, P_{C_j} denotes the amount of power purchased by source S from coalition C_j at p_{C_j} price, such that

$$P_{C_j} = \sum_{R_k \in C_j} P_k^j. \tag{3.13}$$

Substituting (3.13) into (3.12) gives

$$U_S = aR_{S,R,D} - \sum_{C_j \in \mathfrak{C}} p_{C_j} \sum_{R_k \in C_j} P_k^j. \tag{3.14}$$

The optimization problem for the game of buyer or source S can be written as

$$\begin{aligned} &\max_{\{P_k^j\}} U_S = aR_{S,R,D} - \sum_{C_j \in \mathcal{C}} p_{C_j} \sum_{R_k \in C_j} P_k^j \\ &\text{s.t. } P_k^j \geq 0, R_k \in C_j, C_j \in \mathcal{C}. \end{aligned} \tag{3.15}$$

(B) **Relay/Seller:** For a relay R_k, $R_k \in C_j$, the utility function can be defined as

$$U_k^j = p_{C_j} P_k^j - c_k P_k^j = \left(p_{C_j} - c_k\right) P_k^j. \tag{3.16}$$

c_k represents the cost of unit power at which P_k^j amount of power is sold by relay R_k. The utility function for coalition C_j is given by

$$\begin{aligned} U_{C_j} &= \sum_{R_k \in C_j} U_k^j = \sum_{R_k \in C_j} \left(p_{C_j} - c_k\right) P_k^j \\ &= p_{C_j} \sum_{R_k \in C_j} P_k^j - \sum_{R_k \in C_j} c_k P_k^j. \end{aligned} \tag{3.17}$$

To determine optimal price, the optimization problem for the game of seller can be expressed as

$$\max_{\{p_{C_j}\}>0} U_{C_j} = p_{C_j} \sum_{R_k \in C_j} P_k^j - \sum_{R_k \in C_j} c_k P_k^j. \tag{3.18}$$

3.4 Centralized approach

This section provides a conventional description of the power allocation problem which considers selfless cooperation of the relays controlled by a central entity. For K AF relays denoted by $\mathcal{K} = \{R_1,\ R_2, \ldots R_K\}$, the total achievable rate at destination D after MRC can be written as

$${R_{S,R,D}}^C = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{R_k \in \mathcal{K}} \Gamma_{S,R_k,D}\right). \tag{3.19}$$

Here, the aim is to maximize the total achievable rate with optimal allocation of power to relays. Therefore, the centralized optimal power allocation problem is given by

$$
\begin{aligned}
&\max_{\{P_k\}} \frac{W}{K+1}\log_2\left(1+\Gamma_{S,D}+\sum_{R_k\in\mathcal{K}}\Gamma_{S,R_k,D}\right)\\
&\text{s.t. } \textstyle\sum_{R_k\in\mathcal{K}} P_k \le\ P^{tot}, 0\le\ P_k\le\ P_k^{max}\quad \forall\ R_k\in\mathcal{K},
\end{aligned}
\tag{3.20}
$$

where $\Gamma_{S,R_k,D}$ is defined in the same way as in (3.6), P_k is the power allocated to relay R_k, P_k^{max} represents the maximum power that can be allocated to relay R_k, and P^{tot} denotes the total power constraint. As log is a strictly increasing function, after rearranging (3.20), the optimization problem becomes [111]

$$
\begin{aligned}
&\min \sum_{R_k\in\mathcal{K}} \frac{{P_S}^2{q_k}^2+P_Sq_k}{P_Sq_k+P_kr_k+1}\\
&\text{s.t. } \textstyle\sum_{R_k\in\mathcal{K}} P_k\le P^{tot}, 0\le P_k\le P_k^{max}\quad \forall\ R_k\in\mathcal{K},
\end{aligned}
\tag{3.21}
$$

where $q_k=\frac{G_{S,R_k}}{N_0}$ and $r_k=\frac{G_{R_k,D}}{N_0}$. The solution of (3.21) can be solved as

$$
P_k=\left(\sqrt{\frac{{P_S}^2{q_k}^2+P_Sq_k}{r_k}}\mu-\frac{P_Sq_k+1}{r_k}\right)_0^{P_k^{max}}, \tag{3.22}
$$

where μ represents a constant chosen which satisfies P^{tot} and $(x)_l^u$ is defined as

$$
(x)_l^u=\begin{cases} l & \text{for} \quad x<l\\ x & \text{for} \quad l\le x\le u\\ u & \text{for} \quad x>u \end{cases}. \tag{3.23}
$$

The objective function in (3.20) is in concave with P_k. It is noteworthy that the constraint, P^{tot} is used as a redundant constraint whose value in simulation has been taken as $\sum_{R_k\in\mathcal{K}} P_k^{max}$ to obtain the closed-form solution. The value is chosen such so as to draw the fair comparison between the centralized and proposed schemes. The centralized scheme assumes that all the relays are ready to cooperate selflessly. In such schemes, a central authority collects the CSI of every node in the system and allocates power in order to maximize the system performance. No doubt centralized resource allocation schemes seemingly perform better than distributed ones only if the individual utilities of source and relays are not taken into account [112]. However, the individual utilities of source and relays make sense as in real world, the relays are autonomous and rational and further, may refuse to share their resources unless given some incentive to cooperate. Furthermore, it would be worthwhile to first examine disjoint coalitions since this approach incurs a minimal computational overhead as compared to the overlapping ones.

3.5 Disjoint Coalition Formation Game Approach

A CG involves a set of players who form coalitions to strengthen their positions in the game [27].

Definition 3.1 ([21]). A coalition L represents a non-empty subset of $\mathcal{K}$ set of players, i.e. $L \subseteq \mathcal{K}$. A coalition consisting all players is referred as the grand coalition $\mathcal{K}$. If υ denotes the value function, a CG is defined as (L, υ) that maps coalition L to a real value $\upsilon(L)$.

Here, the players are the relays and each relay is allowed to join only one coalition. If R_k, $1 \leq k \leq K$ denotes the relay in coalition L_h, $1 \leq h \leq H$, where H denotes the number of disjoint coalitions formed, then $H \leq K$. For a fixed disjoint coalition structure $\mathcal{L} = \{L_1, L_2, \ldots, L_H\}$, the outcome of both buyer-level and seller-level games gives the unique optimal solution which is the SE.

(A) **Source/Buyer Level Game:** Utility of source S is given by

$$U_S = a{R_{S,R,D}}^D - \sum_{L_h \in \mathcal{L}} p_{L_h} \sum_{R_k \in L_h} P_k^h, \tag{3.24}$$

where p_{L_h} denotes the price per unit of power selling from coalition L_h, P_k^h is the amount of power that source S will purchase from relay R_k in coalition L_h, and ${R_{S,R,D}}^D$ is the achievable rate at destination D which is given by

$${R_{S,R,D}}^D = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{L_h \in \mathcal{L}} \sum_{R_k \in L_h} \Gamma_{S,R_k,D} \right). \tag{3.25}$$

Here, $\Gamma_{S,R_k,D}$ represents the SNR defined in (3.6).

The optimization problem for the buyer level game is

$$\begin{aligned}&\max_{\{P_k^h\}} U_S = aR_{S,R,D}{}^D - \sum_{L_h\in\mathcal{L}} p_{L_h} \sum_{R_k\in L_h} P_k^h, \\ &\text{s.t. } P_k^h \geq 0, P_k^h \leq \ P_k^{max}, R_k \in L_h, L_h \in \mathcal{L}.\end{aligned} \tag{3.26}$$

Partially differentiating (3.26) with respect to P_k^h and equating it to zero gives

$$\frac{a\gamma_L W}{\ln 2} \frac{1}{\left(1 + \frac{P_S G_{S,D}}{N_0} + \sum_{L_n\in\mathcal{L}} \sum_{R_m\in L_n} \frac{P_m^n X_m}{P_m^n + Y_m}\right)} = \frac{p_{L_h}\left(P_k^h + Y_k\right)^2}{X_k Y_k}. \tag{3.27}$$

For any relay on the right hand side (RHS) of (3.27), the left hand side (LHS) is same. Hence, equating RHS of (3.27) for relays R_k, $R_k \in L_h$ and R_l, $R_l \in L_i$ gives

$$P_k^h = \sqrt{\frac{p_{L_h} X_k Y_k}{p_{L_i} X_l Y_l}} \left(P_l^i + Y_l\right) - Y_k. \tag{3.28}$$

Substituting (3.28) into (3.27) and after some manipulations, the optimal power consumption is obtained as

$$P_k^{h^*} = \sqrt{\frac{X_k Y_k}{p_{L_h}}} \left(\frac{C^D + \sqrt{C^{D^2} + 4AB^D}}{2B}\right) - Y_k, \tag{3.29}$$

where $A = a\gamma_L W/\ln 2$, $B^D = 1 + P_S G_{S,D}/N_0 + \sum_{L_h\in\mathcal{L}} \sum_{R_k\in L_h} X_m$, and $C^D = \sum_{L_h\in\mathcal{L}} p_{L_h} \sum_{R_k\in L_h} \sqrt{X_m Y_m}$.

Owing to the transmit power constraint on the relays' power, the optimal power is given by

$$P_k^{h^*} = \left(\sqrt{\frac{X_k Y_k}{p_{L_h}}} \left(\frac{C^D + \sqrt{C^{D^2} + 4AB^D}}{2B}\right) - Y_k\right)_0^{P_k^{max}}, \tag{3.30}$$

where $(x)_l^u$ is defined as (3.23). This is a convex optimization problem, hence a unique solution can be found.

To calculate optimal power for NOMA-based network, the achievable rate at destination D is given by

$$R_{S,R,D}{}^D = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{L_h\in\mathcal{L}} \sum_{R_k\in L_h} \Gamma_{S,R_k,D}\right), \tag{3.31}$$

where $\Gamma_{S,R_k,D}$ is the SNR as defined in (3.10). Since log is a concave function, log is ignored in the formulation for simplicity. Further, by partially differentiating (3.24) with respect to P_k^h and equating it to zero gives

$$P_k^{h*} = \sqrt{\frac{aX_kY_k\left(1+\sum_{i=k+1}^{|L_h|}\frac{X_iP_i^j}{Y_i}\right)}{p_{L_h}}} - Y_k\left(1+\sum_{i=k+1}^{|L_h|}\frac{X_iP_i^j}{Y_i}\right). \tag{3.32}$$

Due to the relay's maximum transmit power constraint, the optimal power can be written as

$$P_k^{h*} = \left(\sqrt{\frac{aX_kY_k\left(1+\sum_{i=k+1}^{|L_h|}\frac{X_iP_i^j}{Y_i}\right)}{p_{L_h}}} - Y_k\left(1+\sum_{i=k+1}^{|L_h|}\frac{X_iP_i^j}{Y_i}\right)\right)_0^{P_k^{max}}, \tag{3.33}$$

where $(x)_l^u$ is defined as (3.23).

(B) **Relay/Seller Level Game:** Utility of relay R_k in coalition L_h can be specified as

$$U_k^h = p_{L_h}P_k^h - c_kP_k^h = \left(p_{L_h} - c_k\right)P_k^h. \tag{3.34}$$

Utility of coalition L_h is the sum of the individual utilities of the member relays, i.e.

$$U_{L_h} = \sum_{R_k\in L_h} U_k^j = p_{L_h}\sum_{R_k\in L_h} P_k^h - \sum_{R_k\in L_h} c_kP_k^h. \tag{3.35}$$

The optimization problem of the seller level game is given by

$$\max_{\{p_{L_h}\}>0} U_{L_h} = p_{L_h}\sum_{R_k\in L_h} P_k^h - \sum_{R_k\in L_h} c_kP_k^h. \tag{3.36}$$

The optimal price for a coalition can be calculated as

$$p_{L_h}{}^{*} = \arg\max_{\{p_{L_h}\}>0} U_{L_h}. \tag{3.37}$$

The optimal price for a coalition is dependent upon the channel gains of its member relays towards source S and destination D, as well as the prices set by the other coalitions in coalition set $\mathcal{L}$. The characteristic function $\upsilon(L_h)$ of coalition L_h,

$L_h \subset \mathcal{L}$ is the aggregated utility of its member relays as defined in (3.35). Relays tend to form a stable coalition structure from which no relay will have an incentive to deviate. Despite that, if this coalition structure turns out to be non-profitable to source, it will be rejected by the same.

Definition 3.2. A disjoint coalition structure $\mathcal{L}$ is called feasible when the utility of source S with cooperation, i.e. U_S, turns out greater than its utility in case of direct transmission, i.e. $aR_{S,D}$.

Assume $\Omega = \{\mathcal{L}_1, \mathcal{L}_2, \ldots, \mathcal{L}_P\}$ is the set of different feasible coalition structures, where P is the total number of possible coalition structures that are feasible. Transition from one coalition structure, $\mathcal{L}_m$ to other coalition structure, $\mathcal{L}_n$ may occur if on transition, there is an increase in the individual utility of that particular relay which enters into any non-singleton coalition in $\mathcal{L}_n$. These conditions are crucial to the convergence of the scheme to a stable coalition structure.

Definition 3.3. A disjoint coalition structure $\mathcal{L}$ is unstable if there exists other feasible coalitional structure $\mathcal{L}'$, in which all the relays in non-singleton coalitions get non-decreasing utility as compared to that of coalition structure $\mathcal{L}$.

The overall disjoint coalition formation game approach has been presented in Algorithm 3.1. A single source-destination (S-D) pair with K, $K \geq 2$ available relays have been considered. An empty set Ω has been initialized to store the feasible disjoint coalition structures. The possible disjoint coalition structures of relays are formed and for each coalition structure, feasibility conditions are checked. Each feasible coalition structure is added to the set Ω. To find out the stable coalition structure, a flag is set and two sets of structures (viz. initial structure and test structure) are initialized as null sets. Each feasible coalition structure in set Ω is checked against the test coalition structure for the increased utility of relays in non-singleton coalitions. If so happens, the corresponding coalition structure is updated. If the initial structure and the test structure turn out to be different, then the initial structure is updated as the test structure. The whole process is continued till these structures get equal and the flag is reset.

Although the disjoint CG has been widely used to study the problems in wireless

Algorithm 3.1 Disjoint Coalition Formation Game Approach

Initialize S, D
Initialize R_k, $k \in \{1, 2, \ldots, K\}$, $K \geq 2$
Initialize $\Omega = \emptyset$
Form $\mathcal{L}_j$, $j \in \{1, 2, \ldots, J\}$ {J denotes the total number of disjoint coalition structures formed}
for $j = 1 : J$ **do**
  Calculate $P_k^{h^*}$ and ${p_{L_h}}^*$, $\forall\, k, L_h, L_h \subset \mathcal{L}_j$
  if ${U_S}^j > aR_{S,D}$ **then** {${U_S}^j$ is the source utility for coalition structure $\mathcal{L}_j$}
    $\mathcal{L}_j \to \Omega$
  end if
end for
Set flag=1, initial structure=ϕ_1 and test structure=ϕ_2 {initially $\phi_1 = \emptyset$ and $\phi_2 = \emptyset$}
while flag **do**
  for $u = 1 : P$ **do** {P is the total number of feasible disjoint coalition structures in set Ω}
    if $U_k^h(\mathcal{L}_u) > U_k^n(\phi_2)$, $\forall\, k, R_k \in L_h, L_h \in \mathcal{L}_u, |L_h| > 1$ **then**
      $\phi_2 = \mathcal{L}_u$
    end if
  end for
  if $\phi_2 = \phi_1$ **then**
    flag=0
  else
    $\phi_1 = \phi_2$
  end if
end while

communications, but practically, allowing the formation of overlapping coalitions can further improve the performance [106]. Here, being the seller, a relay can share greater amount of power to source through multiple coalitions, thus, gaining more profit from the cooperation. This increased power shared with source enhances the total achievable rate at the destination. This has provided motivation to propose the framework based on overlapping coalitions which is capable of achieving performance superior to the disjoint scheme while acknowledging the benefits of cooperating relays from multiple coalitions.

3.6 Overlapping Coalition Formation Game Approach

The proposed scheme is the integration of SG and OCG which are described in detail in this section.

3.6.1 SG Formulation

This section presents the detailed analysis of the SG framework.

(A) **Source/Buyer Level Game Analysis:** Source S decides the amount of power to purchase from the relays according to the prices set by them, with an intent to maximize its utility U_S. Partially differentiating (3.15) with respect to P_k^j gives

$$\frac{\partial U_S}{\partial P_k^j} = a\frac{\partial R_{S,R,D}}{\partial P_k^j} - p_{C_j}, R_k \in C_j, C_j \in \mathcal{C}. \tag{3.38}$$

If $\frac{\partial U_S}{\partial P_k^j} > 0$, $R_k \in C_j$, $C_j \in \mathcal{C}$, source S will have higher utility by increasing P_k^j. It means p_{C_j} must satisfy $p_{C_j} < a\frac{\partial R_{S,R,D}}{\partial P_k^j}$, otherwise coalition C_j will face rejection by source S.

Using (3.8), the first term of U_S becomes

$$aR_{S,R,D} = a\gamma_L W \log_2\left(1 + \frac{P_S G_{S,D}}{N_0} + \sum_{C_j \in \mathcal{C}} \sum_{R_k \in C_j} \frac{P_k^j X_k}{P_k^j + Y_k}\right). \tag{3.39}$$

Substituting (3.39) in (3.38) gives

$$\frac{a\gamma_L W}{\ln 2} \frac{1}{\left(1 + \frac{P_S G_{S,D}}{N_0} + \sum_{C_n \in \mathcal{C}} \sum_{R_m \in C_n} \frac{P_m^n X_m}{P_m^n + Y_m}\right)} = \frac{p_{C_j}\left(P_k^j + Y_k\right)^2}{X_k Y_k}. \tag{3.40}$$

For any relay on the RHS of (3.40), the LHS is same. Thus, equating RHS of (3.40) for relays R_k, $R_k \in C_j$ and R_l, $R_l \in C_i$ gives

$$P_k^j = \sqrt{\frac{p_{C_i} X_k Y_k}{p_{C_j} X_l Y_l}}\left(P_l^i + Y_l\right) - Y_k. \tag{3.41}$$

Substituting (3.41) into (3.40) and further solving it, the optimal power consumption is obtained as

$$P_k^{j*} = \sqrt{\frac{X_k Y_k}{p_{C_j}}}\left(\frac{C + \sqrt{C^2 + 4AB}}{2B}\right) - Y_k, \tag{3.42}$$

where $B = 1 + \frac{P_S G_{S,D}}{N_0} + \sum_{C_n \in \mathcal{C}} \sum_{R_m \in C_n} X_m$ and $C = \sum_{C_n \in \mathcal{C}} p_{C_n} \sum_{R_m \in C_n} \sqrt{X_m Y_m}$. Owing to the transmit power constraint on the relays' power, the optimal power can be calculated as

$$P_k^{j*} = \left(\sqrt{\frac{X_k Y_k}{p_{C_j}}} \left(\frac{C + \sqrt{C^2 + 4AB}}{2B} \right) - Y_k \right)_0^{P_k^{max}}, \tag{3.43}$$

where $(x)_l^u$ is defined as (3.23). Like the disjoint case, this is also a convex optimization problem having a unique solution.

For NOMA-based cooperative network, $R_{S,R,D}$ defined in (3.11) is substituted in (3.38) to get the expression for optimal power consumption as given by

$$P_k^{j*} = \sqrt{\frac{aX_k Y_k \left(1 + \sum_{i=k+1}^{|C_j|} \frac{X_i P_i^j}{Y_i}\right)}{p_{C_j}}} - Y_k \left(1 + \sum_{i=k+1}^{|C_j|} \frac{X_i P_i^j}{Y_i}\right). \tag{3.44}$$

It should be noted that here, log is ignored in the formulation for the sake of simplicity as $\log_2(1 + x)$ is a strictly increasing function of x.

Owing to the maximum transmit power constraint on relays, the expression for optimal power becomes

$$P_k^{j*} = \left(\sqrt{\frac{aX_k Y_k \left(1 + \sum_{i=k+1}^{|C_j|} \frac{X_i P_i^j}{Y_i}\right)}{p_{C_j}}} - Y_k \left(1 + \sum_{i=k+1}^{|C_j|} \frac{X_i P_i^j}{Y_i}\right) \right)_0^{P_k^{max}} \tag{3.45}$$

where $(x)_l^u$ is defined as (3.23). This is a convex optimization problem, hence its unique solution exists.

(B) **Relay/Seller Level Game:** The optimal price for a coalition can be calculated as

$$p_{C_j}{}^* = \arg \max_{\{p_{C_j}\} > 0} U_{C_j}. \tag{3.46}$$

For coalition C_j, the optimal price $p_{C_j}{}^*$ relies on the channel conditions of its member relays towards source S and destination D as well as the prices determined by other existing coalitions. Setting a huge price by coalition C_j makes it less beneficial to source S as compared to other coalitions. Thus, source S may buy less to no power from it. It is clear from the above discussion that the coalition is used only to determine the price of power.

(C) **Existence of SE in the Proposed Game:** In this subsection, the existence of SE is proved in the solutions ${P_k^j}^*$ in (3.42) and ${p_{C_j}}^*$ in (3.46) and their optimality is shown by the following properties [94]. Firstly, the SE of the proposed game can be defined as follows:

Definition 3.4. For a fixed power allocation, ${P_k^j}^{SE}$ and ${p_{C_j}}^{SE}$ form an SE if for every $R_k \in C_j$, $C_j \in \mathcal{C}$ and fixed p_{C_j}, their values are obtained as

$$ {P_k^j}^{SE} = \arg \max_{\{P_k^j\}>0} U_S, \tag{3.47} $$

and when P_k^j is fixed,

$$ {p_{C_j}}^{SE} = \arg \max_{\{p_{C_j}\}>0} U_{C_j}. \tag{3.48} $$

Property 3.1. The utility function U_S of source S is concave in P_k^j,$\forall$ $R_k \in C_j$, $C_j \in \mathcal{C}$, when p_{C_j}, $\forall$ $C_j \in \mathcal{C}$ is constant.

Proof. Taking the second-order derivative of U_S gives

$$ \begin{aligned} \frac{\partial^2 U_S}{\partial {P_k^j}^2} = & -A \frac{1}{\left(1+\frac{P_S G_{S,D}}{N_0}+\sum_{C_n \in \mathcal{C}} \sum_{R_m \in C_n} \frac{P_m^n X_m}{P_m^n + Y_m}\right)^2} \left[\frac{X_k Y_k}{\left(P_k^j + Y_k\right)^2}\right]^2 \\ & - 2A \frac{1}{\left(1+\frac{P_S G_{S,D}}{N_0}+\sum_{C_n \in \mathcal{C}} \sum_{R_m \in C_n} \frac{P_m^n X_m}{P_m^n + Y_m}\right)} \frac{X_k Y_k}{\left(P_k^j + Y_k\right)^3} \end{aligned} \tag{3.49} $$

and

$$ \frac{\partial^2 U_S}{\partial P_k^j \partial P_p^l} = -A \frac{1}{\left(1+\frac{P_S G_{S,D}}{N_0}+\sum_{C_n \in \mathcal{C}} \sum_{R_m \in C_n} \frac{P_m^n X_m}{P_m^n + Y_m}\right)^2} \frac{X_k Y_k}{\left(P_k^j + Y_k\right)^2} \frac{X_p Y_p}{\left(P_p^l + Y_p\right)^2}. \tag{3.50} $$

For each relay in every coalition, by definition, $A > 0$, $X_k > 0$, $Y_k > 0$ and $P_k^j > 0$. Consequently, $\frac{\partial^2 U_S}{\partial {P_k^j}^2} < 0$ and $\frac{\partial^2 U_S}{\partial P_k^j \partial P_p^l} < 0$. It can be verified that $\frac{\partial^2 U_S}{\partial {P_k^j}^2} \frac{\partial^2 U_S}{\partial {P_p^l}^2} - \left(\frac{\partial^2 U_S}{\partial P_k^j \partial P_p^l}\right)^2 > 0$, $\forall$ $k \neq p$, $j \neq l$. Furthermore, U_S is continuous with respect to P_k^j. Therefore, when $P_k^j > 0$, U_S is strictly concave in P_k^j, $\forall$ $R_k \in C_j$, $C_j \in \mathcal{C}$ and jointly concave as well.

Property 3.2 For relay R_k, $R_k \in C_j$, the optimal power consumption P_k^{j*} decreases with increase in p_{C_j}, provided the prices set by other coalitions are fixed.

Proof. Calculating the first-order derivative of P_k^{j*} gives

$$\frac{\partial P_k^{j*}}{\partial p_{C_j}} = \sqrt{\frac{X_k Y_k}{p_{C_j}}} \left(\frac{C + \sqrt{C^2 + 4AB}}{2B} \right) \times \left[-\frac{1}{2p_{C_j}} \left(1 - \frac{\sqrt{p_{C_j}} \sum_{R_k \in C_j} \sqrt{X_k Y_k}}{\sqrt{C^2 + 4AB}} \right) \right] < 0. \tag{3.51}$$

This indicates P_k^{j*} is decreasing with p_{C_j}. This is so because if relays in a coalition increase their price while the relays in other coalitions keep their prices unchanged, source S will buy less power from the former.

Property 3.3. The utility U_{C_j} of coalition C_j is concave in price p_{C_j}, provided the power consumed is the optimized amount bought by source S as given in (3.42) and the prices set by other coalitions are kept unchanged.

Proof. As P_k^{j*} is continuous function of p_{C_j}, therefore, U_{C_j} is also continuous in p_{C_j}. Calculating the derivatives of U_{C_j} with respect to p_{C_j} gives

$$\frac{\partial U_{C_j}}{\partial p_{C_j}} = \sum_{R_k \in C_j} P_k^{j*} + p_{C_j} \sum_{R_k \in C_j} \frac{\partial P_k^{j*}}{\partial p_{C_j}} - \sum_{R_k \in C_j} c_k \frac{\partial P_k^{j*}}{\partial p_{C_j}}, \tag{3.52}$$

$$\frac{\partial^2 U_{C_j}}{\partial {p_{C_j}}^2} = 2 \sum_{R_k \in C_j} \frac{\partial P_k^{j*}}{\partial p_{C_j}} + p_{C_j} \sum_{R_k \in C_j} \frac{\partial^2 P_k^{j*}}{\partial {p_{C_j}}^2} - \sum_{R_k \in C_j} c_{Rk} \frac{\partial^2 P_k^{j*}}{\partial {p_{C_j}}^2}, \tag{3.53}$$

where

$$\begin{aligned} \frac{\partial^2 P_k^{j*}}{\partial {p_{C_j}}^2} = & \sqrt{\frac{X_k Y_k}{\left(p_{C_j}\right)^5}} \left(\frac{C + \sqrt{C^2 + 4AB}}{8B} \right) \times \left[3 \times \left(1 - \frac{\sqrt{p_{C_j}} \sum_{R_k \in C_j} \sqrt{X_k Y_k}}{\sqrt{C^2 + 4AB}} \right) \right. \\ & \left. - \frac{\sqrt{p_{C_j}} \left(\sum_{R_k \in C_j} \sqrt{X_k Y_k} \right)^2}{C^2 + 4AB} \times \left(\frac{C \sqrt{p_{C_j}}}{\sqrt{C^2 + 4AB}} - 1 \right) \right]. \end{aligned} \tag{3.54}$$

Since X_k, Y_k, p_{C_j}, c_k, C, A, and $B > 0$, $\frac{\partial^2 U_{C_j}}{\partial {p_{C_j}}^2} < 0$ is obtained. Therefore, U_{C_j} is concave with respect to p_{C_j}.

Existence of SE and its optimality in case of NOMA-based network can be proved in the similar aforementioned way.

3.6.2 Overlapping Coalitional Game

In an OCG [113], a player can be a part multiple coalitions by contributing portions of their limited resources to the joined coalitions. When the overlapping is enabled among coalitions, these coalitions are no longer disjoint subsets of the player set as defined in disjoint CG.

Definition 3.5. An overlapping coalition structure $\mathcal{C}$ over $\mathcal{K}$ set of players is defined as a set $\mathcal{C} = \{C_1, C_2, \ldots, C_M\}$, where M denotes the number of coalitions, $\forall\ 1 \leq j \leq M$, $C_j \subseteq \mathcal{K}$ and $\bigcup_{j=1}^{M} C_j = \mathcal{K}$. Since the coalitions are overlapping, $\exists\ C_j,\ C_k \in \mathcal{C}$, $j \neq k$ such that $C_j \cap C_k \neq \emptyset$.

Definition 3.6. An OCG is represented by $G = (\mathcal{K}, \mathcal{C}, \upsilon)$, where

- $\mathcal{K}$ is the set of players which are the relays R_k, $k \in \{1, 2, \ldots, K\}$,
- $\mathcal{C}$ is the overlapping coalition structure formed by relays,
- $\upsilon\,(C_j)$ represents the value mapping function which gives real value for coalition C_j.

For the proposed OCG, the characteristic function $\upsilon\,(C_j)$ represents the utility of the overlapping coalition C_j defined in (3.17). It is noteworthy that the utility of a relay in one coalition is dependent upon two factors, optimal price and optimal power. Optimal power is a function of optimal price and further, optimal price varies according to the prices set by the other coalitions in co-existence, besides its own channel conditions towards source and destination. Thus, the utility obtained by a relay cannot be transferred to other relays. Hence, the proposed OCG is an NTU game.

In the proposed scheme, a coalition exhibits fair distribution of the total payment obtained from source S in return of the power shared by it. Each member relay collects the payment at the respective optimal price set by the coalition, therefore, the payoff received is proportional to the power shared by that coalition. If a relay joins multiple coalitions, the total payoff received will be the sum of the payments obtained from all the coalitions unlike the case in disjoint scheme where the total payoff received corresponds to a single coalition. This naturally helps in achieving enhanced payoffs for individual relays of the overlapping coalitions. This is likely to be reflected in terms of enhanced average utility. Assuming that a relay R_k forms $\mathbb{C}_{R_k}$ set of coalitions, such that $\mathbb{C}_{R_k} \in \mathcal{C}$, P_{R_k} is the power shared by relay R_k to each coalition of $\mathbb{C}_{R_k}$, U_{R_k} is the utility of R_k from each coalition of $\mathbb{C}_{R_k}$, the total utility of relay R_k from all the set of coalitions can be expressed as

$$\begin{aligned} U_{Tk} &= \sum_{\mathbb{C}_{R_k} \in \mathcal{C}} U_{R_k} \\ &= \sum_{\mathbb{C}_{R_k} \in \mathcal{C}} p_{\mathbb{C}_{R_k}} P_{R_k} - c_k \sum_{\mathbb{C}_{R_k} \in \mathcal{C}} P_{R_k}. \end{aligned} \tag{3.55}$$

Since, the number of time slots occupied by relay R_k is equivalent to $|\mathbb{C}_{R_k}|$. Hence, the average utility of relay R_k per time slot is

$$U_{Ak} = U_{Tk} / \left| \mathbb{C}_{R_k} \right|. \tag{3.56}$$

There is a possibility that the source may not benefit from certain overlapping coalition structures. In other words, there may be no rise in the source's utility, U_S with the formation of a particular overlapping coalition structure over the direct transmission, i.e. $aR_{S,D}$. With the condition mentioned above, the feasible overlapping coalition structures can be defined by the following definition.

Definition 3.7. An overlapping coalition structure $\mathcal{C}$ is called feasible if it satisfies $U_S > aR_{S,D}$.

This feasibility condition limits the formation of overlapping coalition structures which reduces the computational complexity of the proposed algorithm. Each relay makes its own decision of joining a coalition or not without considering its impact on other relays. Therefore, a feasible overlapping coalition structure may or may not be stable. In case of stable coalition structure, it will remain still, else it will transit to other state. This transition process continues till the stable overlapping coalition structure is formed by relays.

Definition 3.8. Overlapping coalition structure $\mathcal{C}$ is unstable if there exists other feasible coalitional structure $\mathcal{C}'$, in which all relays in non-singleton coalitions get higher average utility per coalition than that of coalition structure $\mathcal{C}$.

Theorem 3.1. After a finite number of iterations, the proposed OCG algorithm converges to a stable and feasible overlapping coalition structure.

Proof. While implementing OCG algorithm, the coalition formation process involves sequence of moves of relays resulting in the formation of sequence of feasible coalition structures $\left\{\mathcal{C}^{(0)}, \mathcal{C}^{(1)}, \ldots, \mathcal{C}^{(t)}\right\}$, where t denotes the total number of transitions made by relays. A new overlapping coalition structure is formed due to the instability of the current coalition structure. Also, the number of possible feasible coalition structures is finite, thus, t is a finite number. Now, the contradiction approach is used to show that, if $\mathcal{C}^{(t)}$ is the final coalition structure, then it must be stable. Assume that $\mathcal{C}^{(t)}$ is unstable according to Definition 3.8, then relays will move towards another coalition structure. This contradicts the fact that $\mathcal{C}^{(t)}$ is the final coalition structure. Hence, $\mathcal{C}^{(t)}$ is a stable overlapping coalition structure. Therefore, the proposed OCG algorithm gives a stable overlapping coalition structure after a finite number of iterations.

Algorithm 3.2 describes the overall overlapping coalition formation game approach for a pair of source-destination (S-D) with $R_k, k \in \{1, 2, \ldots, K\}$, available relays such that $K \geq 2$. To store the feasible overlapping structures, an empty set θ is initialized. All the possible structures are generated, tested for feasibility and then, stored in set θ when the condition is fulfiled. To determine the stable overlapping coalition structure, a flag is set and initial and test coalition structures are initialized as null sets. On comparison with the feasible coalition structures, the test structure is checked for instability according to Definition 3.8. If so happens, the existing structure transits to a new one and the corresponding feasible coalition structure is considered the new test structure. This process ends and the flag is reset when the initial and test structures become similar, otherwise the initial structure is updated as the test structure and the process for checking the instability continues.

In Algorithm 3.2, the complexity of finding the stable overlapping coalition structure from the set of feasible structures depends on the number of iterations and comparisons taking place. The existing feasible structures are compared with the current "best" feasible structure instead of all pair-wise comparisons between any

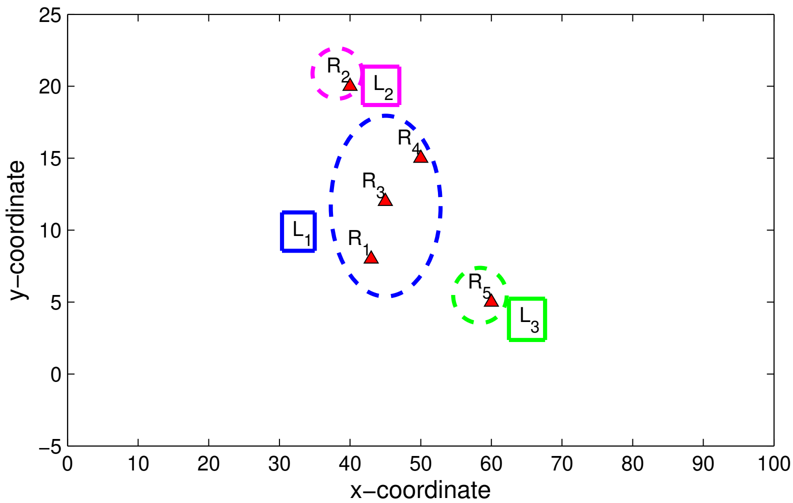
Algorithm 3.2 Overlapping coalition formation game approach

Initialize S, D
Initialize R_k, $k \in \{1, 2, \ldots, K\}$, $K \geq 2$
Initialize $\theta = \emptyset$ {θ represents the set containing feasible overlapping coalition structures}
Generate $\mathcal{C}_q = \{C_1, C_2, \ldots, C_M\}$, $\forall\ 1 \leq j \leq M$, $C_j \subseteq \mathcal{K}$ and $\bigcup_{j=1}^{M} C_j = \mathcal{K}$
for $q = 1 : Q$ **do** {Q is the total number of overlapping coalition structures formed}
  Calculate $P_k^{j^*}$ and $p_{C_j}{}^*$, $\forall\ k$, C_j, $C_j \subset \mathcal{C}_q$
  Calculate P_{R_k}, $\forall\ \mathbb{C}_{R_k}$, $\mathbb{C}_{R_k} \in \mathcal{C}_q$
  if $U_S{}^q > aR_{S,D}$ **then** {$U_S{}^q$ is the the source utility for $\mathcal{C}_q$}
    $\mathcal{C}_q \rightarrow \theta$
  end if
end for
Set flag=1, initial structure=ϕ_1 and test structure=ϕ_2 {initially $\phi_1 = \emptyset$ and $\phi_2 = \emptyset$}
while flag **do**
  for $u = 1 : P$ **do** {P is the total number of feasible overlapping coalition structures in set Ω}
    if $U_{Ak}(\mathcal{C}_u) > U_{Ak}(\phi_2)$, $\forall\ k$, $R_k \in C_j$, $C_j \subset \mathcal{C}_u$, $|C_j| > 1$ **then**
      $\phi_2 = \mathcal{C}_u$
    end if
  end for
  if $\phi_2 = \phi_1$ **then**
    flag=0
  else
    $\phi_1 = \phi_2$
  end if
end while

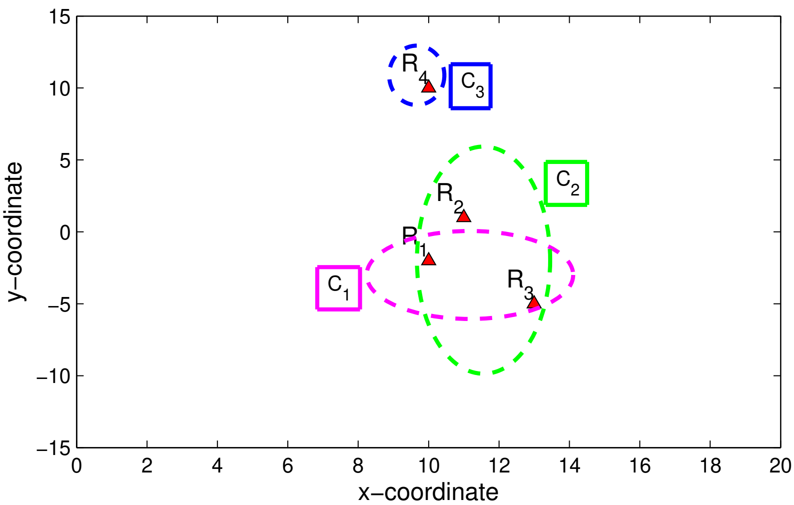
two feasible structures. This reduces the complexity from $O(P^2)$ to $O(P)$. However, at each comparison stage, the average utilities of individual relays are compared which make the number of comparisons equal to the total number of relays K, in the worst case. Assuming that the algorithm converges in T finite number of iterations as proved in Theorem 3.1, the complexity for determination of the stable coalition structure becomes $O(PKT)$. It is clear that with increase in number of relays, computational complexity of the algorithm increases. However, the feasibility condition restricts the formation of larger number of overlapping coalition structures which further reduces the number of comparisons taking place in one iteration. Complexity of Algorithm 3.1 can be calculated in the similar manner.

3.7 Simulation Results and Discussions

This section examines the performance of the proposed game framework in the multi-relay scenario. For simulations, a network of single source-destination pair are assumed to be located at coordinates $(0, 0)$ and $(20, 0)$, respectively, unless specified otherwise. The propagation loss factor is set as 2 (typical value for free space) [114]. Values for other parameters are assumed as $P_S = 10$ mW, $N_0 = 10^{-8}$ W and $W = 1$ MHz [94]. The cost per unit power for each helping relay is 0.1, the gain per unit of achievable rate $a = 0.01$ and the maximum transmit power constraint on each relay is 10 mW unless stated otherwise [94].



(a)



(b)

Figure 3.3: Examples of stable coalition structures. (a) Disjoint, (b) Overlapping

Table 3.1: Utilities of relays in corresponding disjoint coalition structures for 4-relay network.

S. No.	**Feasible Disjoint Coalition Structure**	**Utilities of Relays** ($\times 10^{-3}$)			
		R_1	R_2	R_3	R_4
1	$[R_1],[R_2],[R_3],[R_4]$	7.4224	7.6293	7.3971	7.0564
2	$[R_1],[R_2,R_3,R_4]$	7.4015	8.5027	7.3792	7.0666
3	$[R_2],[R_1,R_3,R_4]$	8.2874	7.6019	7.3860	7.0558
4	$[R_3],[R_1,R_2,R_4]$	7.9840	7.9840	7.3704	7.0427
5	$[R_4],[R_1,R_2,R_3]$	7.7443	7.7443	7.4272	7.0514
6	$[R_1,R_2],[R_3,R_4]$	7.5056	7.5056	7.3269	7.0811
7	$[R_1,R_3],[R_2,R_4]$	7.7844	8.4871	7.4066	7.0616
8	$[R_1,R_4],[R_2,R_3]$	8.1974	7.9685	7.3977	7.0504
9	$[R_1],[R_2],[R_3,R_4]$	7.4152	7.6220	7.3271	7.0813
10	$[R_1],[R_3],[R_2,R_4]$	7.4015	8.4933	7.3778	7.0664
11	$[R_1],[R_4],[R_2,R_3]$	7.4191	7.9967	7.4224	7.0535
12	$[R_2],[R_3],[R_1,R_4]$	8.2009	7.6023	7.3724	7.0533
13	$[R_2],[R_4],[R_1,R_3]$	7.8061	7.6238	7.4260	7.0516
14	$[R_3],[R_4],[R_1,R_2]$	7.5129	7.5129	7.3968	7.0562
15	$[R_1,R_2,R_3,R_4]$	8.0862	8.0862	7.3926	7.0459

Figure 3.3a and 3.3a depict an example of stable disjoint and overlapping coalition structure obtained by implementing the proposed scheme, respectively. Relays R_1, R_3, and R_4 form coalition L_1, whereas relays R_2 and R_5 form singleton coalitions L_2 and L_3, respectively, in Figure 3.3a, with source-destination pair located at coordinates $(0,0)$ and $(100,0)$, respectively. It represents a stable disjoint coalition structure as elaborated in Definition 3.3. Similarly, in Figure 3.3b, relays R_1, R_3 form coalition C_1, relays R_1, R_2 and R_3 are the members of coalition C_2, and relay R_4 constitute a singleton coalition C_3. It is evident that relays R_1 and R_3 are member of two coalitions viz. C_1 and C_2, whereas rest of the relays have a membership to only one of the coalitions. The present depiction represents a stable overlapping coalition structure as elaborated in Definition 3.8.

To illustrate the formation of a stable disjoint coalition structure, 4 relays R_1, R_2, R_3, and R_4 with locations (42, 5), (45, -12), (50, -15), and (53, -7), respectively, are considered. For this case, the source-destination pair are considered to be positioned at coordinates $(0,0)$ and $(100,0)$, respectively. Also, the values of cost per unit power for each helping relay and gain per unit of achievable rate are assumed as 0.5 and 0.05, respectively. All the feasible disjoint coalition structures have been

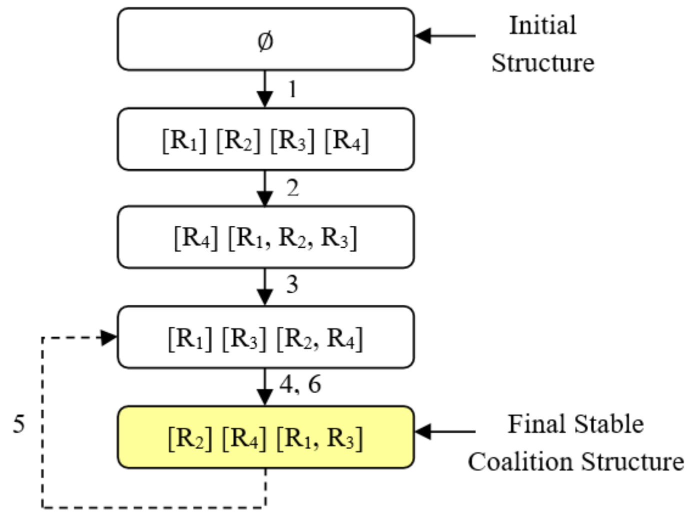


Figure 3.4: State transition diagram for 4-relay network.

enlisted in Table 3.1 with utilities of individual relays shown beside the structures. Figure 3.4 depicts the formation of new disjoint coalition structure in the form of a state transition diagram. It can be verified from Table 3.1 that the transition occurs only when there is a increase in the utilities of each of the relays in non-singleton coalitions according to Definition 3.3. The transitions continue until a stable disjoint coalition structure is identified. In the particular case represented in Figure 3.4, a stable structure is identified at transition number 6. In the first iteration, the first four transitions take place. In the next iteration, the coalition structure at s. no. 10 serve as initial state looking for a better future state. Transition number 5 can be understood by comparing feasible coalition structures at s. no. 13 and 10 of Table 3.1. Here, according to Definition 3.3, a transition is possible from the structure at s. no. 13 to the structure at s. no. 10 since the utilities of R_2 and R_4 are increasing on transition. Further, transition number 6 takes place as the utilities of R_1 and R_3 in coalition are increasing on transition. This peculiar situation poses the danger of a non-terminating state transition loop for which due provisions have been made in the algorithm itself by terminating the loop running more than once.

Nevertheless, in some particular scenario, it is possible to have an acyclic state diagram as depicted in Figure 3.5, which corresponds to a case where a final stable coalition structure is obtained without any further transition to a previous state.

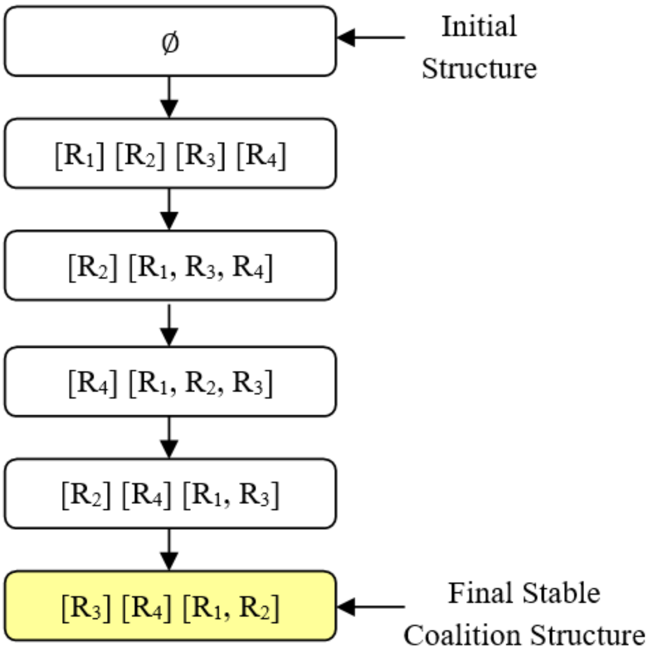
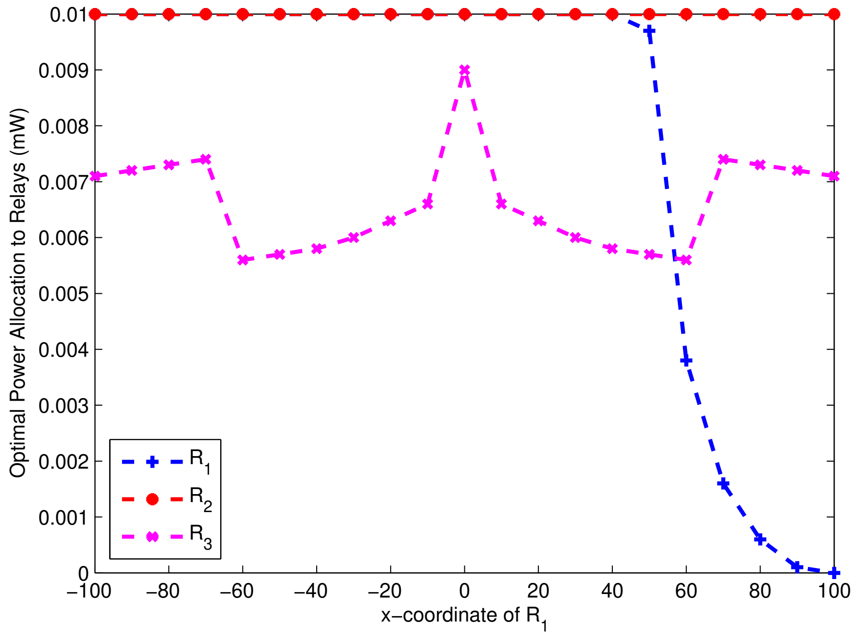


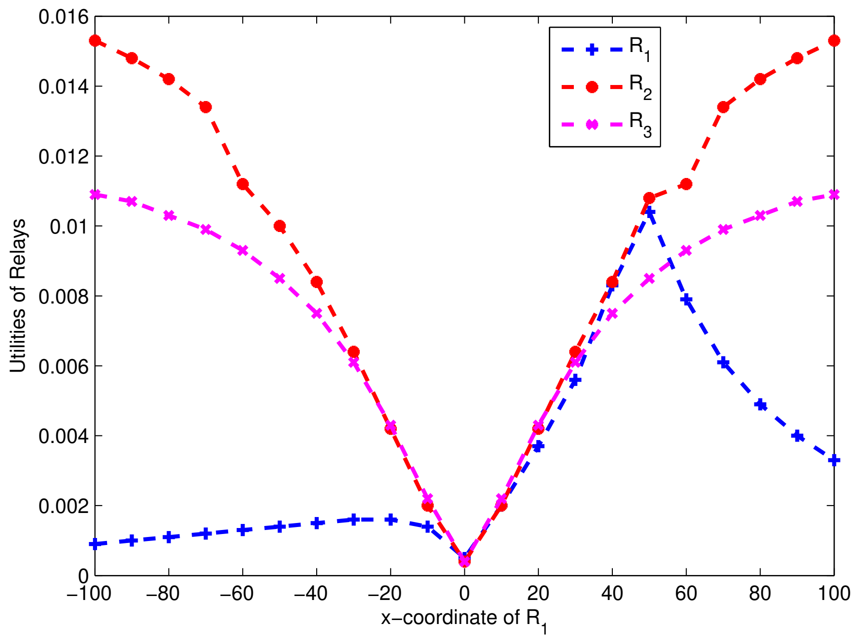
Figure 3.5: An acyclic state transition diagram.

Table 3.2: Formation of stable disjoint coalition structures and their optimal price due to the movement of relay R_1.

S. No.	**x-coordinate of R_1**	**Stable Disjoint Coalition Structure**	**Optimal Price of Coalitions**
1	-100	$[R_1], [R_2, R_3]$	0.0885, 1.5339
2	-90	$[R_1], [R_2, R_3]$	0.0970, 1.4847
3	-80	$[R_1], [R_2, R_3]$	0.1064, 1.4220
4	-70	$[R_1], [R_2, R_3]$	0.1169, 1.3414
5	-60	$[R_1], [R_2], [R_3]$	0.1293, 1.1245, 1.6617
6	-50	$[R_1], [R_2], [R_3]$	0.1415, 0.9974, 1.4982
7	-40	$[R_1], [R_2], [R_3]$	0.1534, 0.8362, 1.2848
8	-30	$[R_1], [R_2], [R_3]$	0.1628, 0.6396, 1.0133
9	-20	$[R_1], [R_2], [R_3]$	0.1638, 0.4176, 0.6881
10	-10	$[R_1], [R_2], [R_3]$	0.1368, 0.1972, 0.3386
11	0	$[R_1, R_3], [R_2]$	0.0458, 0.0356
12	10	$[R_1], [R_2], [R_3]$	0.2044, 0.1972, 0.3386
13	20	$[R_1], [R_2], [R_3]$	0.3685, 0.4176, 0.6881
14	30	$[R_1], [R_2], [R_3]$	0.5614, 0.6396, 1.0133
15	40	$[R_1], [R_2], [R_3]$	0.8362, 0.8347, 1.2848
16	50	$[R_1, R_2], [R_3]$	1.0783, 1.4935
17	60	$[R_1], [R_2], [R_3]$	2.0654, 1.1245, 1.6617
18	70	$[R_1], [R_2, R_3]$	3.7401, 1.3414
19	80	$[R_1], [R_2, R_3]$	8.5407, 1.4220
20	90	$[R_1], [R_2, R_3]$	33.6852, 1.4847
21	100	$[R_1], [R_2, R_3]$	886.0287, 1.5339



(a)



(b)

Figure 3.6: Three-relay case with relay R_1 at different locations (a) Optimal power allocation to each relay, (b) Utility of each relay.

Due to the mobility of relays, changes in power allocation and individual utility of relays for disjoint CG approach in a three-relays case have been shown in Figure 3.6. Relays R_2 and R_3 are considered to be positioned at location (40, 0) and (55, 5), respectively. The source-destination pair is placed at coordinates $(0, 0)$ and $(100, 0)$, respectively. Relay R_1 moves along the line from (10, -2) to (90, -2). Here, the cost per unit power for each helping relay is 0.5 and the gain per unit of achievable rate $a = 0.05$. Figures can be interpreted by observing Table 3.2 which enlists the coalitions formed and their optimal prices due to the movement of relay R_1. Following observations are noteworthy.

- No change in allocated power of relay R_2 can be observed from Figure 3.6a. This happens because the power allocated to relay R_2 overshoots the power constraint, thus, resulting in capping of power to 10 mW.

- A monotonic reduction in the power allocated to relay R_1 with increasing distance from the source in the positive x-direction can be seen. The decrement in power is more pronounced from location (50, -2) because of the rise in prices asked by the relays. A sudden reversal of this trend has been observed for relay R_3 when relay R_1 is at location (60, -2). It is due to the formation of an altogether new coalition structure. It can be verified from Table 3.2 that new coalition structures are formed at locations (50, -2), (60, -2) and (70, -2). Similarly, at locations (-70, -2) and (-60,-2), variations in allocated power can be attributed to the formation of new coalition structures.

- At all the above mentioned points, a noticeable deviation in the trend of the graph can be observed confirming the impact of dynamic coalition formation on the allocated power.

- It can be confirmed from the Table 3.2 that with increase in the prices set by relays, there is a decrease in the amount of allocated power. More power is allocated to the coalitions with less prices in comparison with the other co-existing coalitions.

- No significant change in allocated power to all the three relays can be observed from Figure 3.6a, whereas increase in their prices is apparent from Table 3.2, when the relay R_1 moves from location (10, -2) to (40, -2). This leads to the increase in their utilities as evident from Figure 3.6b. However, utilities of all the relays decrease as relay R_1 moves towards the source from the negative x-direction due to the increase in the prices set by the relays.

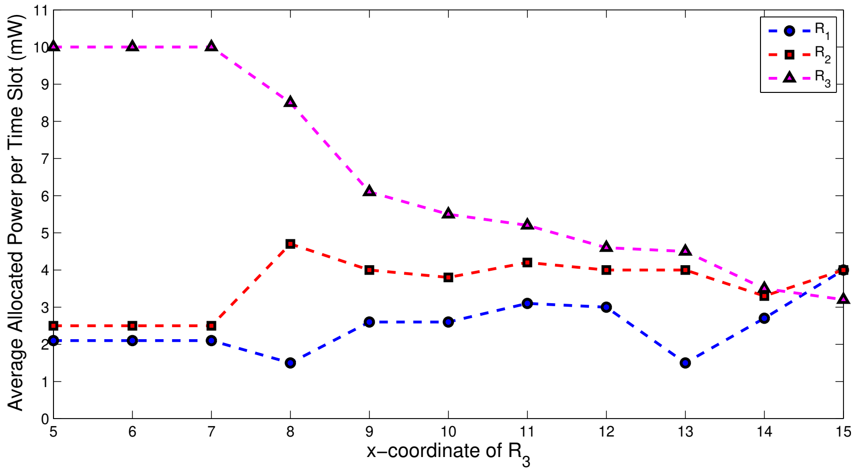
- Due to the reasons mentioned above, there is an increase in utilities of relays R_2 and R_3 as relay R_1 further moves towards the destination. However, a change in the rate of increase in their utilities at locations (50, -2), (60, -2) and (70, -2) of relay R_1 can be attributed to the change in coalition structures at these locations.
- A dip in the utility of relay R_1 from location (50, -2) can be attributed to the marginal decrease in its allocated power.

With the movement of relays, variation in average power allocation per time slot and total utility of relays for OCG has been shown in Figure 3.7. For this, three relays R_1, R_2 and R_3 have been considered. Relays R_1 and R_2 are assumed to be located at $(15, -5)$ and $(15, 10)$, respectively. Relay R_3 moves along the line from $(5, 15)$ to $(15, 15)$. Figures can be interpreted by observing Table 3.3 which enlists the coalitions formed and their optimal prices due to the movement of relay R_3. Following observations are noteworthy.

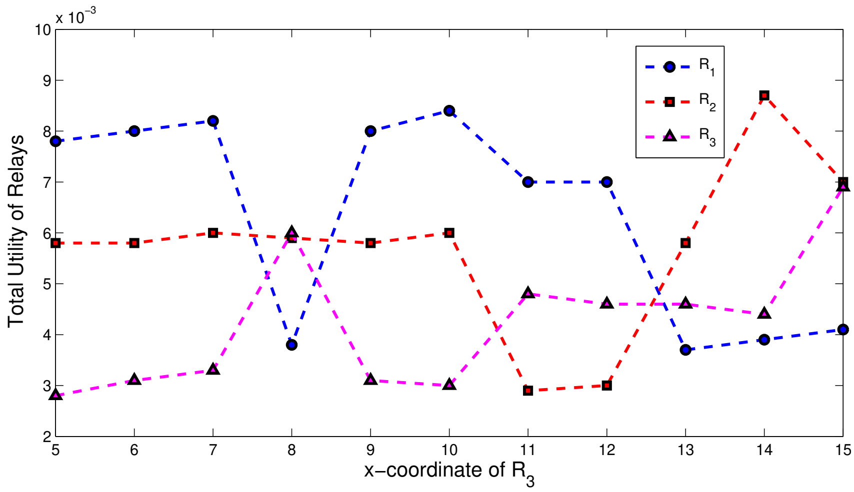
- A monotonic decrement in the average allocated power per time slot to relay R_3 with increasing distance from the source can be observed from Figure 3.7a.
- Due to the mobility of relay R_3, changes in the average power allocated per time slot to relays R_1 and R_2 confirm the impact of dynamic coalition formation on the allocated power.
- Total utility of relays is shown in Figure 3.7b. It can be seen that being a member of multiple coalitions has resulted in enhanced utility of relays. Maximum utility of relay R_3 occurs at location $(15, 15)$, where relay R_3 is a member of three coalitions.
- Taking the case of relay R_2, a dip in its total utility at $(11, 15)$ and $(12, 15)$ can be attributed to its membership to only one coalition, unlike at all other

locations.

In a nutshell, relays joining a single coalition at a particular location have lower utility than those joining multiple ones. Hence, this strategy leads to better allocation of power and has a likely positive effect on the final system throughput.



(a)



(b)

Figure 3.7: Three-relay case with relay R_3 at different locations (a) Average allocated power per time slot to each relay, (b) Total utility of each relay.

Different optimal prices for similar coalition structures can be observed from Table 3.3 (s. no. 1-3, 5-6 and 7-8). This is due to the dependency of the price of a coalition on the channel coefficients of the member relays towards the source and destination as well as the prices set by the existing coalitions in the coalition structure.

To further examine the proposed scheme, a multiple-relay case is set up in which dif-

Table 3.3: Formation of stable overlapping coalition structures and their optimal price due to the movement of relay R_3.

S. No.	**x-coordinate of R_3**	**Stable Overlapping Coalition Structure**	**Optimal Price of Coalitions**
1	5	$[R_1], [R_2], [R_3], [R_1, R_2]$	2.5418, 0.2824, 0.9577, 1.4046
2	6	$[R_1], [R_2], [R_3], [R_1, R_2]$	2.6075, 0.3062, 0.9815, 1.4399
3	7	$[R_1], [R_2], [R_3], [R_1, R_2]$	2.6829, 0.3325, 1.0088, 1.4805
4	8	$[R_1], [R_2], [R_3], [R_2, R_3]$	2.4864, 0.9352, 0.3249, 0.4393
5	9	$[R_1], [R_1, R_2], [R_2, R_3]$	2.6759, 1.4752, 0.5004
6	10	$[R_1], [R_1, R_2], [R_2, R_3]$	2.7818, 1.5321, 0.5493
7	11	$[R_1], [R_3], [R_1, R_2, R_3]$	2.4842, 0.3760, 0.6931
8	12	$[R_1], [R_3], [R_1, R_2, R_3]$	2.5094, 0.3968, 0.7397
9	13	$[R_1], [R_2], [R_3], [R_2, R_3]$	2.4916, 0.9336, 0.4104, 0.5703
10	14	$[R_2], [R_1, R_2], [R_2, R_3]$	0.9896, 1.4549, 0.6296
11	15	$[R_3], [R_2, R_3], [R_1, R_2, R_3]$	0.5342, 0.7494, 1.0272

ferent number of relays with same maximum transmit power constraint,i.e. 10 mW, are available for cooperation. The relays are uniformly located in $(0, 20)$ on x-axis and $(-20, 20)$ on y-axis. Here, both orthogonal and non-orthogonal transmissions of signals are considered by the relays within a coalition. In Figure 3.8a, a decreasing trend in the average utility per time slot per helping relay is observed. This can be attributed to the fact that with increase in the number of relays, the possibility of forming large number of coalitions increases, thus, making the competition among the coalitions more severe and affecting the utilities of the member relays in case of singleton [94], disjoint as well as overlapping coalitions in both the cases. In OCG, relays forming multiple coalitions garner more average payoff unlike the case in disjoint approach, where a relay can enjoy the benefits from a single coalition, and singleton coalitions, where a relay does not form a coalition with other relays at all. Hence, average utility per time slot per helping relay in overlapping coalitions for both OMA as well as NOMA is more than that of disjoint coalitions and singleton coalitions.

With increase in the number of relays, possibility of forming more number of coalitions increases. This further decreases the weight, γ_L which is defined in (3.8). Therefore, average source utility decreases with increase in number of relays as depicted in Figure 3.8b. It is evident that decrement in source utility is less steep in the case of overlapping coalitions than that in singleton and disjoint coalitions.

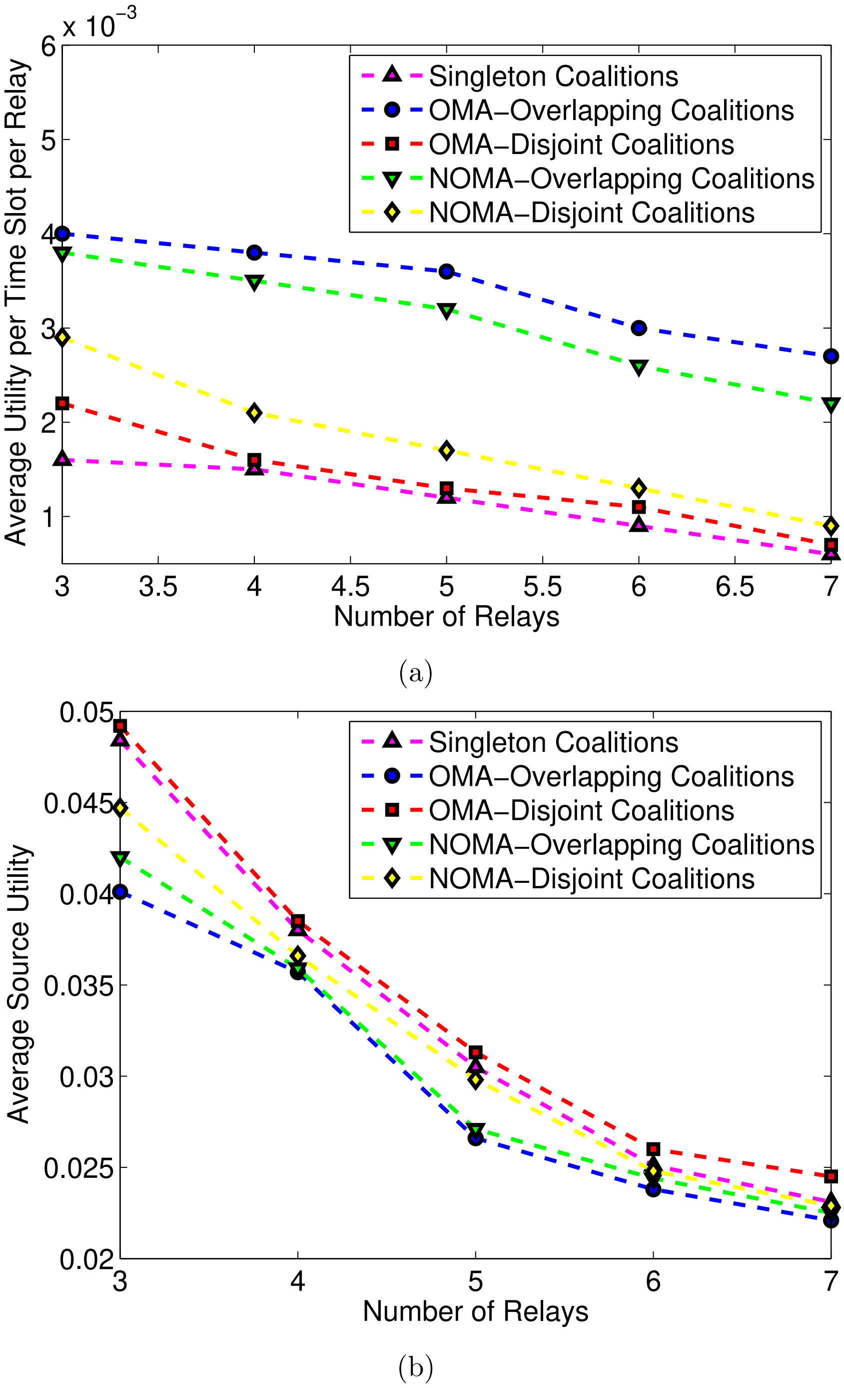
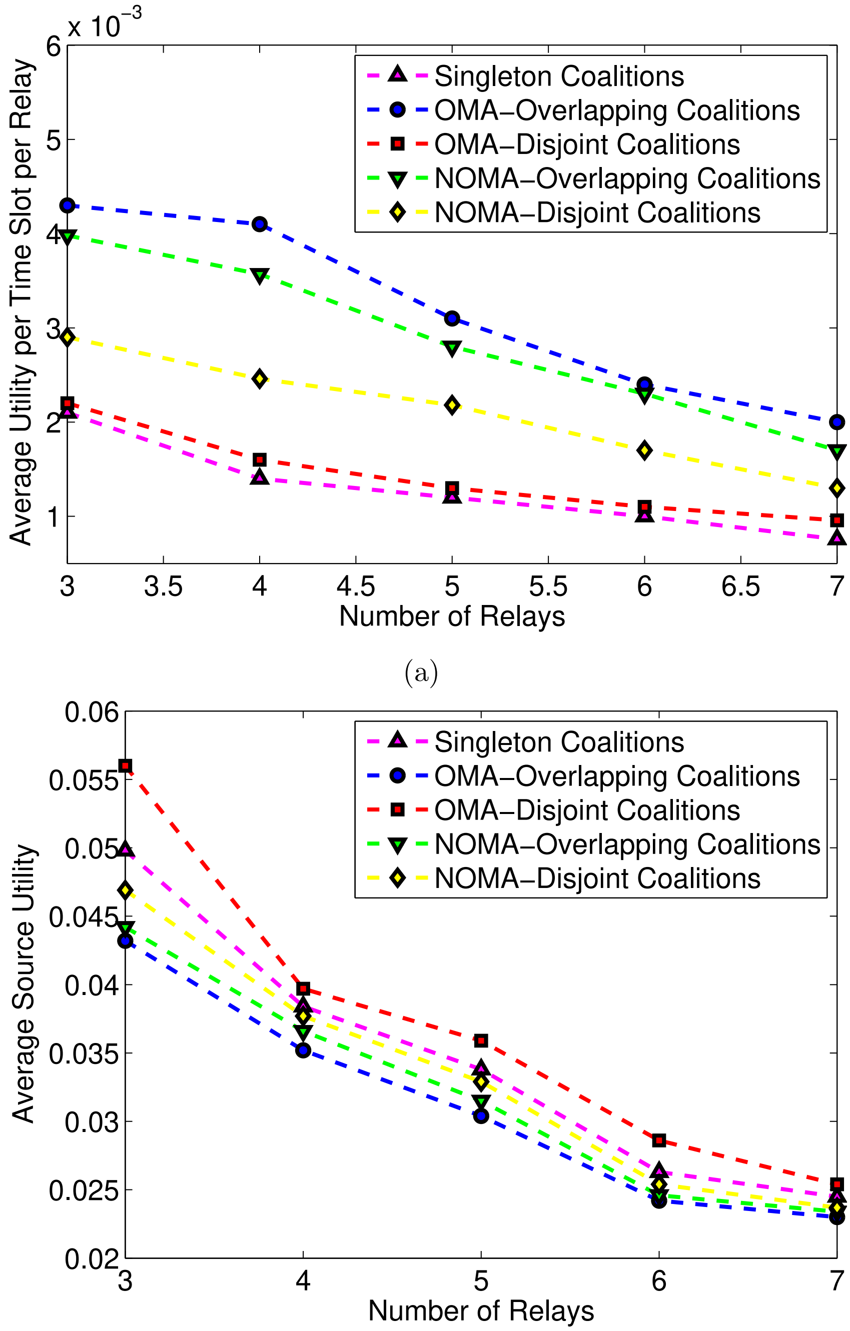


Figure 3.8: Performance comparison of different approaches versus number of helping relays having same maximum transmit power constraint (a) Average utility per helping relay, (b) Average source utility.

This explains the source utility of OCG being comparable to that of singleton and disjoint coalitions even with large number of relays. Since the possibility of forming larger number of coalitions is more for the OCG, source utility is minimum in this case. Moreover, both the source and relays tend to maximize their output, there is a tradeoff in their utilities which exists due to the tradeoff in optimal power and optimal price as discussed earlier in Section 6.1. This certainly explains the decreased source utility in case of overlapping coalitions as compared to that of singleton and disjoint coalitions for both OMA and NOMA transmissions.

To investigate the proposed game for varying maximum relay transmit power constraint, multiple relays that are uniformly located in $(0, 20)$ on x-axis and $(-20, 20)$ on y-axis are considered. The relays are assigned an integral value from range $[8, 12]$ mW randomly as their maximum transmit power constraint. It can be seen from Figure 3.9 that the same trend in both average utility per time slot per relay and average source utility is followed in case of both OMA and NOMA as that of same maximum relay transmit power constraint (Figure 3.8). The average utility per time slot per relay in the case of overlapping coalitions is more than that of disjoint as well as singleton coalitions, whereas the average source utility in overlapping coalitions is less as compared to both disjoint and singleton coalitions.

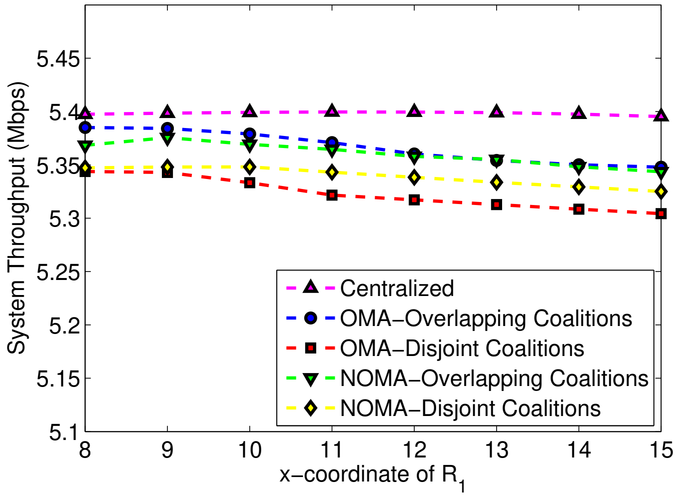
Comparative performance of the disjoint and overlapping coalition schemes for both OMA and NOMA has been analyzed by computing the system throughput at different locations of one of the relays along the x-coordinate. Individual relays are supposed to be initially located at R_1 $(15, -15)$, R_2 $(17, -12)$ and R_3 $(14, -10)$. Three such graphs have been plotted as Figures 3.10a-3.10c corresponding to the movement of relays R_1, R_2, and R_3, respectively. It can be clearly observed that the CG approaches, in general, have yielded fairly good system throughput which are comparable to that obtained using the centralized scheme. For example, in the case of moving relay R_3, the difference between system throughput obtained using overlapping coalition scheme comes out to be a meagre 0.05 Mbps in case of OMA and 0.06 Mbps for NOMA, whereas for disjont coalition scheme, it comes out to be 0.09 Mbps and 0.08 Mbps for OMA and NOMA, respectively. In particular, application of the OCG-SG framework yielded a system throughput much closer to the centralized scheme than that obtained using the disjoint coalition formation



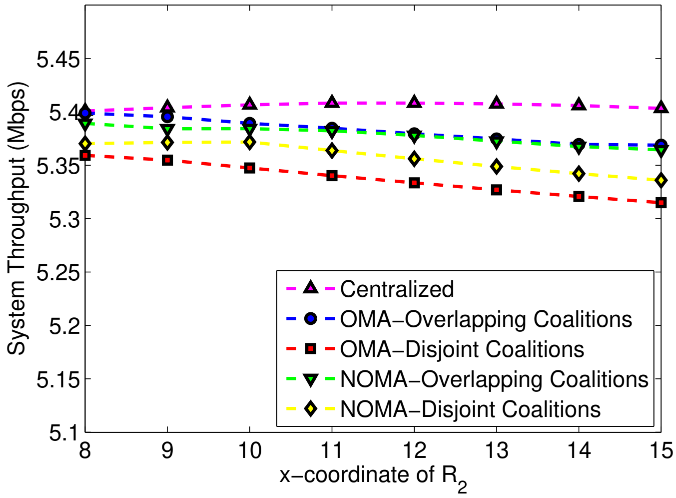
(a)

(b)

Figure 3.9: Performance comparison of different approaches versus number of helping relays having different maximum transmit power constraint (a) Average utility per helping relay, (b) Average source utility.



(a)



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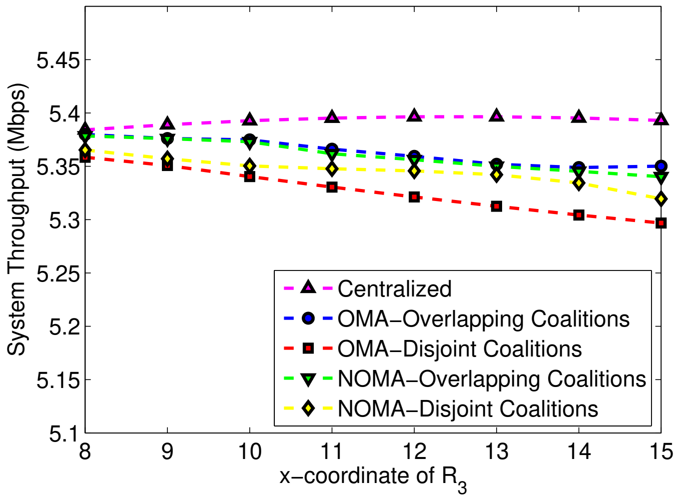


(c)

Figure 3.10: System throughput for centralized approach, disjoint coalition formation game approach and overlapping coalition formation game approach with the mobility of different relays in network. (a) Movement of relay R_1, (b) Movement of relay R_2, (c) Movement of relay R_3

game for both OMA and NOMA transmissions. This can be attributed to better allocation of power to individual relays in the case of OCG framework since a relay is now a stakeholder in multiple coalitions and is, thus, entitled to allocation of more power subject to individual constraints. Further, being an interference-limited scheme, careful relay grouping is essential to reap the potential benefits of NOMA. This proves tricky when relays are allowed to form multiple coalitions with sole purpose of increasing their own utility. This explains the better performance of OMA as compared to NOMA in case of overlapping coalitions, whereas system throughput for NOMA is better than that of OMA for disjoint scheme. The efficacy of CGs approach in general and OCG-SG in particular can be established from the above discussion.

3.8 Chapter Summary

In this chapter, an incentives-based integrated game framework has been proposed to address power allocation problem in a single source, multiple-AF-relay network. Introduction of the OCG-SG framework to ensure optimal power allocation was motivated by the desire to consider the joint benefits of the source and relays. This approach has paid dividend by ensuring an optimal solution and better throughput. Optimality of the obtained solution in terms of power and price has been analytically established by proving the existence of SE in the proposed game. As an initial step, formation of disjoint coalitions has resulted in the system throughput comparable to that obtained by the centralized approach. However, when the relays are allowed to form overlapping coalitions, they exhibit higher utility due to payoffs received from multiple coalitions. Furthermore, significantly enhanced throughput as compared to the disjoint approach confirms the efficacy of this technique which seems to be more relevant to practical scenarios. In the next chapter, an SG has been presented for joint relay selection and optimal power allocation in cooperative D2D network under channel uncertainties.

Chapter 4

A Robust SG Approach for Joint Relay Selection and Optimal Power Allocation for Cooperative D2D Communication Under Channel Uncertainties

D2D communication enables direct communication among users in close proximity without traversing the core network. With relay assistance, D2D users can have the leverage of transmitting data directly over long distances with increased throughput. However, due to the dynamic nature of wireless networks, there may be uncertainty in the channel parameters known to a user. This chapter addresses the joint problem of relay selection and optimal power allocation in single-source multi-relay D2D networks when the perfect CSI for relay channels is unknown. This uncertainty has been modeled as a bounded difference between actual and nominal values. An incentives-based robust SG is proposed in which the relay devices (RDs) determine the price of power allocated to them by the source device (SD). A closed-form expression for the optimal power is obtained. Further, the SE is derived and its existence and uniqueness are demonstrated. The performance of the proposed game is compared with the nominal game. Simulation results confirm the effectiveness of the robust game theoretic solution in an incomplete information environment.

4.1 Introduction

D2D communication is envisioned as one of the most promising technologies for the future 5G cellular networks [115]. Establishing D2D links means allowing "devices" to communicate directly without the need for routing data through network infrastructure. This not only decreases the load on BSs or access points but also increases the coverage capacity and spectral efficiency of the network [116]. Performance and throughput of the system can be further enhanced by employing the concept of relaying to assist the devices.

Most of the existing studies are based on the assumption that each user is completely aware of the transmission parameters of the other users. Due to the random and dynamic nature of wireless environment, information uncertainties are bound to appear and the assumption of perfect information may not be practical. In contrast, authors in [117], [118] have addressed the resource allocation problem in D2D communications with incomplete channel information. However, both these studies have assumed the selfless behavior of relays. In spite of these studies, optimal relay selection and power allocation in D2D systems remains a critical challenge when the channel conditions are uncertain, i.e. channel gains are unknown.

In addition, cooperative systems are viable only if the relays are willing to cooperate. Practically, relaying nodes may not help and share their power unless they are provided with some reimbursement. All this provided motivation to propose an incentives-based game theoretic solution to address the joint problem of relay selection and power allocation for throughput maximization in cooperative D2D communications under channel uncertainties. In this chapter, this uncertainty is introduced by assuming imperfect CSI of relaying channels.

To model interactions between *SD* and *RD*s, multi-leader single-follower SG has been employed, where *RD*s act as leaders while *SD* acts as a follower. *SD* allocates optimal power to *RD*s at optimal prices, thereby, establishing the SE of the game considering the mutual benefits of *SD* and *RD*s. To the best of the author's knowledge, this is the first work to apply incentives-based SG for joint relay selection and optimal power allocation in a cooperative D2D network under uncertain channel conditions.

The main contributions of this work are written as follows:

- Based on multi-leader single-follower SG, a convex optimization problem for joint relay selection and optimal power allocation among *RD*s is formulated in cooperative D2D network.

- As opposed to most of the prior research addressing resource allocation problem with complete channel information, a robust game theoretic solution is proposed where RDs are paid at optimal prices by SD for the power they use for cooperation under the uncertainty in CSI of relaying channels.

- The existence and uniqueness of SE for the proposed game are proved.

The remaining chapter is structured as follows. Section 4.2 describes the system model. The problem is discussed and formulated in Section 4.3. Section 4.4 gives the detailed insight of the proposed game. The performance of the proposed game is evaluated through simulation results in Section 4.5. Finally, Section 4.6 summarizes the chapter.

4.2 System Model

Consider a wireless network comprising of a single pair of source-destination device (SD-DD) with N AF relay devices RD_k, $k \in \{1, 2, \ldots, N\}$. SD transmits its information to DD over two phases. It is assumed that all the network channels are quasi-static, i.e. they remain unaffected over each transmission phase. SD can figure out the available RDs by broadcasting a signal and listening to the feedback of relays on whether to cooperate or not.

TDMA transmission is considered in the system model. The first time slot is used by the SD to transmit its signal. The subsequent time slots are used by the different RDs in a TDMA manner, which is one RD per time slot, therefore, no interference is perceived from other RDs during transmission. An example of system model with $N = 5$ is depicted in Figure 4.1.

(A) **Direct Transmission Phase:** In this phase, SD broadcasts its message symbol x_S with unit energy. The signal received at DD is given by

$$y_{S,D} = \sqrt{P_S G_{S,D}} x_S + \eta_{S,D}, \tag{4.1}$$

whereas the signal received at RD_k is

$$y_{S,R_k} = \sqrt{P_S G_{S,R_k}} x_S + \eta_{S,R_k}, \tag{4.2}$$

where P_S is the transmit power at SD, $G_{S,D}$ and G_{S,R_k} represent the channel gains

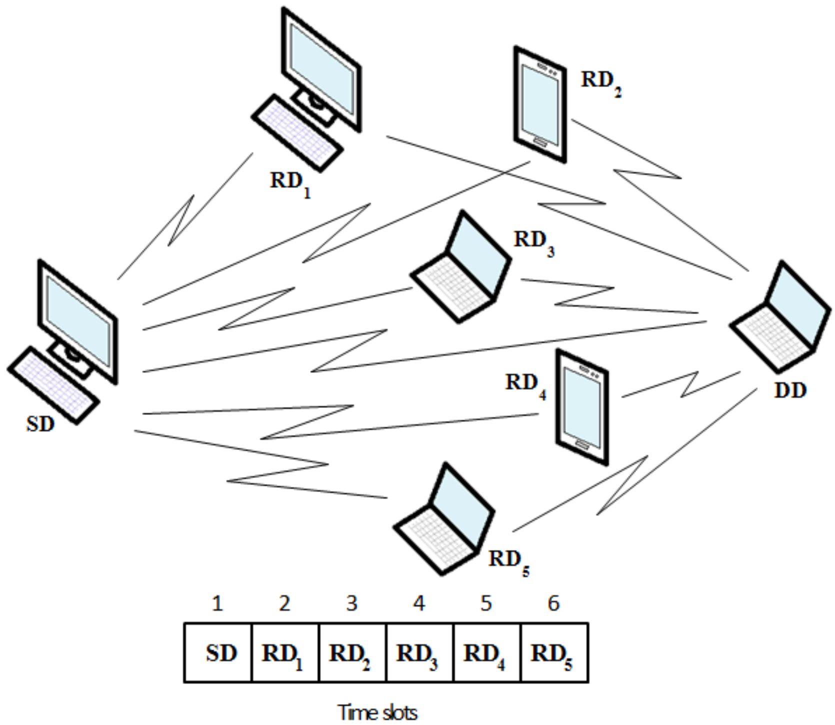


Figure 4.1: System model for a multi-relay cooperative network with $N = 5$.

from SD to DD and RD_k, respectively, and $\eta_{S,D}$ and η_{S,R_k} are the AWGN samples with N_0 noise power. The SNR due to direct transmission can be written as

$$\Gamma_{S,D} = \frac{P_S G_{S,D}}{N_0} \tag{4.3}$$

and the rate at DD is

$$R_{S,D} = W \log_2 \left(1 + \Gamma_{S,D}\right), \tag{4.4}$$

where W denotes the bandwidth of the system.

(B) **Cooperative Transmission Phase:** In this phase, RD_k amplifies the received signal $y_{S,D}$ before forwarding it to DD. The signal received by DD can be expressed as

$$y_{R_k,D} = \frac{\sqrt{P_k G_{R_k,D}}\left(\sqrt{P_S G_{S,R_k}} x_S + \eta_{S,R_k}\right)}{\sqrt{P_S G_{S,R_k} + N_0}} + \eta_{R_k,D}, \tag{4.5}$$

where P_k is the power transmitted by the RD_k, $G_{R_k,D}$ is the channel gain between RD_k and DD, and $\eta_{R_k,D}$ is the AWGN with N_0 noise power. The SNR due to relayed transmission is given by

$$\Gamma_{S,R_k,D} = \frac{P_S G_{S,R_k} P_k G_{R_k,D}}{N_0(P_S G_{S,R_k} + P_k G_{R_k,D} + N_0)}. \tag{4.6}$$

After MRC of both the direct and relayed paths, the rate at DD can be expressed as

$$R_{S,R_k,D} = \frac{W}{2} \log_2 \left(1 + \Gamma_{S,D} + \Gamma_{S,R_k,D}\right). \tag{4.7}$$

If the set consisting of relay devices is $\mathcal{R} = \{RD_1, RD_2, \ldots, RD_N\}$, the total system capacity is given by

$$R_{S,R,D} = \gamma_L W \log_2 \left(1 + \Gamma_{S,D} + \sum_{RD_k \in \mathcal{R}} R_{S,R_k,D}\right), \tag{4.8}$$

where weight $\gamma_L = \frac{1}{N+1}$ reflects the total number of time slots used for transmission.

Here, imperfect CSI of relaying channels is considered which brings uncertainty into the network. In order to model the channel gain uncertainty explicitly, its actual value is represented as the summation of estimated nominated value and an uncertainty term as follows:

$$G_{S,R_k} = \bar{G}_{S,R_k} + \Delta G_{S,R_k} \tag{4.9}$$

and

$$G_{R_k,D} = \bar{G}_{R_k,D} + \Delta G_{R_k,D}, \tag{4.10}$$

where $\bar{G}_{S,R_k}$ and $\bar{G}_{R_k,D}$ represent the nominal values, whereas $\Delta G_{S,R_k}$ and $\Delta G_{R_k,D}$ denote the uncertainty terms of G_{S,R_k} and $G_{R_k,D}$, respectively.
Here, worst-case approach based on robust optimization [119] is followed as it assumes uncertainty term to be bounded within an uncertainty region. This guarantees certain level of performance for every realization in the uncertainty set by preventing undesirable fluctuations in performance [120]. Owing to the analytical tractability, the channel uncertainty is modeled using column-wise model as follows:

$$G_{S,R_k} = \left\{\bar{G}_{S,R_k} + \Delta G_{S,R_k} : |\Delta G_{S,R_k}| \leq \varepsilon_{S,R_k}\right\} \tag{4.11}$$

and

$$G_{R_k,D} = \left\{\bar{G}_{R_k,D} + \Delta G_{R_k,D} : |\Delta G_{R_k,D}| \leq \varepsilon_{S,R_k}\right\}, \tag{4.12}$$

where ε_{S,R_k} and $\varepsilon_{R_k,D}$ denote the column-wise uncertainty bounds for $\Delta G_{S,R_k}$ and $\Delta G_{R_k,D}$, respectively.

4.3 Problem Formulation

To achieve the cooperative diversity, it is necessary for SD to determine that which RDs will be beneficial and what will be the optimum power that can be allocated to them. Practically, an RD may only help when the cooperation improves its own utility. Therefore, an incentives-based SG theoretic solution is proposed where RDs, as leaders, set prices for their power and SD, as a follower, allocates power and pays them accordingly.

(A) SD/**follower:** SD can be represented as a follower who wants to attain more profit at the smallest achievable expenditure. The utility of SD is given as

$$U_S = aR_{S,R,D} - \sum_{RD_k \in \mathcal{R}} p_k P_k, \tag{4.13}$$

where a is termed as the gain per unit of the total achievable rate, $R_{S,R,D}$ and p_k represents the price per unit of power P_k shared by RD_k. If P_k^{max} denotes the constraint on an RD's transmit power, the optimization problem for SD becomes

$$\max_{\{P_k\}} U_S, \quad \text{s.t. } 0 \leq P_k \leq P_k^{max}. \tag{4.14}$$

(B) RD/**Leader:** In this approach, RDs can be represented as leaders. The aim of a leader is to set price in such a way that it can earn as much extra profit as possible through cooperation. For RD_k, the utility function is defined as

$$U_k = p_k P_k - c_k P_k = (p_k - c_k) P_k, \tag{4.15}$$

where c_k represents the cost per unit power for the shared power P_k. RD_k will play the game only if U_k is non-negative, i.e. $p_k \geq c_k$. Hence, the optimization problem for RD_k is

$$\max_{\{p_k\}} U_k, \quad \text{s.t. } p_k \geq c_k. \tag{4.16}$$

4.4 The Proposed Game

This section presents the detailed analysis of the proposed SG. The closed-form outcomes for the optimization problems of both SD and RDs are obtained and then, equilibrium for the game is shown. Further, an iterative price update function is formulated for RDs.

(A) SD/**Follower Level Game Analysis:** SD needs to choose RDs with good channel conditions and reject the ones with bad channel conditions. After selecting the RDs, SD determines the amount of power it requires according to the prices set by them.

Partially differentiating (4.13) with respect to P_k gives

$$\frac{\partial U_S}{\partial P_k} = a\frac{\partial R_{S,R,D}}{\partial P_k} - p_k. \tag{4.17}$$

If $\frac{\partial U_S}{\partial P_k} > 0$, SD will have greater utility by increasing P_k. This means p_k must satisfy $p_k < a\frac{\partial R_{S,R,D}}{\partial P_k}$, else RD_k will be rejected by SD.

Since log is a concave function, it is ignored in the formulation for simplicity. Further, using the uncertainty models specified in (4.11)-(4.12) and taking the worst-case into account, (4.8) is given by

$$R_{S,R,D} = \frac{P_S G_{S,D}}{N_0} + \sum_{RD_k \in \mathcal{R}} \frac{P_k X_k}{P_k + Y_k}, \tag{4.18}$$

where $X_k = \frac{P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right)}{N_0}$ and $Y_k = \frac{P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right) + N_0}{\left(\bar{G}_{R_k,D} + \varepsilon_{R_k,D}\right)}$.

Differentiating (4.18) with respect to P_k gives

$$\frac{\partial R_{S,R,D}}{\partial P_k} = \frac{X_k Y_k}{\left(P_k + Y_k\right)^2}. \tag{4.19}$$

Substituting (4.19) in (4.17) and then equating it to zero, the optimal power consumption is obtained as

$$
\begin{aligned}
{P_k}^* &= \sqrt{\frac{aX_kY_k}{p_k}} - Y_k \\
&= \sqrt{\frac{aP_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right)\left(P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right) + N_0\right)}{p_kN_0\left(\bar{G}_{R_k,D} + \varepsilon_{R_k,D}\right)}} - \frac{P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right) + N_0}{\left(\bar{G}_{R_k,D} + \varepsilon_{R_k,D}\right)}.
\end{aligned}
\tag{4.20}
$$

Owing to the maximum transmit power constraint on the RD's power, the optimal power is given by

$$
\begin{aligned}
{P_k}^* = \Bigg(&\sqrt{\frac{aP_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right)\left(P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right) + N_0\right)}{p_kN_0\left(\bar{G}_{R_k,D} + \varepsilon_{R_k,D}\right)}} \\
&- \frac{P_S\left(\bar{G}_{S,R_k} + \varepsilon_{S,R_k}\right) + N_0}{\left(\bar{G}_{R_k,D} + \varepsilon_{R_k,D}\right)}\Bigg)_0^{P_k^{max}},
\end{aligned}
\tag{4.21}
$$

where $(x)_l^u$ is defined as in (3.23). This is a convex optimization problem, hence a unique solution can be found.

(B) RD/**Leader Level Game Analysis:** The optimal price for RD_k can be calculated as

$$
{p_k}^* = \arg\max_{\{p_k\} \geq c_k} U_k. \tag{4.22}
$$

For RD_k, ${p_k}^*$ depends on its channel conditions towards SD and DD. If RD_k sets a high price for its power, then SD will consume less power from it or even overlook it.

(C) **Existence of Equilibrium in the Proposed Game:** This subsection shows that the set of obtained solution from (4.21) and (4.22) is the unique equilibrium called SE of the game which is defined below [94].

Definition 4.1. ${P_k}^{SE}$ and ${p_k}^{SE}$ form an SE if for every $RD_k \in \mathcal{R}$ and fixed p_k, their values are obtained as

$$
{P_k}^{SE} = \arg\max_{0 \leq \{P_k\} \leq P_k^{max}} U_S, \tag{4.23}
$$

and when P_k is fixed,

$$
{p_k}^{SE} = \arg\max_{\{p_k\} \geq c_k} U_k. \tag{4.24}
$$

Property 4.1. The utility function of SD, U_S is concave in P_k when p_k is kept unchanged.

Proof. Calculating the second-order derivative of U_S gives

$$\frac{\partial^2 U_S}{\partial {P_k}^2} = -2\frac{aP_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)\left(P_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)+N_0\right)\left(\bar{G}_{R_k,D}+\varepsilon_{R_k,D}\right)^2}{N_0\left(P_k\left(\bar{G}_{R_k,D}+\varepsilon_{R_k,D}\right)+P_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)+N_0\right)^3} \tag{4.25}$$

It can be clearly seen that $\frac{\partial^2 U_S}{\partial {P_k}^2} < 0$. Furthermore, U_S is continuous with respect to P_k. Hence, when $P_k > 0$, U_S is strictly concave in P_k, $\forall\ RD_k \in \mathfrak{R}$.

Property 4.2. For every $RD_k \in \mathfrak{R}$, ${P_k}^*$ decreases with increase in p_k when the prices of the RDs are kept unchanged.

Proof. Calculating the first-order derivative of ${P_k}^*$ gives

$$\frac{\partial {P_k}^*}{\partial p_k} = -\frac{1}{2}\sqrt{\frac{aP_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)\left(P_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)+N_0\right)}{{p_k}^3 N_0\left(\bar{G}_{R_k,D}+\varepsilon_{R_k,D}\right)}} < 0. \tag{4.26}$$

This indicates ${P_k}^*$ is decreasing with p_k. This is so because if an RD raises its price with other RDs keeping their prices unchanged, SD will purchase less power from the former.

Property 4.3. For every $RD_k \in \mathfrak{R}$, the utility U_k is concave in terms of its price p_k, provided its power consumption is the optimized amount allocated by SD as given in (4.21) and the prices of other RDs are fixed.

Proof. Calculating the second-order derivative of U_k with respect to p_k, gives

$$\frac{\partial^2 U_k}{\partial {p_k}^2} = -\frac{1}{4}\sqrt{\frac{aP_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)\left(P_S\left(\bar{G}_{S,R_k}+\varepsilon_{S,R_k}\right)+N_0\right)}{{p_k}^5 N_0\left(\bar{G}_{R_k,D}+\varepsilon_{R_k,D}\right)}}\left(p_k+3c_k\right) < 0 \tag{4.27}$$

Since $\frac{\partial^2 U_k}{\partial {p_k}^2} < 0$, U_k is concave with respect to p_k.

(D) **Iterative Price Updating Function:** By setting the initial prices to respective costs, RDs increase their utilities iteratively reaching towards the optimal values [94]. For every $RD_k \in \mathfrak{R}$, p_k is updated in such a way that

$$\frac{\partial U_k}{\partial p_k} = {P_k}^*\left(p_k\right) + \left(p_k - c_k\right)\frac{\partial {P_k}^*\left(p_k\right)}{\partial p_k} = 0. \tag{4.28}$$

After re-arranging, (4.28) can be represented as

$$p_k = c_k - {P_k}^* \left(p_k\right) \left(\frac{\partial {P_k}^* \left(p_k\right)}{\partial p_k}\right)^{-1} = I_i \left(\mathbf{p}\right), \tag{4.29}$$

where $I_i\left(\mathbf{p}\right)$ is the price updating function for RD_k. For all RDs, price updating function can be expressed in the vector form as

$$\mathbf{p} = I\left(\mathbf{p}\right), \tag{4.30}$$

where $\mathbf{p} = \{p_k\}_{RD_k \in \mathfrak{R}}$ and $\mathbf{I}\left(\mathbf{p}\right) = \{I\left(\mathbf{p}\right)\}_{RD_k \in \mathfrak{R}}$. Here, $I\left(\mathbf{p}\right)$ is a standard function which can proved in similar way as in [94] for the proposed scheme. Consequently, the iterations of (4.30) are given by

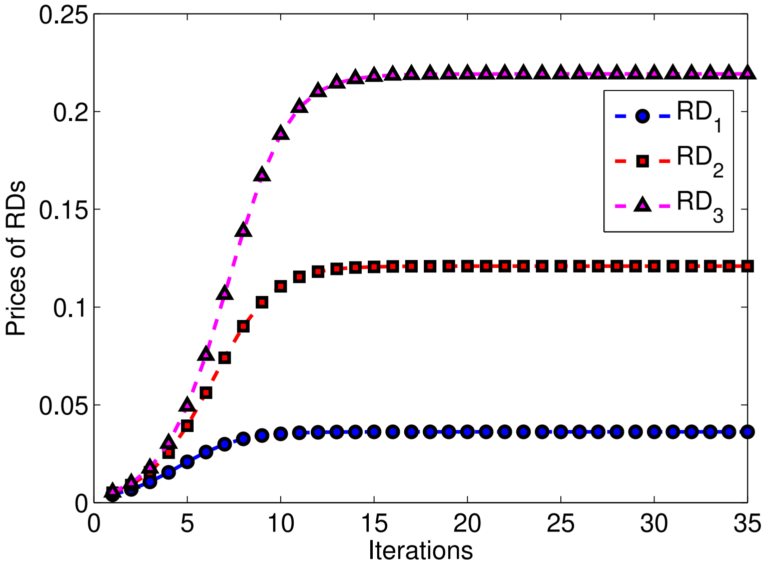
$$\mathbf{p}\left(t+1\right) = \mathbf{I}\left(\mathbf{p}\left(t\right)\right). \tag{4.31}$$

Initiating from the price values set to costs, $\mathbf{p}$ will converge to a unique equilibrium after sufficient number of iterations.

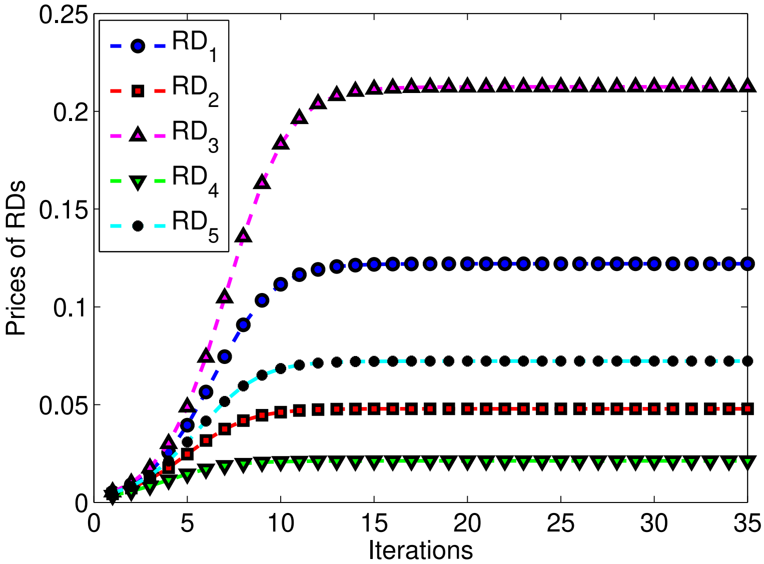
Algorithm 4.1 SG-based Power Allocation Algorithm

Initialize S, D
Initialize RD_k, $k \in \{1, 2, \ldots, N\}$
Initialize $p_k(0) = c_k$, $t = 0$
repeat
  for $k = 1 : N$ **do**
    Calculate $P_k\left(t+1\right)$ with (4.21) {power allocation}
    Calculate $p_k\left(t+1\right)$ with (4.31) {price updation}
  end for
  $t = t + 1$;
until Convergence, i.e. there are no further changes in $p_k\left(t\right)$, $\forall\, k \in \{1, 2, \ldots, N\}$ with additional iterations

Algorithm 4.1 describes the overall SG approach for a single SD-DD pair and $R_k, k \in \{1, 2, \ldots, N\}$, available RDs. For one iteration, the complexity of calculating price and power is $O(N)$, where N is the total number of RDs. If the algorithm converges after M number of iterations, the overall complexity of the proposed game is $O(NM)$.



(a)



(b)

Figure 4.2: Convergence of the prices of RDs. (a) Prices of 3 RDs versus iterations, (b) Prices of 5 RDs versus iterations

4.5 Simulation Results and Discussion

In this section, the performance of the proposed scheme is examined. For simulations, a network with uniformly distributed devices having independent and identically distributed Rayleigh fading channels is assumed. The parameters for this analysis are given as: $P_S = 10$ mW, $P_k^{max} = 10$ mW, $N_0 = 10^{-8}$ W, $W = 1$ MHz, $c_k = 0.1$ and $a = 0.01$ [94]. For the uncertainty models, the uncertainty terms are

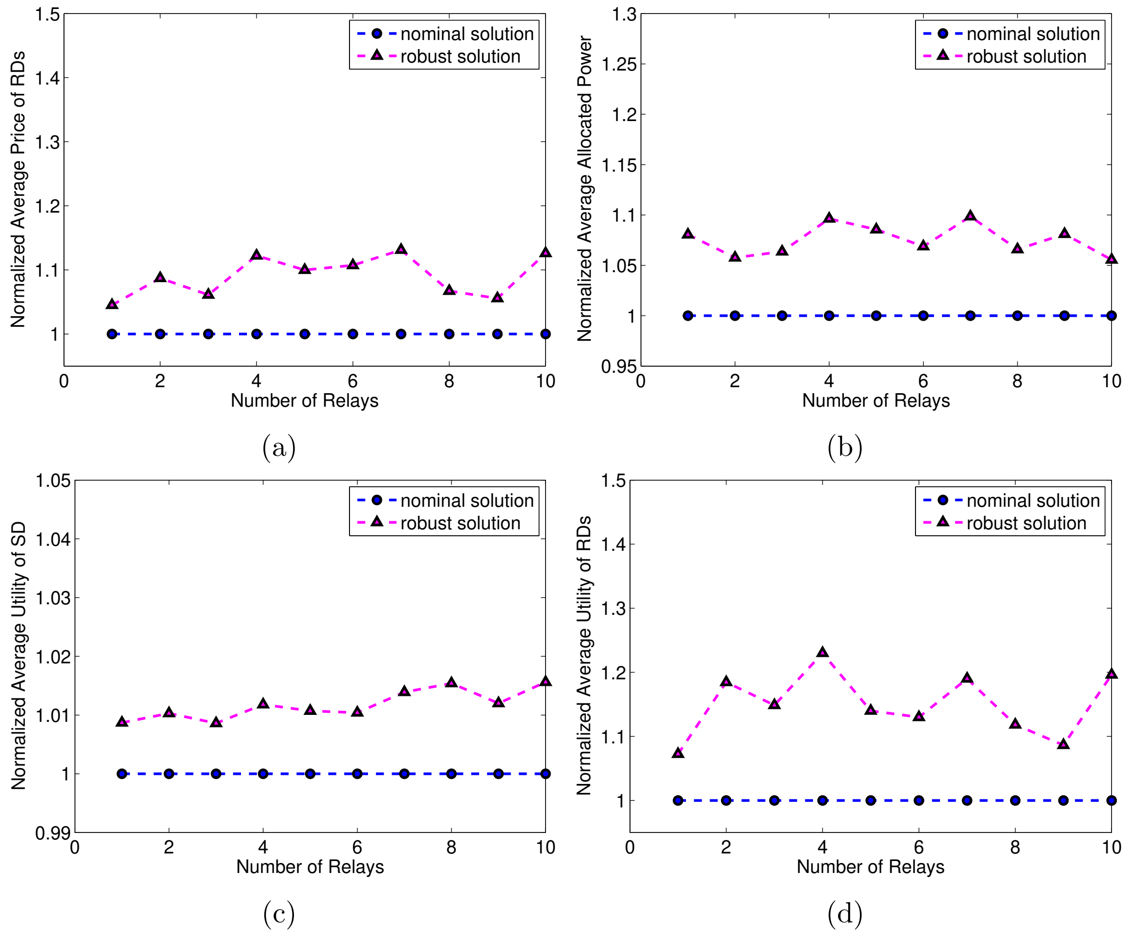


Figure 4.3: Comparison of robust solution and nominal solution versus number of relays. (a) Normalized average price of RDs, (b) Normalized average allocated power, (c) Normalized average utility of SD, (d) Normalized average utility of RDs

assumed to vary linearly with the respective nominal values such that $\varepsilon_{S,R_k} = \theta\bar{G}_{S,R_k}$ and $\varepsilon_{R_k,D} = \theta\bar{G}_{R_k,D}$, where θ represents the degree of uncertainty.
Firstly, the convergence of the scheme for 3 RDs and 5 RDs with $\theta = 0.3$ is shown in Figure 4.2a and 4.2b, respectively. RDs update their prices iteratively and converge to the optimal ones. It can be seen that prices for both the cases converge in less than 15 number of iterations. Convergence speed remains almost same even with more RDs in the network.

The proposed robust solution is compared with the nominal solution against increasing number of RDs in Figure 4.3. Apart from the nominal solution (i.e. $\theta = 0$, considering the nominal values only), the robust solution for $\theta = 0.3$ has been calculated. Figure 4.3a represents the normalized average price of RDs and Figure 4.3b indicates the normalized average power allocated to RDs with respect to the increasing number of relays. Normalized average SD utility and RD utility are depicted in Figure 4.3c and 4.3d, respectively. It can be clearly seen that irrespective of the number of RDs in the network, all the four aforementioned parameters attain higher values when the CSI is imperfect as compared to that of nominal solution. As the actual values of the relaying channel gain deviate from the nominal values, SD allocates more power to the RDs even if RDs set higher price for their power while establishing the SE. This results in enhanced average utility for both SD and RDs as compared to their nominal counterparts even with increase in the number of RDs.

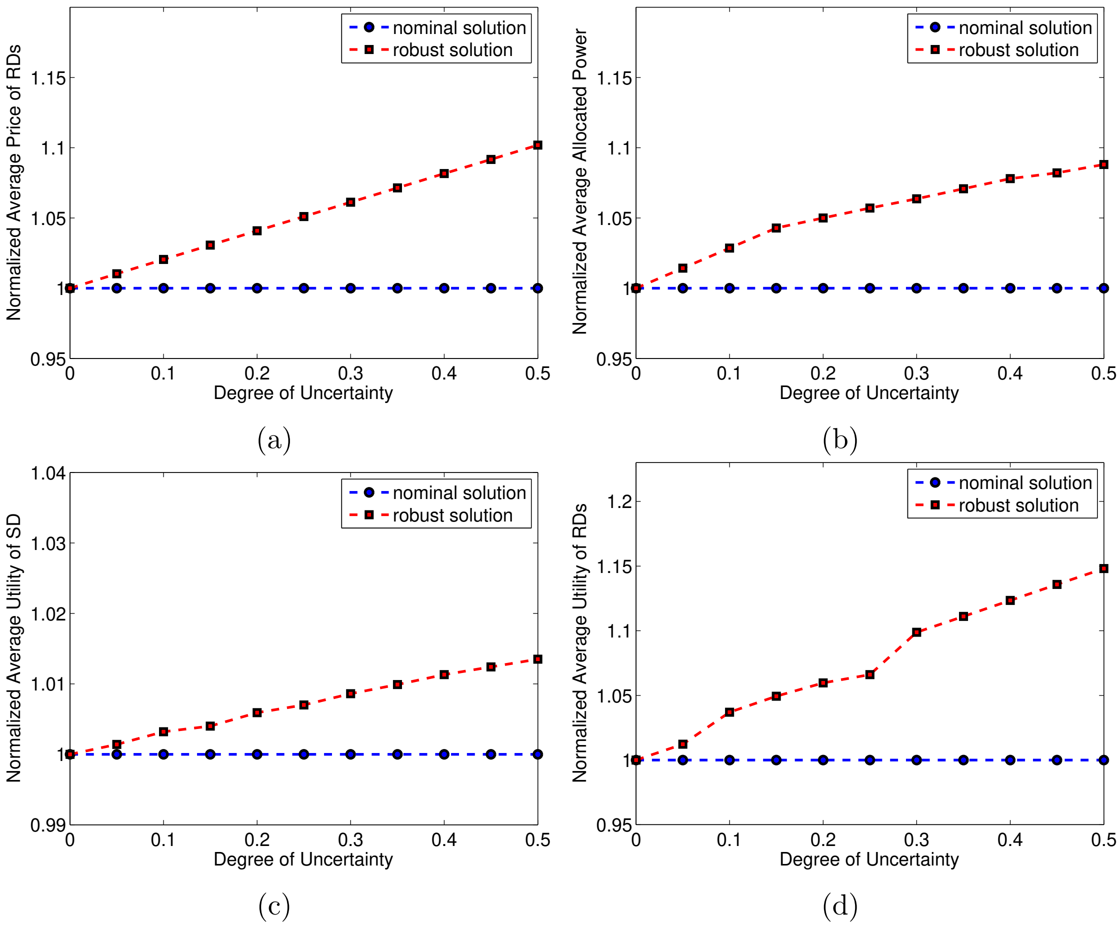
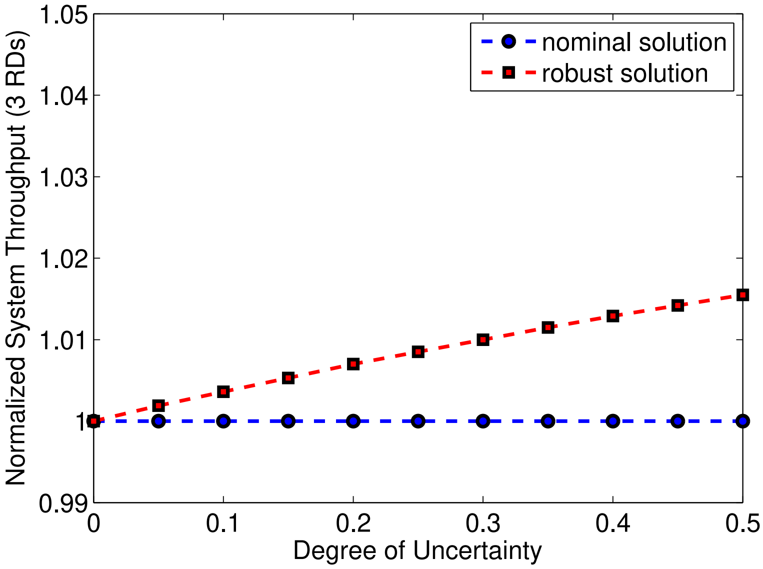
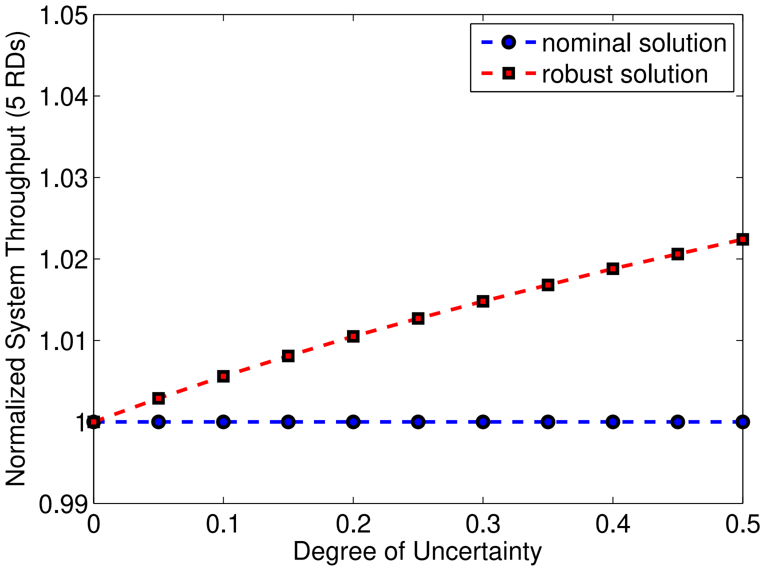


Figure 4.4: Comparison of robust solution and nominal solution versus degree of uncertainty. (a) Normalized average price of RDs, (b) Normalized average allocated power, (c) Normalized average utility of SD, (d) Normalized average utility of RDs



(a)



(b)

Figure 4.5: Performance comparison of robust solution and nominal solution versus degree of uncertainty. (a) Normalized system throughput for 3 RDs, (b) Normalized system throughput for 5 RDs

To investigate the effect of the degree of uncertainty on the proposed scheme, a cooperative D2D network with 3 RDs is considered and θ is varied from 0 to 0.5. Normalized average price, power, SD utility and RD utility for both robust and nominal solution are depicted in Figure 4.4a-4.4d, respectively. With increase in the uncertainty of CSI of a relaying path, the actual value deviates from the nominal value such that the uncertainty term lies within uncertainty bound. This increase in relaying channel gain leads RDs to up their prices and SD to allocate more amount of power. This further increases their respective average utilities with increase in the value of θ.

To compare the performance of the cooperative D2D network under the robust solution and nominal solution, the normalized system throughput is examined with increase in the value of θ for 3 RDs and 5 RDs cases in Figure 4.5a and 4.5b, respectively. It is evident that the robust solution yields better performance than the nominal solution in terms of system throughput. The performance gap increases with increase in the degree of uncertainty. This can be attributed to the fact that as θ increases, the amount of power allocated to RDs also increases as already shown in Figure 4.4b. Thus, the proposed robust game theoretic solution performs better than that of the nominal solution under imperfect CSI environment.

4.6 Chapter Summary

In this chapter, the joint problem of relay selection and optimal power allocation in cooperative D2D communications has been investigated under uncertainties in relaying channel conditions. Each of the uncertain parameters has been modeled by a bounded difference between actual and estimated values. The competitive interactions in SD and RDs have been analyzed using a robust SG, where RDs, as leaders, set the prices first and SD, who acts as a follower, determines the power to be allocated. SE has been attained and its existence and uniqueness have been proved, thus, signifying the optimality of the obtained solution in terms of price and power. Effectiveness of the robust solution in terms of utility of SD and RDs has been established through simulation results. Further, enhanced throughput as compared to the nominal game confirms the efficacy of the proposed robust game under varying degree of uncertainty which seems to be more relevant to practical scenarios. In the next chapter, auction-based schemes have been proposed for power allocation in downlink NOMA and hybrid NOMA-OMA systems.

Chapter 5

Auction-based Power Allocation in Downlink NOMA and Hybrid NOMA-OMA Systems

NOMA is viewed as one of the key enabling candidate for next generation wireless networks. The effectiveness of such networks heavily relies on the power allocation. This chapter addresses the problem of power allocation in a downlink cellular NOMA network as well as hybrid NOMA-OMA network, where NOMA is integrated into OMA. For downlink cellular NOMA network, an auction-based mechanism is proposed in which the users compete for the transmit power being sold by the BS. Each user places its bid iteratively to maximize its own utility. On the other hand, the auction game proposed for the downlink hybrid NOMA-OMA network, firstly, pairs the users with strong channel conditions with the users having weak channel conditions through a random mechanism. These user pairs then compete for the transmit power by placing bids in an iterative manner so as to attain maximum gains. The existence of a unique NE has been proved theoretically for both the games. Simulation results demonstrate the effectiveness of the auction game with user pairing in terms of the average sum rate of users as compared to an existing algorithm and the auction gain without user pairing. This chapter highlights the significance of user pairing in NOMA systems.

5.1 Introduction

NOMA is considered as one of the disruptive technology for future wireless networks [121]. Unlike OMA, NOMA exploits power domain to serve multiple users in the same frequency and time resources, thereby, increasing the system's spectral efficiency [122]. This is achieved by superposition coding at the transmitter side with SIC at the receiver end [43]. NOMA significantly improves the spectral efficiency of the system and scales up the number of users being served in comparison to OMA. The performance of NOMA systems is heavily influenced by resource allocation. Efficient resource allocation controls the interference among the users. Authors in [122], [123] employed SG to address the power allocation problem in cellular NOMA networks. Auction game has been used in several areas of wireless communications, e.g., CR networking [124] and time slot allocation [125]. However, to the best of the author's knowledge, the application of auction game in power allocation for downlink cellular NOMA systems is still missing in the literature.

In this chapter, an auction game is presented to address the power allocation problem in a downlink cellular NOMA network. BS is modeled as an auctioneer which sells its transmit power, whereas each user acts as a player and bids for maximum utility. Further, the existence of a unique NE is proved mathematically. However, this scheme allows all the users to be served simultaneously which may not be practically feasible as the user with the best channel conditions will require to decode the rest 99 users' signal for a 100-user NOMA system [126].

Hence, in addition, an auction-based scheme for hybrid NOMA-OMA systems is proposed in which user pairing is done and each pair is allocated a different SB for transmission. This not only decreases the computational complexity at the receiver end but also manages the interference experienced by the user. To the best of the author's knowledge, this is the first work to employ auction theory to address the problem of power allocation in user pairs in a downlink multi-user hybrid NOMA-OMA network. In this auction-based scheme, BS has been modeled as an auctioneer which aims to sell its transmit power, while each user pair acts as a player, bidding for its maximum utility. A user having good channel conditions (or strong user) and a user having poor channel conditions (or weak user) are paired and then, assigned a SB simultaneously, according to the proposed random mechanism. Furthermore, the convergence of the game to a unique NE is proved theoretically. Simulation results confirm that the proposed auction game for hybrid NOMA-OMA systems yields better results in terms of the average sum rate of users as compared to the existing algorithm in [123] and the auction-based scheme for downlink NOMA systems.

The key contributions of the work are described as follows:

- The novel auction-based schemes for power allocation in downlink NOMA and hybrid NOMA-OMA systems are proposed in which BS acts as an auctioneer whereas users and user pairs are modeled as bidders, respectively.

- Convergence of both the games to a unique NE is established mathematically.

- Simulation results confirm the effectiveness of auction-based scheme for hybrid NOMA-OMA systems than that of the existing NOMA algorithm in [123] and the auction-based scheme for downlink NOMA systems in terms of average sum rate of users. The importance of user pairing in improving the performance of NOMA systems is proved.

The remaining chapter is structured as follows. In Section 5.2, the auction-based power allocation scheme for downlink NOMA systems is presented. Section 5.3 describes the auction-based power allocation in downlink hybrid NOMA-OMA systems. Section 5.4 examines the performance of the proposed schemes. Finally, the chapter is summarized in Section 5.5.

5.2 Auction-based Power Allocation for Downlink NOMA Systems

5.2.1 System Model

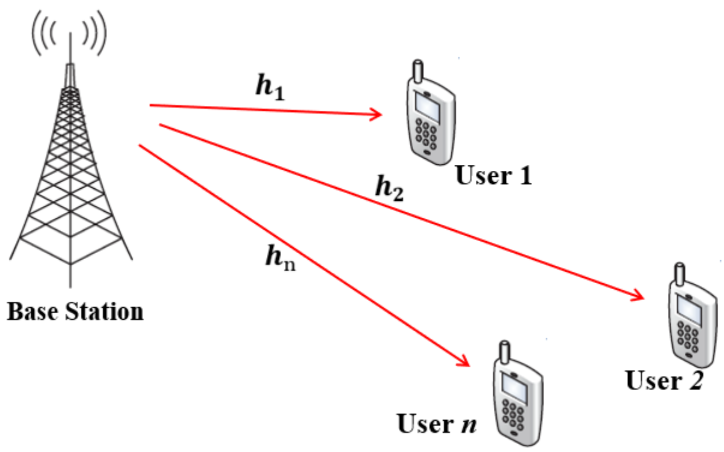


Figure 5.1: System model for a downlink NOMA system.

Consider a cellular downlink transmission system consisting of a BS and a set of N users denoted by $\mathcal{N} = \{1, 2, \ldots, N\}$ as shown in Figure 5.1. Assume that each node has a single antenna. Represent the channel fading coefficient between the BS and nth user as h_n, $n \in \mathcal{N}$. In NOMA, BS transmits signals using superposition coding to serve multiple users simultaneously. Then, the signal received by the nth user is given by

$$y_n = h_n \sum_{j=1}^{N} \sqrt{p_j} x_j + \eta_n, \tag{5.1}$$

where x_j denotes the message sent by BS for the jth user, p_j is the transmit power allocated to the jth user, and $\eta_n \sim \mathcal{CN}(0, \sigma^2)$ is the AWGN for nth user with σ^2 noise variance. Without loss of generality, assume that the users are ordered as $|h_1| \geq |h_2| \geq \ldots \geq |h_N|$. Then, by the NOMA protocol, higher power is allocated to the users with lower channel fading coefficients leading to $|p_1| \leq |p_2| \leq \ldots \leq |p_N|$ [43].

Hence, nth user decodes the signals of jth user for $j > n$ and remove them from its received signal, whilst treating the signals of jth user for $j < n$ as interference. Hence, the signal to interference plus noise ratio (SINR) of nth user is given by

$$\gamma_n = \frac{|h_n|^2 p_n}{\sigma^2 + |h_n|^2 \sum_{j=1}^{n-1} p_j}. \tag{5.2}$$

Thus, the achievable data rate of nth user is

$$R_n = \log_2 \left(1 + \frac{|h_n|^2 p_n}{\sigma^2 + |h_n|^2 \sum_{j=1}^{n-1} p_j} \right). \tag{5.3}$$

Users tend to compete for more transmit power to attain higher achievable data rates.

5.2.2 Proposed Power Allocation Scheme

In the proposed auction-based power allocation scheme, nth user submits its bid $b_n(t)$ to the BS, then the BS updates $p_n(t)$ proportionally to its payment $b_n(t)\, p_n(t)$ as

$$p_n(t+1) = \frac{b_n(t)\, p_n(t)}{\sum_{j=1}^{N} b_j(t)\, p_j(t) + \varepsilon} P_{tot}, \tag{5.4}$$

where t is the iteration index, P_{tot} denotes the total transmit power at the BS and ε represents the non-zero reserved price adjusted by the BS. For example, if the power demand is high, BS may set a higher reserved price to obtain more payments as a user needs to submit a higher bid for the same amount of power. On the other hand, each user seeks the most benefit at the lowest possible bid. The utility function of nth user is given by

$$U_n(t) = R_n(t) - b_n(t)\, p_n(t). \tag{5.5}$$

Definition 5.1. For a power auction game, the optimal power profile $\mathbb{P}^* = (p_1^*, \ldots, p_N^*)$ is the desired outcome by which every users attains maximum utility, i.e.

$$U_n\left(p_n^*; \mathbb{P}_{-n}^*\right) \geq U_n\left(p_n; \mathbb{P}_{-n}\right),\ n \in \mathcal{N},$$

where $\mathbb{P}_{-n} \triangleq (p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N)$ is the supplementary power profile of p_n. The game reaches NE when $\mathbb{P}^*$ occurs.

According to [20], there exists a pure strategy NE for auction game $\langle N, p_n, U_n \rangle$ $\forall\ n \in \mathcal{N}$ if, 1) the allocated power set $\mathbb{P}$ is a nonempty compact convex subset of a Euclidean space; 2) the utility function U_n is continuous and quasi-concave in p_n.

Theorem 5.1. The proposed auction game in (5.5), with the optimal power profile $\mathbb{P}^*$ in Definition 5.1, has an NE.

Proof. 1) is satisfied for any feasible power value. For 2), as U_n is clearly continuous, it is required to show that it is quasi-concave in p_n. t is omitted in the following proof for simplicity.

Taking the derivatives of (5.5) with respect to p_n gives

$$\frac{\partial U_n}{\partial p_n} = \frac{\partial R_n}{\partial p_n} - b_n = \frac{(\ln 2)^{-1} |h_n|^2}{\sigma^2 + |h_n|^2 p_n + |h_n|^2 \sum_{j=1}^{n-1} p_j} - b_n, \tag{5.6}$$

$$\frac{\partial^2 U_n}{\partial {p_n}^2} = -\frac{(\ln 2)^{-1} |h_n|^4}{\left(\sigma^2 + |h_n|^2 p_n + |h_n|^2 \sum_{j=1}^{n-1} p_j\right)^2} < 0. \tag{5.7}$$

Therefore, the utility function U_n is a concave function of p_n, hence it is quasi-concave in p_n [127]. Thus, the existence of NE is proved.

Before the game starts, BS specifies the reserve bid ε. Then, each user initializes its bid $b_n(0)$ to ε and calculates the required original power $p_n(0)$ and further, submits them to the BS. For $b_n(0) = \varepsilon$, $p_n(0)$ can be obtained by setting $\frac{\partial U_n}{\partial p_n} = 0$ from (5.6), as each user aims to obtain as many benefits as possible. Thus, $p_n(0)$ can be expressed as

$$p_n(0) = \left(\frac{(\ln 2)^{-1}}{\varepsilon} - \frac{\sigma^2}{|h_n|^2} - \sum_{j=1}^{n-1} p_j \right)_0^+ . \tag{5.8}$$

At each iteration, each user updates its bid $b_n(n)$ such that

$$\frac{\partial U_n(t+1)}{\partial p_n(t+1)} = \frac{\partial R_n(t+1)}{\partial p_n(t+1)} - b_n(t+1) = 0. \tag{5.9}$$

On rearranging (5.9), the bid update expression is obtained as

$$b_n(t+1) = \frac{(\ln 2)^{-1} |h_n|^2}{\sigma^2 + |h_n|^2 p_n(t+1) + |h_n|^2 \sum_{j=1}^{n-1} p_j(t+1)}. \tag{5.10}$$

During the auction game, for each user, the allocated power and bid are iterated alternatively, until the game reaches the optimum. The proposed auction-based power allocation scheme is summarized in Algorithm 5.1.

For one iteration, the time complexity of calculating the bid and the allocated

Algorithm 5.1 Auction-based Power Allocation Algorithm for Downlink NOMA Systems

1: Initialization: set $t = 0$, $b_n(0) = \varepsilon$ and calculate $p_n(0)$ by using (5.8) for $n = \{1, 2, \ldots, N\}$
2: **repeat**
3:   **for** $n = 1 : N$ **do**
4:     Calculate $p_n(t+1)$ with (5.4) {power allocation}
5:     Calculate $b_n(t+1)$ with (5.10) {bid updation}
6:   **end for**
7:   $t = t + 1$;
8: **until** Convergence, i.e. there are no further changes in $b_n(t)$ $\forall\ n \in \mathcal{N}$ with additional iterations

power is $O(N)$, where N is the total number of users. If the algorithm converges after M number of iterations, the overall time complexity of the proposed game is $O(NM)$. In the next section, an auction game for power allocation in downlink hybrid NOMA-OMA systems is demonstrated.

5.3 Auction-based Power Allocation for Downlink Hybrid NOMA-OMA Systems

5.3.1 System Model

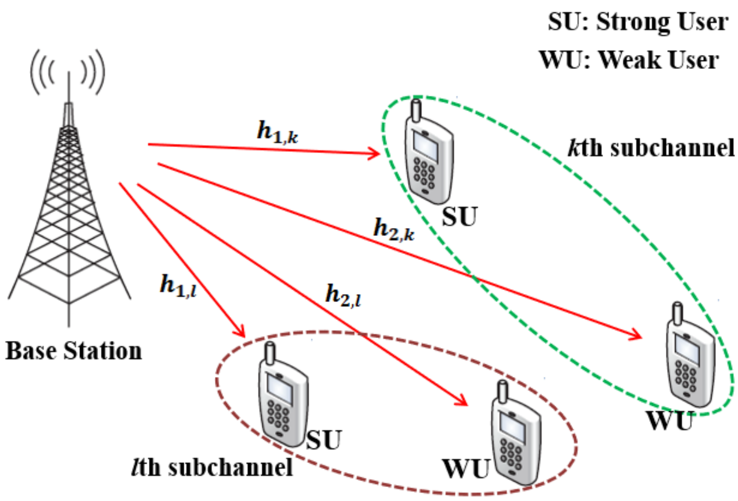


Figure 5.2: System model for a downlink hybrid NOMA-OMA system.

Consider a downlink cellular network which comprises of a BS and a set of $2M$ available users represented by $\mathcal{M} = \{1, 2, \dots, 2M\}$ as shown in Figure 5.2. The total system bandwidth B is equally divided into K, $K \geq M$ SBs of bandwidth B/K. Each user pair is assigned one SB. For notational simplicity, it is assumed that $K = M$ and each mth user pair, $\forall\ 1 \leq m \leq M$ is multiplexed on the mth SB. P_m is the power allocated to the mth SB. The channel fading coefficient between the BS and jth user in the mth SB is represented as $h_{j,m}$. In NOMA, BS uses superposition coding at the receiver end to serve several users simultaneously. For mth user pair, the superposition coded signal transmitted by the BS is given by

$$x_m = \sqrt{P_m} \sum_{j=1}^{2} \sqrt{\alpha_{j,m}} x_{j,m}, \tag{5.11}$$

where $x_{j,m}$ represents the message sent by the BS to the jth user and $\alpha_{j,m}$ denotes the coefficient of power allocation of the jth user such that

$$\sum_{j=1}^{2} \alpha_{j,m} = 1. \tag{5.12}$$

The signal received by the nth user on the mth SB is

$$y_{n,m} = h_{n,m}\sqrt{P_m}\sum_{j=1}^{2}\sqrt{\alpha_{j,m}}x_{j,m} + \eta_{n,m}, \tag{5.13}$$

where $\eta_{n,m} \sim \mathcal{CN}(0, \sigma^2)$ represents the AWGN for the nth user on mth SB with σ^2 noise variance. It is assumed that the users in a pair are ordered as $|h_{1,m}| \geq |h_{2,m}|$ without loss of generality. The NOMA protocol allocates higher power to the users with lower channel fading coefficients, such that $|\alpha_{1,k}P_m| \leq |\alpha_{2,k}P_m|$ [43].
Therefore, the user with weak channel conditions, i.e. the 2nd user (or weak user) deciphers its own signal by considering the signal meant for the user with strong channel conditions, i.e. the 1st user (or strong user), as an interference. However, 1st user decodes the signal meant for the 2nd user and then, applies SIC to remove it from the received superimposed signal so as to get its own signal. Hence, the SINR for both 1st and 2nd user on the mth SB are expressed as

$$\gamma_{1,m} = \frac{|h_{1,m}|^2\alpha_{1,m}P_m}{\sigma^2} \tag{5.14}$$

and

$$\gamma_{2,m} = \frac{|h_{2,m}|^2\alpha_{2,m}P_m}{\sigma^2 + |h_{2,m}|^2\alpha_{1,m}P_m}, \tag{5.15}$$

respectively. Thus, the achievable data rates of 1st and 2nd user on the mth SB are

$$R_{1,m} = \log_2\left(1 + \frac{|h_{1,m}|^2\alpha_{1,m}P_m}{\sigma^2}\right) \tag{5.16}$$

and

$$R_{2,m} = \log_2\left(1 + \frac{|h_{2,m}|^2\alpha_{2,m}P_m}{\sigma^2 + |h_{2,m}|^2\alpha_{1,m}P_m}\right), \tag{5.17}$$

respectively. User pairs compete for higher transmit power to obtain enhanced achievable data rates.

5.3.2 Proposed Power Allocation Scheme

In the proposed scheme, a strong user is paired with a weak user in order to form a NOMA pair. The mechanism for user pairing exploits the channel gain difference among users to enhance the achievable throughput of the system. The achievable data rate for the strong user on the mth SB given in (5.16) clearly depends upon the power allocation coefficient, $\alpha_{1,m}$ and the channel fading coefficient, $|h_{1,k}|$. It is unaffected by the interference due to the weak user within the same SB. Although, the NOMA protocol assigns lower power to the user with higher channel fading coefficient, the achievable data rate can be enhanced by choosing the user with sufficiently high channel gain such that the effect of the allocated power on the achievable data rate reduces. Hence, it is desirable to distribute strong users in different SB to attain higher system throughput. Further, pairing a weak user with a strong user increases the weak user's achievable data rate as the NOMA protocol assigns more power to the user with lower channel fading coefficient.

On the basis of the above concepts, for $m = 1$ SB, the available users are sorted in the descending order of their channel coefficients such that $|h_{1,1}| \geq |h_{2,1}| \geq \ldots \geq |h_{2M,1}|$. The strongest user, i.e. user with channel fading coefficient $|h_{1,1}|$, is paired with a random weak user with channel fading coefficient $|h_{l,1}|$ such that $M + 1 \leq l \leq 2M$. This process is carried out for the other SBs with the remaining users. This random NOMA user pairing and SB assignment mechanism is summarized in Algorithm 5.2.

In the proposed auction game, mth user pair places the bid $b_m(t)$ to the BS. The

Algorithm 5.2 Random NOMA User Pairing and SB Assignment Mechanism

1: Initialization: set $\mathcal{M} = \{1,\ 2, \ldots,\ 2M\}$, $\mathcal{P}_m = \emptyset\ \forall\ m = \{1,\ 2, \ldots, M\}$;
2: **for** $m = 1 : M$ **do**
3: Sort the available users $\mathcal{M}_A$ in the descending order of their channel fading coefficients on mth SB;
4: Select the first user as the strong user on mth SB;
5: Select a random user with channel fading coefficient $|h_{l,1}|$ such that $M + 1 \leq l \leq 2M$ as the weak user on mth SB;
6: The strong user from step 4 and the weak user from step 5 form the NOMA pair $\mathcal{P}_m$ on mth SB;
7: Remaining available users $\mathcal{M} \leftarrow \mathcal{M} \backslash \mathcal{P}_m$;
8: **end for**

BS, then, updates the power allocated to the mth user pair, $P_m(t)$, proportional to its payment $b_m(t)\, P_m(t)$ as

$$P_m(t+1) = \frac{b_m(t)\, P_m(t)}{\sum_{k=1}^{M} b_k(t)\, P_k(t) + \varepsilon} P^{tot}, \tag{5.18}$$

where t represents the iteration index, P^{tot} denotes the total transmit power at the BS such that $\sum_{k=1}^{M} P_k = P^{tot}$, and ε represents the nonzero reserved price adjusted by the BS. e.g. in case of high power demand scenario, BS may set high reserved price in order to get more payments as a user pair is required to place a higher value of bid to obtain the same amount of power. At the same time, each user pair desires more profit with the least possible bid value.

The utility functions of 1st and 2nd users on the mth SB can be defined as

$$U_{1,m}(t) = R_{1,m}(t) - b_m(t)\,\alpha_{1,m} P_m(t) \tag{5.19}$$

and

$$U_{2,m}(t) = R_{2,m}(t) - b_m(t)\,\alpha_{2,m} P_m(t)\,. \tag{5.20}$$

The utility function of the mth user pair can be expressed as the sum of the utilities of 1st and 2nd user, i.e.

$$\begin{aligned} U_m(t) &= U_{1,m}(t) + U_{2,m}(t)\,, \\ &= R_{1,m}(t) + R_{2,m}(t) - b_m(t)\,P_m. \end{aligned} \tag{5.21}$$

In NOMA, it is necessary for any user to differentiate the signal to be deciphered from the rest of the non-decoded signals. Hence, the power allocation within mth user pair must satisfy [128]

$$(\alpha_{2,m} - \alpha_{1,m})\,P_m \geq P^{diff}, \tag{5.22}$$

where P^{diff} represents the minimum power difference needed to discriminate the message signal to be deciphered from the rest of the non-decoded signals. Using (5.12) and (5.22) gives

$$\alpha_{1,m} = \max\left\{0, \frac{1}{2} - \frac{P^{diff}\sigma^2}{2P_m\,|h_{1,m}|^2}\right\} \tag{5.23}$$

and

$$\alpha_{2,m} = \min\left\{\frac{1}{2} + \frac{P^{diff}\sigma^2}{2P_m\,|h_{1,m}|^2}, 1\right\}. \tag{5.24}$$

According to [20], for auction game $\langle M, P_m, U_m \rangle \ \forall \ m \in \mathcal{M}$, a pure strategy NE exists if, 1) the assigned power set $\mathbb{P}$ is a nonempty compact convex subset of a Euclidean space; 2) the utility function U_m is continuous as well as quasi-concave in P_m.

Theorem 5.2. With the optimal power profile $\mathbb{P}^*$ in Definition 5.1, the proposed auction game in (5.21) has an NE.

Proof. 1) occurs for any feasible value of power. In case of 2), as U_m is evidently continuous in nature, it is required to prove its quasi-concavity on P_m. For simplicity, t is omitted in the following proof.

Differentiating (5.21) with respect to P_m gives

$$\frac{\partial U_m}{\partial P_m} = \frac{\partial R_{1,m}}{\partial P_m} + \frac{\partial R_{2,m}}{\partial P_m} - b_m, \tag{5.25}$$

$$= \frac{(\ln 2)^{-1} |h_{1,m}|^2}{2A + |h_{1,m}|^2 P_m} + \frac{(\ln 2)^{-1} \sigma^2 |h_{2,m}|^2 B}{\left(\sigma^2 + |h_{2,m}|^2 P_m\right)\left(C + |h_{1,m}|^2 |h_{2,m}|^2 P_m\right)} - b_m, \tag{5.26}$$

where $A = \sigma^2 \left(1 - P^{diff}\right)$, $B = \left(|h_{1,m}|^2 - |h_{2,m}|^2 P^{diff}\right)$, and $C = \sigma^2 \left(2 |h_{1,m}|^2 - |h_{2,m}|^2 P^{diff}\right)$.

Further, differentiating (5.26) with respect to P_m gives

$$\begin{aligned} \frac{\partial^2 U_m}{\partial {P_m}^2} = -\Bigg(& \frac{(\ln 2)^{-1} |h_{1,m}|^4}{\left(2A + |h_{1,m}|^2 P_m\right)^2} \\ & + \frac{(\ln 2)^{-1} \sigma^2 |h_{2,m}|^4 B \left(C + \sigma^2 |h_{1,m}|^2 + 2 |h_{1,m}|^2 |h_{2,m}|^2 P_m\right)}{\left(\sigma^2 + |h_{2,m}|^2 P_m\right)^2 \left(C + |h_{1,m}|^2 |h_{2,m}|^2 P_m\right)^2} \Bigg) < 0. \end{aligned} \tag{5.27}$$

Hence, U_m is concave in P_m, thus it is a quasi-concave function of P_m [127]. Therefore, the existence of the NE is confirmed.

In the beginning of the game, BS specifies the reserved bid ε. All user pairs, then set their bids $b_m(0) = \varepsilon$ and calculate the required original power $P_m(0)$ by using (5.26), as each user pair seeks as many benefits as possible. The value of $P_m(0)$ is, then, submitted to the BS. At each and every iteration, bid value $b_m(t)$ is updated by each user pair such that

$$\frac{\partial U_m(t+1)}{\partial P_m(t+1)} = \frac{\partial R_{1,m}(t+1)}{\partial P_m(t+1)} + \frac{\partial R_{2,m}(t+1)}{\partial P_m(t+1)} - b_m(t+1) = 0. \tag{5.28}$$

On rearranging (5.28), the expression for bid expression is obtained as

$$b_m(t+1) = \frac{(\ln 2)^{-1} |h_{1,m}|^2}{2A + |h_{1,m}|^2 P_m} + \frac{(\ln 2)^{-1} \sigma^2 |h_{2,m}|^2 B}{\left(\sigma^2 + |h_{2,m}|^2 P_m\right)\left(C + |h_{1,m}|^2 |h_{2,m}|^2 P_m\right)} \tag{5.29}$$

During the auction game, both bid and allocated power of each user pair are updated iteratively in an alternate manner. This process continues until the game attains convergence. The proposed auction-based power allocation scheme for downlink hybrid NOMA-OMA systems is summed up in Algorithm 5.3.

The time complexity of bid and allocated power calculation for single iteration

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Algorithm 5.3 Auction-based Power Allocation Algorithm for Downlink Hybrid NOMA-OMA systems

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1: Initialization: set $t = 0$, $b_m(0) = \varepsilon$ and calculate $P_m(0)$ for $\mathcal{P}_m, 1 \leq m \leq M$ by using (5.26)
2: **repeat**
3:   **for** $m = 1 : M$ **do**
4:     Determine $P_m(t+1)$ by using (5.18) {power allocation}
5:     Determine $b_m(t+1)$ by using (5.29) {bid updation}
6:   **end for**
7:   $t = t + 1$;
8: **until** Convergence, i.e. no change in $b_m(t)$ $\forall\, 1 \leq m \leq M$ with further iterations

---

is $O(M)$, M being the total user pairs. If the algorithm reaches the optimum, i.e. convergence, after N iterations, the overall time complexity of the power allocation algorithm with user pairing becomes $O(MN)$. However, the complexity of the algorithm in [123] in the worst case is $O(L)$, whereas the complexity of the power allocation algorithm without user pairing is $O(LN)$, where L is the total number of users. Hence, the complexity of the auction-based power allocation scheme with user pairing is more than that of the algorithm in [123], but equivalent to that of the auction-based power allocation scheme without user pairing.

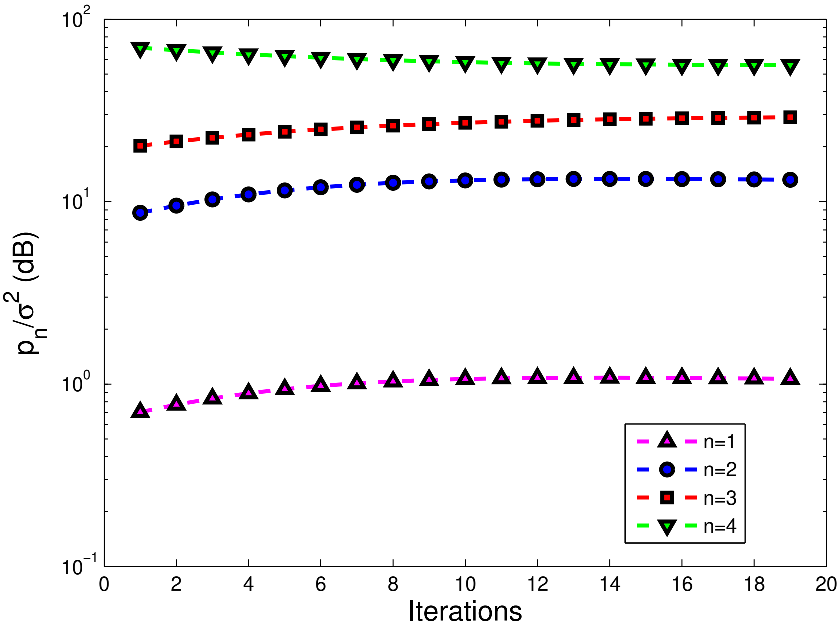


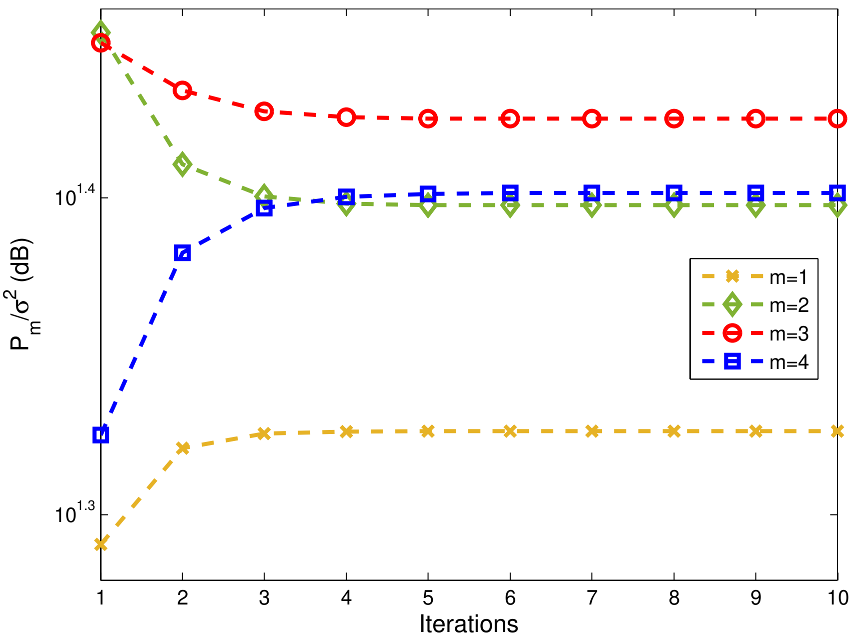
Figure 5.3: The convergence performance of the auction-based power allocation scheme without user pairing.

5.4 Simulation Results and Discussion

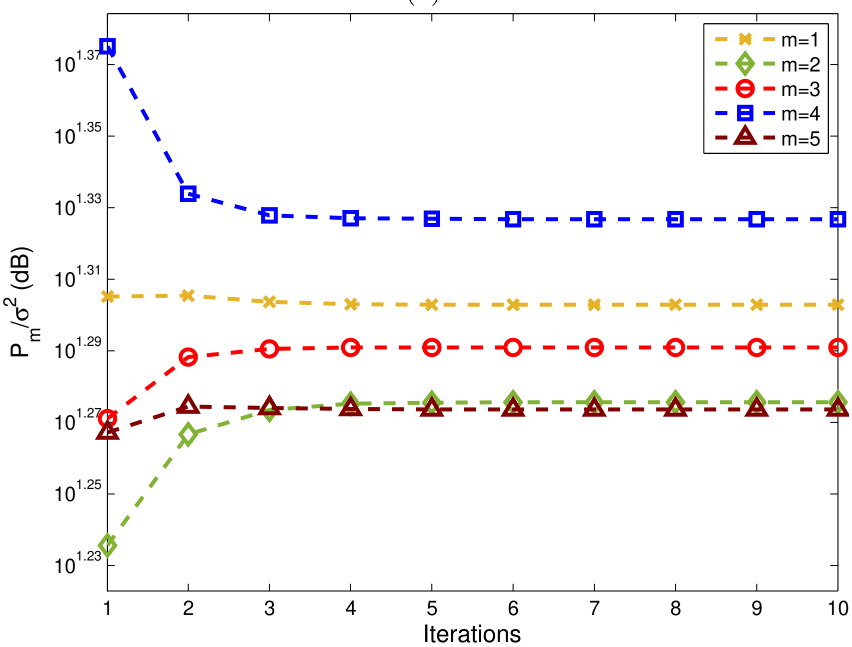
This section examines the performance of the proposed auction-based power allocation schemes. For simulations, the channel fading coefficients are modeled as $h_n \sim \mathcal{CN}(0, \delta_n^2)$, $n \in \mathcal{N}$ and $h_{j,m} \sim \mathcal{CN}\left(0, \delta_{j,m}^2\right)$, $j = \{1, 2\}$, $1 \leq m \leq M$, where δ_n^2 and $\delta_{j,m}^2$ represent the variance of h_n and $h_{j,m}$, respectively. The reserved price is $\varepsilon = 0.01$. The detection threshold at SIC receiver is $P^{diff} = 10$ dBm [128].

First, the convergence of the auction-based power allocation scheme without user pairing for $N = 4$ is shown in Figure 5.3. The variance of different channel fading coefficients is assumed as $\delta_1^2 = 0.25$, $\delta_2^2 = 0.5$, $\delta_3^2 = 0.75$ and $\delta_4^2 = 1$. The total transmit power at the BS to noise power ratio is $P_{tot}/\sigma^2 = 20$ dB. Figure 5.3 clearly depicts the convergence of the proposed scheme within several iterations only.

Further, the convergence of the auction scheme with user pairing is examined for $M = 4$ in Figure 5.4a and $M = 5$ in Figure 5.4b. In this case, the ratio of the total transmit power at the BS to the noise power, P^{tot}/σ^2 is taken as 20 dB and the values of $\delta_{j,m}^2$ are assumed randomly in the range of $(0, 1)$. Figure 5.4a and 5.4b clearly show that the proposed power allocation scheme converges within few iterations only.



(a)



(b)

Figure 5.4: The convergence performance of the auction-based power allocation scheme with user pairing for (a) $M = 4$, (b) $M = 5$.

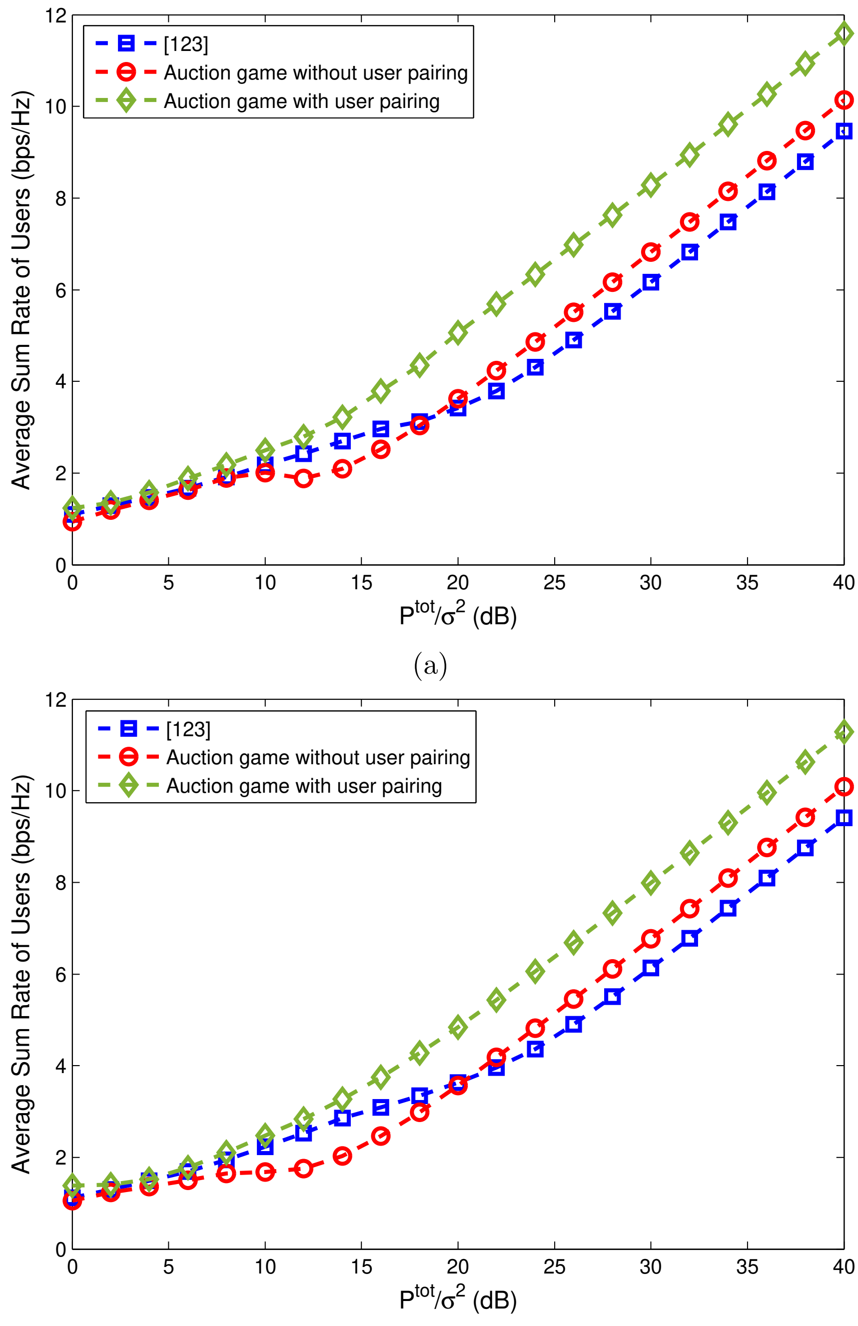


Figure 5.5: Average sum rate of the users versus P^{tot}/σ^2 for (a) $M = 3$, (b) $M = 4$.

The comparison of the proposed auction-based schemes with the existing algorithm in [123] is shown in Figure 5.5a for $M = 3$ and Figure 5.5b for $M = 4$. The values of δ_n^2 and $\delta_{j,m}^2$ are assumed randomly in the range of $(0, 1)$. It is quite apparent that the auction-based power allocation scheme with user pairing demonstrates superiority in terms of the average sum rate of the users for different values of P^{tot}/σ^2 in comparison with the existing algorithm in [123] and the auction-based scheme without user pairing. For $M = 3$, the average sum rate of the users for the auction-based scheme with user pairing improves by roughly 48.2% and 39.9% of the algorithm proposed in [123] and the auction-based scheme without user pairing, respectively. Similarly, for $M = 4$, the average sum rate of the users for the auction-based scheme with user pairing improves by roughly 33.5% and 35.7% of the algorithm proposed in [123] and the auction-based scheme without user pairing, respectively. This can be attributed to the fact that both the algorithm in [123] and the auction-based scheme without user pairing allow all the users to transmit in the same frequency and time resource, resulting in high interference at the user's end. On the contrary, the proposed scheme allows users to form pairs and then, each pair is allocated a separate SB, thus, limiting the inter-user interference at the receiver's end.

5.5 Chapter Summary

Power allocation is a critical issue in NOMA systems. In this chapter, auction-based power allocation schemes for downlink cellular NOMA systems and hybrid NOMA-OMA systems have been proposed. The BS is modeled as an auctioneer selling its transmit power. In auction-game for downlink NOMA systems, the users are modeled as bidders competing for the power to obtain the maximum utility. On the other hand, in auction-based scheme for hybrid NOMA-OMA systems, users are first paired through a random mechanism in such a manner that each pair consists of a strong and a weak user. These user pairs, then, act as bidders competing for the power being sold by the BS to attain maximum utility. Outcomes of both the games have been investigated and convergence to a unique NE has been established mathematically for both schemes. Simulation results clearly depict that the auction-based scheme with user pairing attains higher average sum rate of the users in comparison with the existing algorithm in [123] and the auction-based scheme without user pairing. This confirms the effectiveness of user pairing in improving the performance of NOMA systems. The next chapter addresses the problem of user pairing, subchannel assignment and power allocation in a downlink cooperative NOMA network.

Chapter 6

A Joint User Pairing, Subchannel Assignment and Power Allocation in Cooperative NOMA Networks

This chapter addresses the problem of user pairing, subchannel assignment and power allocation in a downlink cooperative NOMA network. A joint user pairing and subchannel assignment algorithm is proposed that pairs a user having strong channel conditions with a user having weak channel conditions and assigns them a subchannel simultaneously. Each strong user behaves as a relay for the weak user. An SG is employed and a closed-form solution is given to allocate power among the users by the BS, considering the mutual benefits of each user and the BS. Simulation results prove the effectiveness of the proposed scheme in terms of average sum rate of users in comparison with the cooperative OMA scheme and existing NOMA schemes.

6.1 Introduction

In the recent years, NOMA has garnered the interest of researchers as a promising technology for next generation wireless networks [121]. NOMA differs fundamentally from the OMA techniques, where several users are served in the same frequency band and time slot by multiplexing them in the power domain. This is achieved by employing superposition coding and SIC at the transmitter and receiver sides, respectively [43]. Due to enhanced system throughput and extended coverage area of cooperative wireless networks, NOMA has been paired with cooperative relaying to further enhance the performance of NOMA systems.

Different research works [129, 99, 122, 47] employed game theory to address various problems in cooperative NOMA networks. Authors in [47] presented a low complexity game theoretic algorithm for user clustering, and a closed-form solution for power allocation in mm-wave-NOMA systems for maximization of the cell sum rate.

A coalition game formulation was introduced to dynamically allocate users into varying size clusters, which use NOMA scheme. The authors assumed an equal power allocation across different clusters which somehow simplifies the problem. However, the resource demands to satisfy the users' QoS requirements of each cluster can be quite different [130]. As opposed to the OFDM AF relay used in [99], the users with strong channel conditions, often termed as strong users, itself act as relays for the users with weak channel conditions, or weak users, in the proposed cooperative NOMA scheme. A multi-leader multi-follower SG was formulated between the small base stations (SBSs) and macro base stations (MBSs) in heterogeneous NOMA networks for energy efficiency maximization in [129]. Instead of giving equal priorities, the structure of the SG is such that MBSs, being the leaders, change their strategy after the followers' strategy, i.e. SBSs. Also, neither cooperation among users nor user clustering is considered in [129]. In [122], authors proposed a sub-optimal power allocation scheme based on SG via decoupling the revenue of the BS into three optimization sub-problems. Apart from being a non-cooperative scheme, it is unrealistic to allow all the users to access the same subchannel at once while considering their individual performance due to high multi-user interference for large number of users [131].

Therefore, in this chapter, two users are considered to be multiplexed on the same subchannel rather than the multiple users. Multi-user interference increases with increase in the number of users being multiplexed on the same subchannel, thereby, degrading their individual performance. Also, the processing complexity due to SIC detection at the receivers increases considerably with increase in the number of users being served on the same subchannel [126].

In this chapter, a novel joint algorithm for user pairing and subchannel assignment is proposed where a strong user is paired up with a weak user and each NOMA pair is assigned a subchannel simultaneously. The proposed joint algorithm is novel in the sense that it not only uses the BS-user links for signal transmission [54], but also exploits the user-user links which play a significant role in increasing the achievable data rate of the weak users. For each subchannel, BS broadcasts a superimposed message intended for the corresponding user pair in the first time slot. The strong user, then, decodes both the messages and forwards the weak user's message in the second time slot. Further, an SG is employed for price-based power allocation to the users where the BS acts as a leader while the users are modeled as followers. Each user pays for the power allocated to it by the BS. To the best of the author's knowledge, this is the first work to address the problem of user pairing, subchannel assignment and power allocation using SG in a downlink cooperative NOMA network.

The key contributions of the work are described below:

- A novel cooperative NOMA scheme is proposed which consists of a joint user pairing and subchannel assignment algorithm and SG-based power allocation. The low-complexity joint user pairing and subchannel assignment algorithm exploits the BS-user links as well as (strong) user- (weak) user links. SG models the BS as a leader and users as followers where all the players seek to maximize their own utilities.

- Closed-form expressions for the optimal price set up by the BS and the power allocated among the users are given.

- The performance of the proposed cooperative NOMA scheme is compared against the corresponding cooperative OMA scheme with random user pairing cooperative OMA scheme with random user pairing and subchannel assignment. Simulation results indicate that the proposed cooperative scheme outperforms the cooperative OMA scheme and existing NOMA schemes in terms of average sum rate of users.

The remaining chapter is structured as follows. The system model is presented in Section 6.2, followed by the proposed cooperative NOMA scheme in Section 6.3. Simulation results are discussed in Section 6.4, whereas the chapter is summarized in Section 6.5.

6.2 System Model

Consider a downlink cellular system which comprises of a BS and a set of $2M$ users where each node is equipped with a single antenna. The total bandwidth of the system B is equally divided into K subchannels of bandwidth B/K, $K \geq M$.

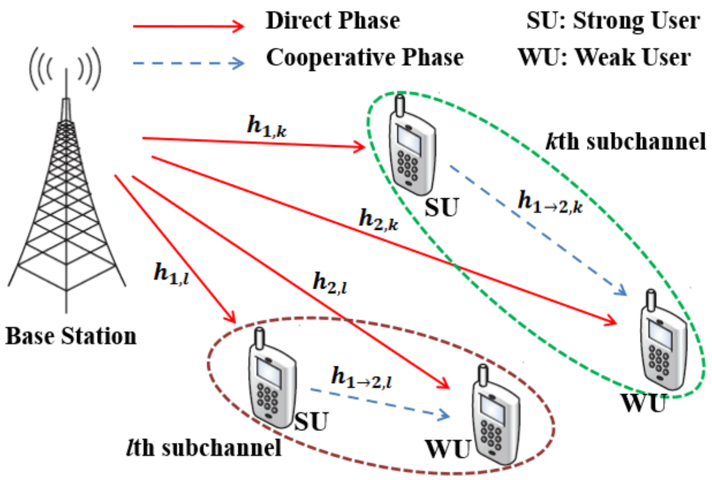


Figure 6.1: System model for a downlink cooperative NOMA system.

However, for the simplicity of the analysis, it is assumed that $K = M$. Assume that the channel responses of different subchannels are independent of each other for analytical simplicity. Different NOMA pairs occupy different subchannels without inter-pair interference. In each subchannel, a strong user and a weak user form a NOMA pair to communicate with BS and the transmission of data occurs over two phases (or slots), namely direct (first) and cooperative (second). Assume that all the subchannels in the network are quasi-static. BS transmits the superimposed signals with the full transmit power P_t on each subchannel. For analytical simplicity, the maximum power allocated for each subchannel is P_t.
The system model is shown in Figure 6.1.

(A) **Direct Transmission Phase:** In this phase, BS transmits the superposition coded signal

$$x_k = \sum_{j=1}^{2} \sqrt{P_{j,k}} x_{j,k}, \tag{6.1}$$

on kth subchannel. Here $x_{j,k}$ represents the message sent by the BS to the jth user on kth subchannel, whereas $P_{j,k}$ denotes the power allocated to the jth user on kth subchannel such that

$$\sum_{j=1}^{2} P_{j,k} \leq P_t. \tag{6.2}$$

The signal received by the nth user on the kth subchannel can be expressed as

$$y_{n,k} = h_{n,k} \sum_{j=1}^{2} \sqrt{P_{j,k}} x_{j,k} + \eta_{n,k}. \tag{6.3}$$

Here, $h_{n,k}$ is the channel coefficient of the link between the BS and nth user on the kth subchannel and $\eta_{n,k} \sim \mathcal{CN}(0, \sigma^2)$ is the zero-mean circularly-symmetric complex AWGN. Without loss of generality, it is assumed that the users in a pair are ordered as $|h_{1,k}| \geq |h_{2,k}|$. The NOMA protocol allocates more power to the users having smaller channel coefficient such that $|P_{1,k}| \leq |P_{2,k}|$ [43]. Hence, the 1st user (or strong user) decodes the message of the 2nd user (or weak user), and then, uses SIC to remove it from the received signal to attain its own message. The SINR and achievable data rate for the 1st user to decode $x_{2,k}$ on the kth subchannel are, respectively, given by

$$\gamma_{BS\to 1,k}^{(x_{2,k})} = \frac{|h_{1,k}|^2 P_{2,k}}{\sigma^2 + |h_{1,k}|^2 P_{1,k}}, \tag{6.4}$$

$$R_{1,k}^{(x_{2,k})} = \frac{1}{2} \log_2 \left(1 + \frac{|h_{1,k}|^2 P_{2,k}}{\sigma^2 + |h_{1,k}|^2 P_{1,k}} \right). \tag{6.5}$$

Under the condition that $R_{1,k}^{(x_{2,k})} \geq R_{req}^{(1,k)}$, i.e.

$$\frac{1}{2} \log_2 \left(1 + \frac{|h_{1,k}|^2 P_{2,k}}{\sigma^2 + |h_{1,k}|^2 P_{1,k}} \right) \geq R_{req}^{(1,k)}, \tag{6.6}$$

the 1st user will be able to decode $x_{2,k}$ correctly before detecting its own message, where $R_{req}^{(1,k)}$ denotes the minimum rate required for the 1st user on the kth subchannel [132]. At the same time, the 2nd user decodes its own message by assuming the interference from the 1st user's message as additional noise. Thus, the SNR for the 1st user and the SINR for the 2nd user to decode their intended messages on the kth subchannel due to direct transmission are, respectively, given by

$$\gamma_{BS\to 1,k}^{(x_{1,k})} = \frac{|h_{1,k}|^2 P_{1,k}}{\sigma^2}, \tag{6.7}$$

$$\gamma_{BS\to 2,k}^{(x_{2,k})} = \frac{|h_{2,k}|^2 P_{2,k}}{\sigma^2 + |h_{2,k}|^2 P_{1,k}}. \tag{6.8}$$

(B) **Cooperative Transmission Phase:** During this phase, the 1st user forwards the decoded message of the 2nd user with full transmit power. Thus, the corresponding signal received by the 2nd user on kth subchannel is given by

$$y_{1\to 2,k} = h_{1\to 2,k}\sqrt{P_t}x_{2,k} + \eta_{1\to 2,k}, \tag{6.9}$$

where $h_{1\to 2,k}$ represents the channel coefficient of the link between the 1st and 2nd user, whereas $\eta_{1\to 2,k} \sim \mathcal{CN}(0, \sigma^2)$ denotes the AWGN. The SNR of the relayed transmission is

$$\gamma_{1\to 2,k}^{(x_{2,k})} = \frac{|h_{1\to 2,k}|^2 P_t}{\sigma^2}. \tag{6.10}$$

After MRC of both signals received through direct and cooperative paths, the SINR at 2nd user is

$$\gamma_{2,k} = \frac{|h_{2,k}|^2 P_{2,k}}{\sigma^2 + |h_{2,k}|^2 P_{1,k}} + \frac{|h_{1\to 2,k}|^2 P_t}{\sigma^2}. \tag{6.11}$$

The achievable data rate for both 1st and 2nd user on the kth subchannel are given by [81]

$$R_{1,k} = \frac{1}{2}\log_2\left(1 + H_{1,k}P_{1,k}\right), \tag{6.12}$$

and

$$R_{2,k} = \frac{1}{2}\log_2\left(1 + \frac{H_{2,k}P_{2,k}}{1 + H_{2,k}P_{1,k}} + H_{1\to 2,k}P_t\right), \tag{6.13}$$

respectively, where $H_{1,k} = \frac{|h_{1,k}|^2}{\sigma^2}$, $H_{2,k} = \frac{|h_{2,k}|^2}{\sigma^2}$ and $H_{1\to 2,k} = \frac{|h_{1\to 2,k}|^2}{\sigma^2}$. The rates are scaled by $\frac{1}{2}$ as the communication takes place over two slots. The users can successfully decode their intended messages only if their achievable data rates are greater than or equal to their minimum data rate requirements, i.e., [132]

$$\frac{1}{2}\log_2\left(1 + H_{1,k}P_{1,k}\right) \geq R_{req}^{(1,k)}, \tag{6.14}$$

$$\frac{1}{2}\log_2\left(1 + \frac{H_{2,k}P_{2,k}}{1 + H_{2,k}P_{1,k}} + H_{1\to 2,k}P_t\right) \geq R_{req}^{(2,k)}, \tag{6.15}$$

$k \in \{1, 2, \ldots, K\}$. For the simplicity of analysis, it is assumed that $R_{req}^{(1,k)} = R_{req}^{(2,k)} = R_{req}$, $k \in \{1, 2, \ldots, K\}$.

User pairs tend to compete for more transmit power to obtain higher achievable data rates.

6.3 Problem Formulation

In the proposed scheme, SG disseminates power among users in each pair at optimal prices. It is formulated as below.

(A) **BS/Leader:** The BS is modeled as the leader who charges $p_{j,k}$ per unit power to the jth user on the kth subchannel for the allocated power in order to maximize its own revenue. The revenue of the BS obtained from the jth user on the kth subchannel is $p_{j,k}P_{j,k}$ and hence, the utility of BS, U_{BS} is $\sum_{k=1}^{K}\sum_{j=1}^{2} p_{j,k}P_{j,k}$. Therefore, the revenue maximization problem of the BS is given by

$$\text{maximize } U_{BS}\left(p_{1,k}, p_{2,k}\right) = \sum_{k=1}^{K}\sum_{j=1}^{2} p_{j,k}P_{j,k} \tag{6.16a}$$

$$\text{subject to } \sum_{j=1}^{2} P_{j,k} \leq P_t, k \in \{1, 2, \ldots, K\}, \tag{6.16b}$$

$$R_{1,k}^{(x_2,k)} \geq R_{req}, k \in \{1, 2, \ldots, K\}, \tag{6.16c}$$

$$R_{1,k} \geq R_{req}, k \in \{1, 2, \ldots, K\}, \tag{6.16d}$$

$$R_{2,k} \geq R_{req}, k \in \{1, 2, \ldots, K\}. \tag{6.16e}$$

(B) **User/Follower:** On the other hand, the revenue maximization problem of the jth user on the kth subchannel can be written as

$$\begin{aligned} &\text{maximize } U_{j,k}\left(P_{j,k}\right) = R_{j,k} - p_{j,k}P_{j,k} \\ &\text{subject to } P_{j,k} \geq 0, k \in \{1, 2, \ldots, K\}, j \in \{1, 2\}. \end{aligned} \tag{6.17}$$

Here, $U_{j,k}$ denotes its utility which includes the income from its achievable data rate and its payment $p_{j,k}P_{j,k}$ to the BS.

The problems in (6.16) and (6.17) constitute the SG.

6.4 The Proposed Cooperative NOMA Scheme

This section explains the proposed scheme which includes the SG-based power allocation and algorithm for joint user pairing and subchannel assignment.

6.4.1 SG-based Power Allocation

(A) **BS/Leader Level Game Analysis:** The relationship between the power allocated to a user on kth subchannel, $P_{j,k}$, and its price, $p_{j,k}$ are described by the lemma given below.

Lemma 6.1. For a given price $(p_{1,k}, p_{2,k})$, $k \in \{1, 2, \ldots, K\}$, if

$$p_{1,k} \leq \frac{(2\ln 2)^{-1} H_{1,k}}{1 + H_{1,k}P_{1,k}} \tag{6.18}$$

and

$$p_{2,k} \leq \frac{(2\ln 2)^{-1} H_{2,k}}{1 + H_{1\to 2,k}P_t\left(1 + H_{2,k}P_{1,k}\right) + H_{2,k}\left(P_{1,k} + P_{2,k}\right)} \tag{6.19}$$

the optimal power allocated to both the strong user and the weak user on kth subchannel satisfy the following equations

$$p_{1,k} = \frac{(2\ln 2)^{-1} H_{1,k}}{1 + H_{1,k}P_{1,k}} \tag{6.20}$$

and

$$p_{2,k} = \frac{(2\ln 2)^{-1} H_{2,k}}{1 + H_{1\to 2,k}P_t\left(1 + H_{2,k}P_{1,k}\right) + H_{2,k}\left(P_{1,k} + P_{2,k}\right)} \tag{6.21}$$

respectively.

Proof. Differentiating (6.17) with respect to $P_{j,k}$, $j \in \{1, 2\}$ and equating them to zero gives

$$\frac{\partial U_{1,k}\left(P_{1,k}\right)}{\partial P_{1,k}} = \frac{(2\ln 2)^{-1} H_{1,k}}{1 + H_{1,k}P_{1,k}} - p_{1,k} = 0 \tag{6.22}$$

and

$$\frac{\partial U_{2,k}\left(P_{2,k}\right)}{\partial P_{2,k}} = \frac{(2\ln 2)^{-1} H_{2,k}}{1 + H_{1\to 2,k}P_t\left(1 + H_{2,k}P_{1,k}\right) + H_{2,k}\left(P_{1,k} + P_{2,k}\right)} - p_{2,k} = 0 \tag{6.23}$$

respectively, for $k \in \{1, 2, \ldots, K\}$.

Substituting (6.20) and (6.21) into (6.16), the revenue maximization problem of the BS is rewritten as the following problem

$$\text{maximize } U_{BS}\left(P_{1,k}, P_{2,k}\right) = \sum_{k=1}^{K}\left(\frac{(2\ln 2)^{-1} H_{1,k}P_{1,k}}{1+H_{1,k}P_{1,k}} + \frac{(2\ln 2)^{-1} H_{2,k}P_{2,k}}{1+H_{1\to 2,k}P_t\left(1+H_{2,k}P_{1,k}\right)+H_{2,k}\left(P_{1,k}+P_{2,k}\right)}\right) \tag{6.24a}$$

$$\text{subject to} \sum_{j=1}^{2} P_{j,k} \le P_t, k \in \{1,2,\ldots,K\}, \tag{6.24b}$$

$$P_{j,k} \ge 0, k \in \{1,2,\ldots,K\}, \tag{6.24c}$$

$$R_{1,k}^{(x_{2,k})} \ge R_{req}, k \in \{1,2,\ldots,K\}, \tag{6.24d}$$

$$R_{1,k} \ge R_{req}, k \in \{1,2,\ldots,K\}, \tag{6.24e}$$

$$R_{2,k} \ge R_{req}, k \in \{1,2,\ldots,K\}. \tag{6.24f}$$

Lemma 6.2. For a given P_t, let $(P_{1,k}, P_{2,k})$, $k \in \{1,2,\ldots,K\}$ be the optimal solution to (6.24) such that $P_{1,k}+P_{2,k} = P_t$.

Proof. It is proved by contradiction. Let $(P_{1,k}, P_{2,k})$, $k \in \{1,2,\ldots,K\}$ be the optimal solution to (6.24) that satisfies $P_{1,k}+P_{2,k} < P_t$. Let $\delta = \frac{P_t}{P_{1,k}+P_{2,k}}$, ${P_{1,k}}^* = \delta P_{1,k}$ and ${P_{2,k}}^* = \delta P_{2,k}$, then ${P_{1,k}}^* + {P_{2,k}}^* = \delta P_{1,k} + \delta P_{2,k} = P_t$ holds true. With $P_{1,k}+P_{2,k} < P_t$ implying $\delta > 1$, the following conditions are fulfilled

$$\frac{(2\ln 2)^{-1} H_{1,k}{P_{1,k}}^*}{1+H_{1,k}{P_{1,k}}^*} > \frac{(2\ln 2)^{-1} H_{1,k}P_{1,k}}{1+H_{1,k}P_{1,k}}, \tag{6.25}$$

$$\begin{aligned} &\frac{(2\ln 2)^{-1} H_{2,k}{P_{2,k}}^*}{1+H_{1\to 2,k}P_t\left(1+H_{2,k}{P_{1,k}}^*\right)+H_{2,k}\left({P_{1,k}}^*+{P_{2,k}}^*\right)} > \\ &\frac{(2\ln 2)^{-1} H_{2,k}P_{2,k}}{1+H_{1\to 2,k}P_t\left(1+H_{2,k}P_{1,k}\right)+H_{2,k}\left(P_{1,k}+P_{2,k}\right)} \end{aligned} \tag{6.26}$$

which contradicts the assumption that $(P_{1,k}, P_{2,k})$, $k \in \{1,2,\ldots,K\}$ is the optimal solution to (6.24).

By substituting $P_{1,k}+P_{2,k} = P_t$ into (6.24) and omitting $(2\ln 2)^{-1}$ for simplicity, the revenue maximization problem of the BS is rewritten as

$$\begin{aligned}
&\text{maximize } U_{BS}\left(P_{1,k}, P_{2,k}\right) \\
&\quad = \sum_{k=1}^{K}\left(\frac{H_{1,k}P_{1,k}}{1+H_{1,k}P_{1,k}} + \frac{H_{2,k}P_{2,k}}{1+H_{1\to 2,k}P_t\left(1+H_{2,k}P_{1,k}\right)+H_{2,k}P_t}\right)
\end{aligned} \tag{6.27a}$$

$$\text{subject to} \sum_{j=1}^{2} P_{j,k} \le P_t, k \in \{1,2,\ldots,K\}, \tag{6.27b}$$

$$P_{j,k} \ge 0, k \in \{1,2,\ldots,K\}, \tag{6.27c}$$

$$R_{1,k}^{(x_{2,k})} \ge R_{req}, k \in \{1,2,\ldots,K\}, \tag{6.27d}$$

$$R_{1,k} \ge R_{req}, k \in \{1,2,\ldots,K\}, \tag{6.27e}$$

$$R_{2,k} \ge R_{req}, k \in \{1,2,\ldots,K\}. \tag{6.27f}$$

Lemma 6.3. For a given P_t, the objective function in (6.27) is quasi-concave function for $0 \le P_{j,k} \le P_t$, $k \in \{1,2,\ldots,K\}$, $j \in \{1,2\}$.

Proof. It is proved by using bordered Hessian matrix [133] for $U_{BS}\left(P_{1,k}, P_{2,k}\right)$ which is defined as

$$H = \begin{bmatrix} 0 & \frac{dU_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}} & \frac{dU_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}} \\ \frac{dU_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}} & \frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}{}^2} & \frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}dP_{2,k}} \\ \frac{dU_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}} & \frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}dP_{1,k}} & \frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}{}^2} \end{bmatrix}. \tag{6.28}$$

Taking the first order derivatives of $U_{BS}\left(P_{1,k}, P_{2,k}\right)$ with respect to $P_{1,k}$ and $P_{2,k}$ gives

$$\frac{dU_{BS}\left(P_{1,k}, P_{2,k}\right)}{dP_{1,k}} = \frac{H_{1,k}}{\left(1+H_{1,k}P_{1,k}\right)^2} - \frac{H_{1\to 2,k}H_{2,k}{}^2P_{2,k}P_t}{\left(1+\left(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k}\right)P_t\right)^2}, \tag{6.29}$$

$$\frac{dU_{BS}\left(P_{1,k}, P_{2,k}\right)}{dP_{2,k}} = \frac{H_{2,k}}{1+\left(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k}\right)P_t}. \tag{6.30}$$

The corresponding second order partial derivatives are given by

$$\frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}{}^2}=-\frac{2H_{1,k}{}^2}{\left(1+H_{1,k}P_{1,k}\right)^3}+\frac{2H_{1\to 2,k}{}^2H_{2,k}{}^3P_{2,k}P_t{}^2}{\left(1+\left(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k}\right)P_t\right)^3}, \tag{6.31}$$

$$\frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}{}^2}=0, \tag{6.32}$$

$$\frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{1,k}dP_{2,k}}=-\frac{H_{1\to 2,k}H_{2,k}{}^2P_t}{\left(1+\left(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k}\right)P_t\right)^2}, \tag{6.33}$$

$$\frac{d^2U_{BS}\left(P_{1,k},P_{2,k}\right)}{dP_{2,k}dP_{1,k}}=-\frac{H_{1\to 2,k}H_{2,k}{}^2P_t}{\left(1+\left(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k}\right)P_t\right)^2}. \tag{6.34}$$

Let D_i be the ith-ordered determinant of the bordered Hessian matrix H. Then,

$$D_1=-\left[\frac{dU_{BS}\left(P_{1,k}\right)}{dP_{1,k}}\right]^2<0 \tag{6.35}$$

$$D_2=\frac{2H_{1,k}H_{2,k}{}^2(H_{1,k}+H_{1,k}H_{2,k}P_t+H_{1\to 2,k}(H_{1,k}-H_{2,k})P_t)}{(1+H_{1,k}P_{1,k})^3(1+(H_{1\to 2,k}+H_{2,k}+H_{1\to 2,k}H_{2,k}P_{1,k})P_t)^3}>0. \tag{6.36}$$

As $D_1<0$ and $D_2>0$ since $H_{1,k}\geq H_{2,k}$, $k\in\{1,2,\ldots,K\}$, therefore, $U_{BS}\left(P_{1,k},P_{2,k}\right)$ is quasi-concave in $P_{1,k}$ and $P_{2,k}$ [133].

By putting $P_{2,k}=P_t-P_{1,k}$ into (6.27), the objective function in (6.27) becomes

$$U_{BS}\left(P_{1,k}\right)=\sum_{k=1}^{K}\frac{H_{1,k}P_{1,k}}{1+H_{1,k}P_{1,k}}+\frac{H_{2,k}\left(P_t-P_{1,k}\right)}{1+H_{1\to 2,k}P_t\left(1+H_{2,k}P_{1,k}\right)+H_{2,k}P_t} \tag{6.37a}$$

$$\text{subject to}\sum_{j=1}^{2}P_{j,k}\leq P_t, k\in\left\{1,2,\ldots,K\right\}, \tag{6.37b}$$

$$P_{j,k}\geq 0, k\in\left\{1,2,\ldots,K\right\}, \tag{6.37c}$$

$$R_{1,k}^{(x_{2,k})}\geq R_{req}, k\in\left\{1,2,\ldots,K\right\}, \tag{6.37d}$$

$$R_{1,k}\geq R_{req}, k\in\left\{1,2,\ldots,K\right\}, \tag{6.37e}$$

$$R_{2,k}\geq R_{req}, k\in\left\{1,2,\ldots,K\right\}. \tag{6.37f}$$

Lemma 6.4. The feasible solution to the objective function in (6.37) is bounded by $\left[P_{1,k}^{min}, P_{1,k}^{max}\right]$, $k \in \{1, 2, \ldots, K\}$ such that

$$P_{1,k}^{min} = \frac{\varepsilon}{H_{1,k}}, \tag{6.38}$$

and

$$P_{1,k}^{max} = \min\left\{\frac{1}{H_{1,k}}\left(\frac{1 + H_{1,k}P_t}{\varepsilon + 1} - 1\right), \frac{1}{H_{2,k}}\left(\frac{P_t\left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon}{\varepsilon + 1 - H_{1\to 2,k}P_t}\right), P_t\right\}, \tag{6.39}$$

provided $H_{1\to 2,k}P_t - 1 < \varepsilon \leq \min\left\{P_t\left(H_{2,k} + H_{1\to 2,k}\right), H_{1,k}P_t\right\}$, where $\varepsilon = 2^{2R_{req}} - 1$.

Proof. By putting $P_(2,k) = P_t - P_(1,k)$ in (6.6) and (6.14), the constraints (6.37) and (6.37e), respectively, become

$$P_{1,k} \leq \frac{1}{H_{1,k}}\left(\frac{1 + H_{1,k}P_t}{\varepsilon + 1} - 1\right) \tag{6.40}$$

and

$$P_{1,k} \geq \frac{\varepsilon}{H_{1,k}}. \tag{6.41}$$

Since $P_{1,k} \geq 0$, then $\frac{1}{H_{1,k}}\left(\frac{1+H_{1,k}P_t}{\varepsilon+1} - 1\right) \geq 0$, which implies

$$\varepsilon \leq H_{1,k}P_t. \tag{6.42}$$

Further, by putting $P_{2,k} = P_t - P_{1,k}$ in (6.15), the constraint (6.37f) yields

$$P_{1,k}\left(\varepsilon + 1 - H_{1\to 2,k}P_t\right) \leq \frac{1}{H_{2,k}}\left(P_t\left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon\right) \tag{6.43}$$

Case 1: If $\varepsilon + 1 - H_{1\to 2,k}P_t < 0$, then

$$P_{1,k} \geq \frac{1}{H_{2,k}}\left(\frac{P_t\left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon}{\varepsilon + 1 - H_{1\to 2,k}P_t}\right) \tag{6.44}$$

For $\frac{1}{H_{2,k}}\left(\frac{P_t\left(H_{2,k}+H_{1\to 2,k}\right)-\varepsilon}{\varepsilon+1-H_{1\to 2,k}P_t}\right) \geq 0$, $P_t\left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon \leq 0$ since $\varepsilon + 1 - H_{1\to 2,k}P_t < 0$. This implies $\frac{\varepsilon+1}{H_{1\to 2,k}} < P_t \leq \frac{\varepsilon}{H_{2,k}+H_{1\to 2,k}}$ which is not feasible as $\frac{\varepsilon+1}{H_{1\to 2,k}} > \frac{\varepsilon}{H_{2,k}+H_{1\to 2,k}}$.

Case 2: If $\varepsilon + 1 - H_{1\to 2,k}P_t > 0$,, then

$$P_{1,k} \leq \frac{1}{H_{2,k}} \left(\frac{P_t \left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon}{\varepsilon + 1 - H_{1\to 2,k}P_t} \right) \tag{6.45}$$

For $\frac{1}{H_{2,k}} \left(\frac{P_t\left(H_{2,k}+H_{1\to 2,k}\right)-\varepsilon}{\varepsilon+1-H_{1\to 2,k}P_t} \right) \geq 0$, $P_t \left(H_{2,k} + H_{1\to 2,k}\right) - \varepsilon \geq 0$ since $\varepsilon + 1 - H_{1\to 2,k}P_t > 0$. This implies

$$H_{1\to 2,k}P_t - 1 < \varepsilon \leq P_t \left(H_{2,k} + H_{1\to 2,k}\right). \tag{6.46}$$

Hence, (6.41) gives the lower bound $P_{1,k}^{min}$, whereas (6.40) and (6.45) gives the upper bound $P_{1,k}^{max}$, provided $H_{1\to 2,k}P_t - 1 < \varepsilon \leq \min\left\{P_t \left(H_{2,k} + H_{1\to 2,k}\right), H_{1,k}P_t\right\}$.

By using Lemma 6.4, the revenue maximization problem of the BS in (6.37) becomes

$$U_{BS}\left(P_{1,k}\right) = \sum_{k=1}^{K} \frac{H_{1,k}P_{1,k}}{1 + H_{1,k}P_{1,k}} + \frac{H_{2,k}\left(P_t - P_{1,k}\right)}{1 + H_{1\to 2,k}P_t\left(1 + H_{2,k}P_{1,k}\right) + H_{2,k}P_t} \tag{6.47a}$$

$$\text{subject to } P_{1,k}^{min} \leq P_{1,k} \leq P_{1,k}^{max}, k \in \{1, 2, \ldots, K\} \tag{6.47b}$$

Differentiating (6.47a) with respect to $P_{1,k}$ gives

$$\frac{dU_{BS}\left(P_{1,k}\right)}{dP_{1,k}} = \frac{H_{1,k}}{\left(1 + H_{1,k}P_{1,k}\right)^2} - \frac{H_{2,k}(1 + H_{1\to 2,k}P_t)(1 + H_{2,k}P_t)}{\left(1 + (H_{1\to 2,k} + H_{2,k} + H_{1\to 2,k}H_{2,k}P_{1,k})P_t\right)^2}. \tag{6.48}$$

Let $\frac{dU_{BS}\left(P_{1,k}\right)}{dP_{1,k}} = 0$, two solutions are obtained as follows

$$P_{1,k}^{(1)} = \frac{E(-A + {H_{1\to 2,k}}^2 {P_t}^2) + C\sqrt{E(1 + H_{1\to 2,k}P_t)A}}{E(H_{1,k}\left(A + H_{1\to 2,k}P_t\right) + D)}, \tag{6.49}$$

$$P_{1,k}^{(2)} = \frac{E\left(-A + {H_{1\to 2,k}}^2 {P_t}^2\right) - C\sqrt{E(1 + H_{1\to 2,k}P_t)A}}{E(H_{1,k}\left(A + H_{1\to 2,k}P_t\right) + D)}, \tag{6.50}$$

where $A = 1 + H_{2,k}P_t$, $C = H_{1,k}A + H_{1\to 2,k}(H_{1,k} - H_{2,k})P_t$, $D = (H_{1,k} - H_{1\to 2,k})H_{1\to 2,k}H_{2,k}{P_t}^2$ and $E = H_{1,k}H_{2,k}$.

Lemma 6.5 For a given P_t, $P_{1,k}^{(1)} > 0$ and $P_{1,k}^{(2)} < 0$ provided $|h_{2,k}| \geq |h_{1\to 2,k}|$.

Proof. The numerator of ${P_{1,k}}^{(1)}$, i.e.

$$E\left(-A + {H_{1\to 2,k}}^2 {P_t}^2\right) + C\sqrt{E\left(1 + H_{1\to 2,k}P_t\right)A} = EA\Bigg(-1 + \frac{{H_{1\to 2,k}}^2 {P_t}^2}{A} + \left(\sqrt{\frac{H_{1,k}}{H_{2,k}}} + \frac{H_{1\to 2,k}\left(H_{1,k} - H_{2,k}\right)P_t}{A\sqrt{E}}\right)\sqrt{\left(1 + H_{1\to 2,k}P_t\right)A}\Bigg) \tag{6.51}$$

$$= EA\Bigg(-1 + \frac{{H_{1\to 2,k}}^2 {P_t}^2}{A} + \sqrt{\frac{H_{1,k}\left(1 + H_{1\to 2,k}P_t\right)A}{H_{2,k}}} + \frac{H_{1\to 2,k}\left(H_{1,k} - H_{2,k}\right)P_t\sqrt{\left(1 + H_{1\to 2,k}P_t\right)}}{\sqrt{EA}}\Bigg) > 0 \tag{6.52}$$

since the term $\sqrt{\frac{H_{1,k}\left(1+H_{1\to 2,k}P_t\right)A}{H_{2,k}}}$ is clearly greater than 1. Further, the numerator of ${P_{1,k}}^{(2)}$ is

$$\begin{aligned} &E\left(-A + {H_{1\to 2,k}}^2 {P_t}^2\right) - C\sqrt{E(1 + H_{1\to 2,k}P_t)A} \\ &= E{H_{1\to 2,k}}^2 {P_t}^2\Bigg(\frac{-A}{{H_{1\to 2,k}}^2 {P_t}^2} + 1 - \frac{H_{1,k}A\sqrt{\left(1 + H_{1\to 2,k}P_t\right)A}}{{H_{1\to 2,k}}^2 {P_t}^2\sqrt{E}} \\ &- \frac{H_{1\to 2,k}(H_{1,k} - H_{2,k})P_t\sqrt{\left(1 + H_{1\to 2,k}P_t\right)A}}{{H_{1\to 2,k}}^2 {P_t}^2\sqrt{E}}\Bigg) \end{aligned} \tag{6.53}$$

If $|h_{2,k}| \geq |h_{1\to 2,k}|$, then the term

$$\frac{H_{1,k}A\sqrt{\left(1 + H_{1\to 2,k}P_t\right)A}}{{H_{1\to 2,k}}^2 {P_t}^2\sqrt{E}} \geq \frac{H_{1,k}\left(1 + H_{1\to 2,k}P_t\right)^2}{{H_{1\to 2,k}}^2 {P_t}^2\sqrt{E}} \tag{6.54}$$

$$= \frac{\left(1 + 2H_{1\to 2,k}P_t + {H_{1\to 2,k}}^2 {P_t}^2\right)}{{H_{1\to 2,k}}^2 {P_t}^2}\sqrt{\frac{H_{1,k}}{H_{2,k}}} > 1. \tag{6.55}$$

Clearly, the numerator of ${P_{1,k}}^{(2)}$ is negative provided $|h_{2,k}| \geq |h_{1\to 2,k}|$. Further, for $|h_{2,k}| \geq |h_{1\to 2,k}|$, the denominator of both ${P_{1,k}}^{(1)}$ and ${P_{1,k}}^{(2)}$ is positive. Hence, ${P_{1,k}}^{(1)} > 0$ and ${P_{1,k}}^{(2)} < 0$ provided $|h_{2,k}| \geq |h_{1\to 2,k}|$.

However, for $|h_{2,k}| < |h_{1\to 2,k}|$, BS transmits the signal orthogonally to each user with full transmit power on the kth subchannel in different time slots.

Because $\sum_{j=1}^{2} P_{j,k} = P_t,\ P_{j,k} \geq 0,\ k \in \{1, 2, \ldots, K\}$, the optimal solution to the allocated power is given by

$$P_{1,k}{}^{*} = \begin{cases} P_{1,k}^{min}, & P_{1,k}{}^{(1)} < P_{1,k}^{min} \\ P_{1,k}{}^{(1)}, & P_{1,k}^{min} \leq P_{1,k}{}^{(1)} < P_{1,k}^{max} \\ P_{1,k}^{max}, & P_{1,k}{}^{(1)} \geq P_{1,k}^{max} \end{cases}, \tag{6.56}$$

$$P_{2,k}{}^{*} = P_t - P_{1,k}{}^{*}. \tag{6.57}$$

(B) **User/Follower Level Game Analysis:** By using Lemma 6.1, (6.56) and (6.57), the solution for optimal price is given by

$$p_{1,k}{}^{*} = \frac{H_{1,k}}{1 + H_{1,k} P_{1,k}{}^{*}}, \tag{6.58}$$

$$p_{2,k}{}^{*} = \frac{H_{2,k}}{1 + H_{1\to 2,k} P_t \left(1 + H_{2,k} P_{1,k}{}^{*}\right) + H_{2,k} P_t}. \tag{6.59}$$

Hence, the closed-form solution for optimal price and power allocated between a NOMA pair are obtained.

6.4.2 Joint User Pairing and Subchannel Assignment

The optimal user pairing and subchannel assignment is a combinatorial problem which requires an exhaustive search for maximizing the achievable throughput of the system. For one subchannel, the possible number of pairs can be $\binom{2M}{2}$. If a user can be assigned only one subchannel, then the total possible combinations for K subchannels can be $\prod_{k=0}^{K-1} \binom{2M-2k}{2} = \frac{(2M)!}{2^K \times (2M-2K)!}$. For $K = M$, the optimal user pairing and subchannel assignment scheme needs to check a total of $\frac{(2M)!}{2^M}$ combinations. Clearly, it is not feasible for the practical systems to find an optimal solution to this problem for large number of users and subchannels because of its extremely high computational complexity. Hence, a novel sub-optimal algorithm for joint user pairing and subchannel assignment is proposed which not only exploits the BS-user links [54], but also considers the user-user links to enhance the system throughput.

The proposed joint algorithm is based on the following concepts:

- The achievable data rate for the strong user on the kth subchannel as given in (6.9) clearly depends upon the power allocated, $P_{1,k}$ and the channel coefficient, $h_{1,k}$. It is unaffected by the interference due to the weak user within the same subchannel. Although, the NOMA protocol allocates lower power to the users having higher channel gain, the achievable data rate can be enhanced by choosing the user having sufficiently high channel gain such that the effect of the allocated power on the achievable data rate reduces. Hence, it is desirable to distribute strong users in different subchannel to attain higher system throughput.

- Pairing a weak user with a strong user increases the achievable data rate of the weak user as the NOMA protocol assigns higher power to the user having lower channel gain. Further, higher is the channel gain of the link between the strong and weak user, $|h_{1\to 2,k}|^2$, larger is the achievable data rate of the weak user as shown in (6.10). Therefore, it is profitable to pair a strong user with a weak user with high channel gain of the link between them.

In the light of aforementioned concepts, a sub-optimal joint user pairing and subchannel assignment algorithm is proposed. At any time, all the available users contend for the available subchannels. For each available subchannel, all the available users are sequenced in the decreasing order of the channel gains from the BS. User having the highest channel gain is chosen as the strong user. From the lower half of the sorted users, user having the highest channel gain from the selected strong user is chosen as the weak user for that subchannel. For example, for $k = 1$ subchannel, the available $2M$ users are sorted in the decreasing order of their channel gains such that $|h_{1,1}|^2 \geq |h_{2,1}|^2 \geq \ldots \geq |h_{2M,1}|^2$. The user having the highest channel gain, i.e. $|h_{1,1}|^2$ is selected as the strong user. At the same time, the user having the highest channel gain $| |h_{1\to m,1}|^2$ among the lower half of the sorted available users, i.e. $M + 1 \leq m \leq 2M$, is chosen as the weak user. The selected strong user and weak user together form a NOMA pair $\mathcal{P}_1$ on the $k = 1$ subchannel. This NOMA user pairing and subchannel assignment process is carried out for the other available subchannels with the remaining users. In this way, two users are paired up from the available set of users and assigned a subchannel simultaneously. The proposed joint algorithm is illustrated in Algorithm 6.1.

Algorithm 6.1 Joint User Pairing and Subchannel Assignment Algorithm

1: Initialization: set $\mathcal{M}_A = \{1, 2, \ldots, 2M\}$, $\mathcal{P}_k = \emptyset \; \forall \; k \in \{1, 2, \ldots, K\}$;
2: **for** $k = 1 : K$ **do**
3: Sort the available users $\mathcal{M}_A$ in the descending order of their channel gains on kth subchannel;
4: Select the first user as the strong user on kth subchannel;
5: Select the mth user with highest channel gain $|h_{1\to m,1}|^2$ among the lower half of the sorted available users as the weak user on kth subchannel;
6: The strong user from step 4 and the weak user from step 5 form the NOMA pair $\mathcal{P}_k$ on kth subchannel;
7: Remaining available users $\mathcal{M}_A \leftarrow \mathcal{M}_A \backslash \mathcal{P}_k$;
8: **end for**

To describe the complexity of the algorithm, a standardized notation, i.e. Big-O is used which here represents how the complexity of the algorithm rises with the number of users asymptotically. The complexity of sorting $2M$ users for the first subchannel is $O\left(2M \log 2M\right)$, i.e. $O\left(M \log M\right))$ and the complexity of finding the user with maximum $|h_{1\to m,1}|^2$ from M users is $O\left(M \log M\right))$. Therefore, for K subchannels, the worst-case complexity of the sub-optimal joint algorithm becomes $O\left(KM \log M\right)$, i.e. $O\left(M^2 \log M\right)$ for $K = M$.

Here, for the sake of designing simplicity, each user is allowed to access only one subchannel. However, the proposed scheme can also be employed in the systems providing users with multiple accesses to the subchannels with the help of "virtual user extension" method. For example, in a system with users that requires two subchannels, each user is considered as two virtual users, each assigned a single subchannel by using the proposed algorithm. Therefore, in this chapter, it is assumed that a user can access one subchannel only.

6.5 Simulation Results

In this section , the performance of the proposed cooperative NOMA scheme is analyzed by comparing it with the corresponding cooperative OMA scheme in which the user pairing and subchannel assignment takes place randomly. For the cooper-

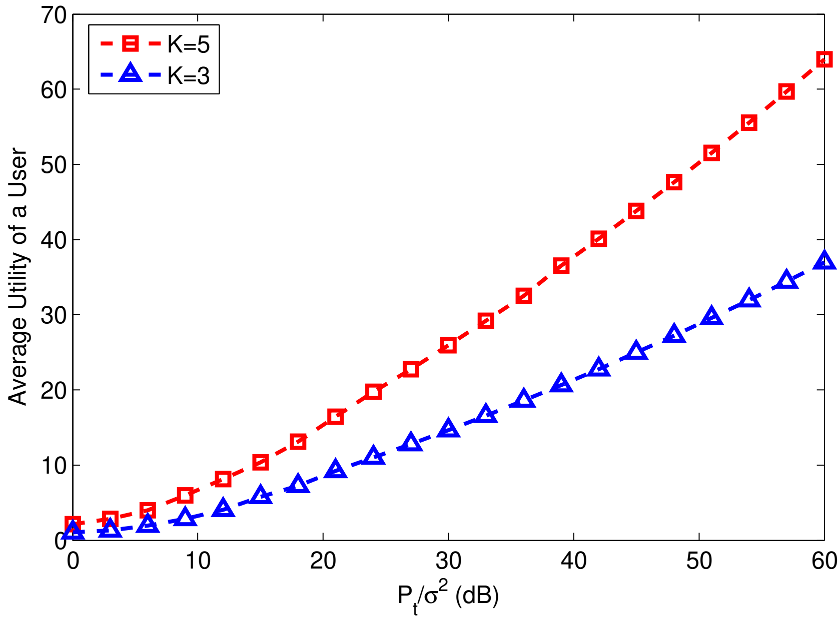


Figure 6.2: Average utility of a user in the proposed cooperative NOMA scheme versus P_t/σ^2.

ative OMA scheme, the transmission of signals takes place over three time slots in each subchannel. The first two time slots are occupied by the BS for broadcasting the signals meant for both the strong user as well as the weak user. The remaining time slot is used for relaying signal by the strong user. Besides cooperative OMA scheme, the proposed scheme is also compared with the optimal cooperative NOMA scheme, random user pairing and fixed power allocation (RUP-FPA) cooperative NOMA scheme as well as existing NOMA schemes in [46], [50] and [83]. In the simulations, the channel coefficients are modeled as $h_{j,k} \sim \mathcal{CN}\left(0, \delta_{j,k}^2\right)$, $j \in \{1, 2\}$, $k \in \{1, 2, \ldots, K\}$. Here, $\delta_{j,k}^2$ denotes of variance of $h_{j,k}$. The values of $\delta_{j,k}^2$ are assumed randomly in the range of $(0, 1)$. The value of ε is chosen randomly such that the constraint in Lemma 6.4 is satisfied. All the simulation results are evaluated by averaging over 10^3 independent Monte-Carlo trials on the channel coefficient realizations.

Firstly, the variation in average utility of a user with respect to P_t/σ^2 for $K = 3$ and $K = 5$ is depicted in Figure 6.2. It is evident that with increase in P_t/σ^2, average utility of a user increases for both $K = 3$ and $K = 5$. This can be attributed to the fact that with increase in P_t/σ^2, more power is available for allocation to the users, thereby, enhancing their respective utilities. With higher value of K, the efficiency

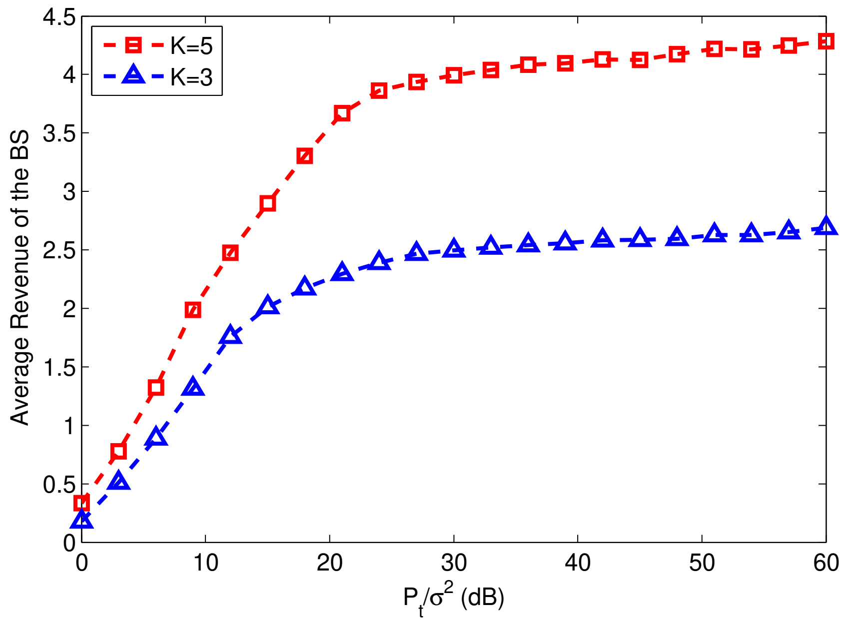


Figure 6.3: Average revenue of the BS in the proposed cooperative NOMA scheme versus P_t/σ^2.

of the joint user pairing and subchannel assignment algorithm increases as a wider set of $\mathcal{M}_A$ is available to form user pairs. Hence, average utility of a user for $K = 5$ is higher than that of $K = 3$.

The variation in average revenue of the BS with respect to P_t/σ^2 for $K = 3$ and $K = 5$ is shown in Figure 6.3. As P_t/σ^2 increases, average revenue of the BS increases for both $K = 3$ and $K = 5$ as with the availability of more power, higher revenue could be earned from the users. However, for higher values of P_t/σ^2, it can be observed that average revenue of the BS rises ever so slightly. This can be attributed to the fact that the price $(p_{1,k}, p_{2,k})$, $k \in \{1, 2, \ldots, K\}$ decreases with increase in the allocated power as shown in (6.38) and (6.39). Furthermore, the BS earns more revenue if higher number of users are available. Therefore, the average revenue of the BS for $K = 5$ is higher as compared to that of $K = 3$.

Figure 6.4 depicts the comparison of average rate of the strong users and the weak users between the proposed cooperative NOMA scheme and the optimal cooperative NOMA scheme with respect to P_t/σ^2 for $K = 3$. As the availability of power to be allocated increases, the average rate of strong and weak users increases with increase in P_t/σ^2. However, the average rate of weak users is higher than that of the strong users as weak users receive signal from both the BS as well as the strong users. It

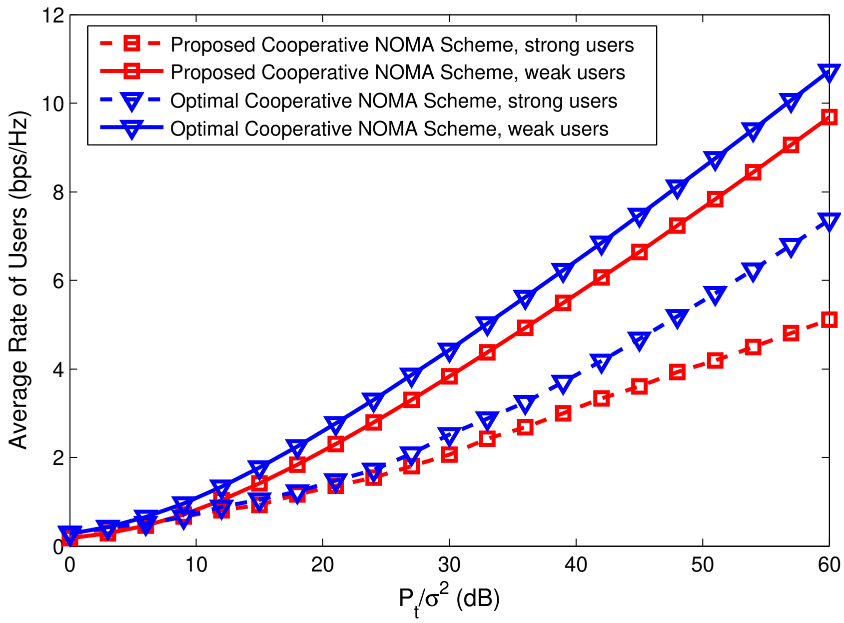


Figure 6.4: Average rate of the strong users and the weak users versus P_t/σ^2.

is evident that for $P_t/\sigma^2 = 30$ dB, the proposed cooperative NOMA scheme attains 82.11% and 86.44% of average rate of the strong users and the weak users of the optimal cooperative NOMA scheme, respectively.

The proposed cooperative NOMA scheme, optimal cooperative NOMA scheme, RUP-FPA cooperative NOMA scheme and cooperative OMA scheme are compared in terms of average sum rate of users for both $K = 3$ and $K = 5$ in Figure 6.5. The variation in the slopes of the optimal cooperative NOMA scheme, RUP-FPA cooperative NOMA scheme and cooperative OMA scheme with that of the proposed cooperative NOMA scheme for large values of P_t/σ^2 can be attributed to the different user pairing methods adopted in the schemes [54]. It is evident that the proposed cooperative NOMA scheme exhibits superior performance than the cooperative OMA scheme in terms of average sum rate of users against P_t/σ^2. It can be attributed to the fact that in the proposed cooperative NOMA scheme, the communication takes place over two time slots in each subchannel as opposed to the three time slots in cooperative OMA scheme. Further, in the proposed cooperative NOMA scheme, the power is allocated dynamically and the user pairing is performed on the basis of the channel gains of both the BS-user links as well as the user-user links. On the other hand, in RUP-FPA cooperative NOMA scheme, power allocation is uniform and users are paired randomly. Hence, the average sum rate of

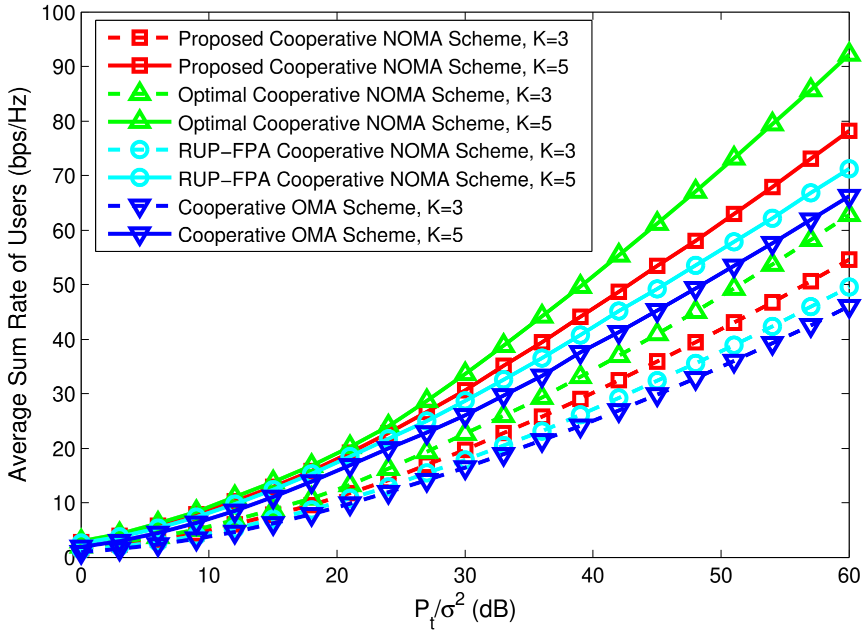


Figure 6.5: Average sum rate of users versus P_t/σ^2 for $K = 3$ and $K = 5$.

users of the proposed cooperative NOMA scheme against P_t/σ^2 is higher than that of the RUP-FPA cooperative NOMA scheme. For example, in case of $P_t/\sigma^2 = 30$ dB, the average sum rate of users for the proposed cooperative NOMA scheme improves roughly by 10.2% and 19.72% of the RUP-FPA cooperative NOMA scheme and cooperative OMA scheme for $K = 3$, respectively. Similarly, for $P_t/\sigma^2 = 30$ dB and $K = 5$, the average sum rate of users for the proposed cooperative NOMA scheme increases roughly by 6.81% and 17.60% of the RUP-FPA cooperative NOMA scheme and cooperative OMA scheme, respectively. However, for $P_t/\sigma^2 = 30$ dB, the average sum rate of users for the proposed cooperative NOMA is roughly 86.69% and 90.96% of the optimal cooperative NOMA scheme for $K = 3$ and $K = 5$, respectively.

To depict the superiority of the proposed cooperative NOMA scheme, it is compared with the NOMA schemes proposed in [46], [50] and [83] in terms of average sum rate of users for different values of P_t/σ^2 for $K = 1$, i.e. two users, as shown in Figure 6.6. The figure clearly depicts that the average sum rate of users of the proposed cooperative NOMA scheme is generally higher than that of the schemes proposed in [46], [50] and [83], except for the small range [6, 18] where it is comparable to that of [50]. For instance, the proposed cooperative NOMA scheme yields 82.09% of the average sum rate of users of the proposed scheme in [50] for $P_t/\sigma^2 = 12$ dB. For

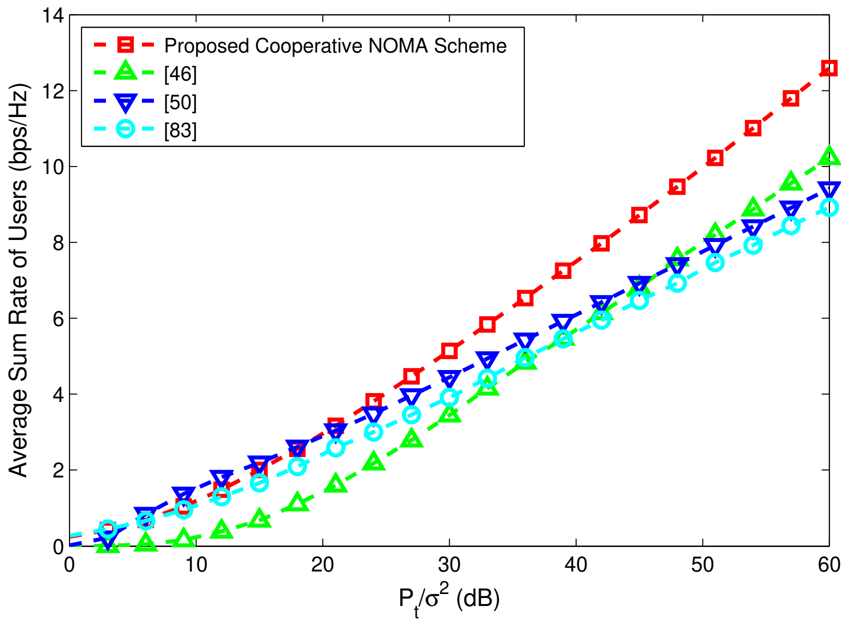


Figure 6.6: Average sum rate of users versus P_t/σ^2 for $K = 1$.

$P_t/\sigma^2 = 30$ dB, the average sum rate of users for the proposed cooperative NOMA improves roughly by 49.22%, 15.68% and 31.24% of the NOMA schemes proposed in [46], [50] and [83], respectively.

Figure 6.7 compares the proposed cooperative NOMA scheme with the optimal cooperative NOMA scheme, the RUP-FPA cooperative NOMA scheme and the cooperative OMA scheme in terms of average sum rate of users against the number of user pairs for $P_t/\sigma^2 = 20$ dB. It is shown in Section 6.3.2 that the computational complexity of the optimal cooperative NOMA scheme grows significantly with increase in number of users. Therefore, the results of the optimal cooperative NOMA scheme are calculated till 15 user pairs. Figure 6.7 clearly depicts the better performance of the proposed cooperative NOMA scheme in comparison with that of the RUP-FPA cooperative NOMA scheme and the cooperative OMA scheme in terms of average sum rate of users against the number of users. For example, the proposed cooperative scheme yields 25.71% and 45.13% higher average sum rate of users than that of the RUP-FPA cooperative NOMA scheme and the cooperative OMA scheme for 25 pairs of users, respectively. However, the average sum rate of users of the proposed cooperative NOMA scheme is roughly 88.36% of the optimal cooperative NOMA scheme for 15 pairs of users.

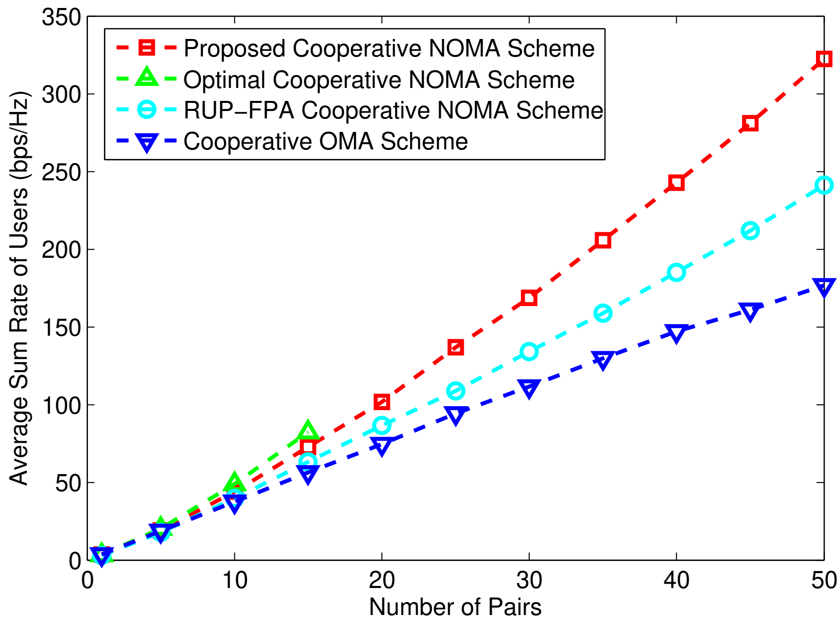


Figure 6.7: Average sum rate of users versus the number of pairs for $P_t/\sigma^2 = 20$ dB.

6.6 Chapter Summary

This chapter has investigated the problem of user pairing, subchannel assignment, and power allocation in cooperative NOMA networks. A cooperative NOMA scheme has been proposed consisting of SG-based power allocation along with the low-complexity sub-optimal joint user pairing and subchannel assignment algorithm. The proposed joint user pairing and subchannel assignment algorithm groups two users to form a NOMA pair and assign them a subchannel based on the channel gains of both the BS-user links and the user-user links. On the other hand, in the proposed single-leader multi-follower SG, the BS has been modeled as a leader which allocates power according to the price paid by the users, i.e. the followers. Closed-form expressions for optimal price and optimal power allocated to the users have been derived. Simulation results have demonstrated the efficacy of the proposed cooperative NOMA scheme over the cooperative OMA scheme as well as existing NOMA schemes proposed in [46], [50] and [83] in terms of average sum rate of users.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

Cooperative relaying has emerged as an efficient transmit strategy in wireless networks affected by fading. With the desire for decentralized, self-organizing, and autonomous networks, it is essential to seek apt game theoretical tools that study and analyze the interactions and behavior of the network nodes. In this research work, various game theoretic models have been proposed to address the problem of resource allocation in different cooperative communication networks. The main objective is to efficiently allocate resources among different nodes to enhance the overall performance of the cooperative networks.

A novel integrated game theoretic solution that has been presented in Chapter 3 guarantees the attainment of an optimal and stable coalition structure of relays for both disjoint and overlapping coalitions. The efficacy of CGs approach in general and OCG-SG in particular has been established through simulation results. The proposed game theoretic solutions have been shown to achieve comparable performance in terms of system throughput against the centralised approach. A meagre difference of 0.05 Mbps in case of OMA and 0.06 Mbps for NOMA in system throughput obtained by using proposed overlapping scheme and centralised approach validates its effectiveness and efficiency. Further, for disjont coalition scheme and centralised approach, the difference in system throughput comes out to be 0.09 Mbps and 0.08 Mbps for OMA and NOMA, respectively. In particular, it can be concluded that the OCG approach yields consistently superior performance than the disjoint CG approach because of the enhanced allocation of power to individual relays.

An incentives-based game theoretic solution that has been proposed in Chapter 4 highlights the effectiveness of the robust solution in an incomplete information environment. Establishment of existence and uniqueness of the SE underscores the optimality of the obtained solutions in terms of price and power. The proposed scheme has been shown to exhibit better performance in terms of system throughput in comparison with the nominal solution. Enhanced throughput as compared to the nominal game confirms the efficacy of the proposed robust game under varying degree of uncertainty which seems to be more relevant to practical scenarios.

Further, the auction-based mechanisms that have been discussed in Chapter 5 confirm that besides efficient power allocation, user pairing significantly improves the performance of NOMA systems. Auction-based scheme with user pairing performs 48.5% and 33.5% better than the existing algorithm in [123] in terms of average sum rate of users for $M = 3$ and $M = 4$, respectively. In addition, the increase in average sum rate of users by 39.9% and 35.7% in case of $M = 3$ and $M = 4$, respectively, for auction-based scheme with user pairing when compared with that of auction-based scheme without user pairing concludes the pivotal role of user pairing in the overall performance of the NOMA systems.

Based on the above results, a novel game theoretic solution for user-assisted downlink cooperative NOMA network has been presented in Chapter 6. Its effectiveness has been demonstrated in terms of average sum rate of users in comparison with that of the cooperative OMA scheme and existing NOMA schemes proposed in [46], [50] and [83] through simulation results. For $P_t/\sigma^2 = 30$ dB, the average sum rate of users for the proposed cooperative NOMA scheme improves roughly by 49.22%, 15.68% and 31.24% of the existing NOMA schemes in [46], [50] and [83], respectively. The improvement in average sum rate of users by 45.13% with $P_t/\sigma^2 = 20$ dB and $K = 15$ as compared to the cooperative OMA scheme establishes the superiority of NOMA with cooperative communication in enhancing the overall performance of cooperative wireless networks.

7.2 Future Work

In the aforementioned research work, each node of the networks is assumed to be equipped with a single antenna. However, the proposed power allocation schemes can be extended to MIMO scenario by using multiple antennas of the source (or BS) for data transmission to different destinations (or users). Also, multi-objective problems can be designed in future for such systems which are quite relevant to the practical scenarios.

Auction theory is a popular market-based mechanism that is used to distribute resources in wireless networks. It is an efficient solution that guarantees a revenue gain for the provider by allocating resources to the users who value the resources most [134], [135]. It eliminates long negotiation periods. Users are well-aware of the fact that they are competing fairly and on the same terms as all other users. Hence, through careful design, it can yield a quick result that satisfies all the nodes and guarantees the fairness. One future research direction can be designing the optimal auction in terms of maximizing social welfare and guaranteeing the individually rational, incentive compatible, and fairness constraints. Also, the general scenario of multiple providers can be explored in future.

Better QoS and efficient resource utilization are competing objectives. One can easily attain more QoS by spending more resources. On the other hand, it is easy to utilize resources more efficiently by providing less QoS. Traffic management is all about getting good QoS and efficient resource management at the same time. It would be interesting to investigate the proposed analysis with different QoS parameters, such as low latency, as the end metrics in future work.

Present wireless systems are quite dependent on mathematical models that define their communication structure. Such mathematical models usually fail to model the systems accurately. In addition, there exists no mathematical models for some of the building blocks of wireless networks and devices and consequently, modeling of such important blocks becomes challenging. On the other hand, the optimization of wireless networks also requires heavy mathematical solutions that are often inefficient in terms of computational complexity and time. Such solutions also consume a large amount of energy. It is quite likely that the aforementioned mathematical models and their solutions will not play much role in improving the capacity and performance of next generation wireless networks [136]. Machine learning, therefore, will play a crucial role in future wireless networks because of its capacity to model systems that cannot be represented by a mathematical equation. Moreover, it is expected that machine learning tools can be very useful in replacing heuristic or brute-force algorithms for optimizing certain localized tasks [137]. Hence, future works include the deep investigation of machine learning techniques for relay selection, power allocation and bandwidth assignment in next generation wireless networks. It would be interesting to study the many aspects of the problem of cooperation, and innovate in machine learning to contribute to solving these problems. Furthermore, additional machine learning actions or predictions could be performed by mobile devices and reported to the network in order to assist the network in decision-making process for resource management, thus, making mobile devices an integral part of the infrastructure resource in future.

In addition, the research on cooperative NOMA is still in its infancy. To fully explore the potential of cooperative NOMA, more advanced technologies can be integrated with it, like full-duplex with MIMO-cooperative NOMA, multi-carrier with MIMO-cooperative NOMA and full-duplex with multi-carrier MIMO-cooperative NOMA. The above mentioned technologies yield much more complex and complicated resource allocation optimization problems which can be considered in future studies.

List of Publications

1. A.K. Lamba, R. Kumar, S. Sharma, "Joint user pairing, subchannel assignment and power allocation in cooperative non-orthogonal multiple access networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 10, pp. 11790-11799, 2020. (Impact Factor: 5.978)
   DOI: *https://doi.org/10.1109/TVT.2020.3018645*
2. A.K. Lamba, R. Kumar, S. Sharma, "Power allocation for downlink multi-user hybrid NOMA-OMA systems: An auction game approach," *International Journal of Communication Systems*, vol. 33, no. 7, 2020. (Impact Factor: 2.047)
   DOI: *https://doi.org/10.1002/dac.4306*
3. A.K. Lamba, R. Kumar, S. Sharma, "A robust Stackelberg game approach for joint relay selection and optimal power allocation for cooperative device-to-device communication under channel uncertainties," *Wireless Personal Communications*, vol. 110, no. 1, pp. 169-183, 2020. (Impact Factor: 1.671)
   DOI: *https://doi.org/10.1007/s11277-019-06718-y*
4. A.K. Lamba, R. Kumar, S. Sharma, "Auction-based power allocation for downlink nonorthogonal multiple access systems," *IET Electronics Letters*, vol. 55, no. 7, pp. 420-422, 2019. (Impact Factor: 1.314)
   DOI: *https://doi.org/10.1049/el.2018.7544*
5. A.K. Lamba, R. Kumar, S. Sharma, "Game-theoretic resource allocation scheme for multiple-amplify-and-forward-relay wireless networks," *IET Communications*, vol. 12, no. 14, pp. 1649-1660, 2018. (Impact Factor: 1.542)
   DOI: *https://doi.org/10.1049/iet-com.2017.1202*
6. A.K. Lamba, R. Kumar, S. Sharma, "A coalitional game-based integrated framework for optimal power allocation in multirelay cooperative environment," *International Journal of Communication Systems*, vol. 31, no. 1, 2018. (Impact Factor: 2.047)
   DOI: *https://doi.org/10.1002/dac.3409*

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