ENERGY-EFFICIENT POWER ALLOCATION FOR DOWNLINK NON-ORTHOGONAL MULTIPLE ACCESS NETWORKS BASED ON GAME THEORY AND GENETIC ALGORITHM

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FACULTY OF ENGINEERING
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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT

The exponential growth in the number of users and their increasingly diverse demands in next-generation wireless networks has created significant challenges in managing limited resources while ensuring energy-efficient communication. The need to meet the quality of service (QoS) requirements for this rapidly expanding user base, particularly with heightened data rate expectations, underscores the urgency for innovative solutions. Although 5G and beyond technologies provide a foundation for next-generation networks, further advancements are required to improve energy efficiency (EE) and spectrum efficiency (SE) to meet these demands. This study focuses on optimizing energy-efficient power allocation in Non-Orthogonal Multiple Access (NOMA) systems, a transformative approach that allows multiple users to share resources simultaneously. The research leverages Artificial Intelligence (AI)-based Genetic Algorithms (GA) and game theory to address critical challenges in resource allocation. GA is specifically chosen for its ability to solve complex, non-linear problems by efficiently navigating large solution spaces. Complementing this, game theory offers a robust framework to model strategic interactions among users, ensuring fair and effective resource distribution. Together, these methods tackle critical gaps in resource allocation, including the trade-off between energy efficiency and data rate, and the challenges posed by both perfect and imperfect channel state information (CSI). The novel power allocation mechanism developed in this study demonstrates significant improvements. The proposed method achieves a 75% enhancement in energy efficiency compared to conventional Orthogonal Multiple Access (OMA) and an 11% improvement over benchmark NOMA algorithms.

Additionally, it reduces outage probability by 25% and 10% relative to OMA and existing NOMA algorithms, respectively. These results validate the algorithm's robustness, particularly under imperfect CSI conditions, where traditional methods often fail. Furthermore, the research explores advanced applications such as integrating NOMA with Millimeter-Wave technology and optimizing user association strategies, enhancing system capacity and overall performance. The findings highlight the pivotal role of Genetic Algorithms and game theory in overcoming the limitations of conventional resource allocation methods. The integration of these advanced techniques ensures adaptability, efficiency, and resilience in dynamic network environments. By achieving substantial gains in energy efficiency and data rates, this study sets a new benchmark for resource allocation strategies in 5G and beyond networks. The proposed method demonstrates how AI-driven solutions, coupled with strategic modeling frameworks like game theory, can address the pressing challenges of next-generation wireless communication systems effectively.

Keywords: 5G Networks, Artificial Intelligence (AI), Game Theory, Genetic Algorithm, Non-Orthogonal Multiple Access (NOMA).

PERUNTUKAN KUASA CEKAP TENAGA UNTUK RANGKAIAN AKSES BERBILANG BUKAN ORTOGONAL BUKAN ORTOGONAL BERDASARKAN TEORI PERMAINAN DAN ALGORITMA GENETIK

ABSTRAK

Pertumbuhan eksponen dalam bilangan pengguna dan permintaan mereka yang semakin pelbagai dalam rangkaian wayarles generasi akan datang telah mewujudkan cabaran yang ketara dalam menguruskan sumber yang terhad sambil memastikan komunikasi yang cekap tenaga. Keperluan untuk memenuhi keperluan kualiti perkhidmatan (QoS) untuk pangkalan pengguna yang berkembang pesat ini, terutamanya dengan jangkaan kadar data yang lebih tinggi, menekankan keperluan untuk penyelesaian inovatif. Walaupun teknologi 5G dan seterusnya menyediakan asas untuk rangkaian generasi akan datang, kemajuan selanjutnya diperlukan untuk meningkatkan kecekapan tenaga (EE) dan kecekapan spektrum (SE) untuk memenuhi permintaan ini. Kajian ini memberi tumpuan kepada mengoptimumkan peruntukan kuasa cekap tenaga dalam sistem Akses Berbilang Bukan Ortogonal (NOMA), pendekatan transformatif yang membolehkan berbilang pengguna berkongsi sumber secara serentak. Penyelidikan itu memanfaatkan Algoritma Genetik (GA) berasaskan Kecerdasan Buatan (AI) dan teori permainan untuk menangani cabaran kritikal dalam peruntukan sumber. GA dipilih secara khusus kerana keupayaannya untuk menyelesaikan masalah yang kompleks dan bukan linear dengan mengemudi dengan cekap ruang penyelesaian yang besar. Melengkapkan ini, teori permainan menawarkan rangka kerja yang mantap untuk memodelkan interaksi strategik di kalangan pengguna, memastikan pengagihan sumber yang adil dan berkesan. Bersama-sama, kaedah ini menangani jurang kritikal dalam peruntukan sumber, termasuk pertukaran antara kecekapan tenaga dan kadar data, dan cabaran yang ditimbulkan oleh maklumat keadaan saluran (CSI) yang sempurna dan tidak sempurna. Mekanisme peruntukan kuasa baru yang dibangunkan dalam kajian ini

menunjukkan peningkatan yang ketara. Kaedah yang dicadangkan mencapai peningkatan kecekapan tenaga sebanyak 75% berbanding dengan Akses Berbilang Ortogonal (OMA) konvensional dan peningkatan 11% berbanding algoritma penanda aras NOMA. Selain itu, ia mengurangkan kebarangkalian gangguan sebanyak 25% dan 10% berbanding dengan OMA dan algoritma NOMA sedia ada, masing-masing. Keputusan ini mengesahkan keteguhan algoritma, terutamanya dalam keadaan CSI yang tidak sempurna, di mana kaedah tradisional sering gagal. Tambahan pula, penyelidikan itu meneroka aplikasi termaju seperti menyepadukan NOMA dengan teknologi Gelombang Milimeter dan mengoptimumkan strategi persatuan pengguna, meningkatkan kapasiti sistem dan prestasi keseluruhan. Penemuan ini menyerlahkan peranan penting Algoritma Genetik dan teori permainan dalam mengatasi batasan kaedah peruntukan sumber konvensional. Penyepaduan teknik canggih ini memastikan kebolehsuaian, kecekapan dan daya tahan dalam persekitaran rangkaian dinamik. Dengan mencapai keuntungan besar dalam kecekapan tenaga dan kadar data, kajian ini menetapkan penanda aras baharu untuk strategi peruntukan sumber dalam 5G dan seterusnya rangkaian. Kaedah yang dicadangkan menunjukkan bagaimana penyelesaian dipacu AI, ditambah dengan rangka kerja pemodelan strategik seperti teori permainan, boleh menangani cabaran mendesak sistem komunikasi wayarles generasi akan datang dengan berkesan.

Keywords: Rangkaian 5G, Kecerdasan Buatan , Teori Permainan, Algoritma Genetik, Capaian Berbilang Bukan Ortogon.

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4G	:	Fourth generation
5G	:	Fifth generation
6G	:	Sixth generation
AI	:	Artificial intelligence
AO	:	Alternating optimization
AWGN	:	Additive white Gaussian noise
B	:	Price of the allocated power collected by transmitter
B5G	:	Beyond fifth generation
BS	:	Base station
CNOMA	:	Cooperative non orthogonal multiple access
CSI	:	Channel state information
CSMA	:	Carrier sense multiple access
D2D	:	Device to device
DDPG	:	Deep deterministic policy gradient
DF	:	Decode and forward
DL	:	Downlink
DQN	:	Deep Q-network
dBm	:	dB milliWatt
E-learning	:	Electronic learning
EE	:	Energy efficiency
FDMA	:	Frequency division multiple access
GA	:	Genetic algorithm
Gbps	:	Giga bits per second
GHz	:	Gigahertzes

GTPA	:	Game theoretic power allocation
H	:	Hessian matrix for M users
HetNets	:	Heterogeneous networks
h_m	:	Channel gain between user m and the Base station
IoT	:	Internet of things
ISI	:	Inter symbol interference
L_b	:	Lower bound of the optimization problem in genetic algorithm
LTE	:	Long term evolution
M	:	Users' number in the cell
MC	:	Multi-Carrier
MCTS	:	Monte Carlo tree search
MHz	:	Megahertz
MIMO	:	Multiple input multiple output
MIoT	:	Mine internet of things
MISO	:	Multi input single output
mMTS	:	Massive machine-type communications
mmWaves	:	Millimeter-waves
n_m	:	Additive white Gaussian noise at the user m
N_o	:	Power spectrum density of the AWGN
NGMN	:	Next generation mobile networks
NOMA	:	None orthogonal multiple access
OFDMA	:	Orthogonal frequency division multiple access
OFDM	:	Orthogonal frequency division multiplexing
OMA	:	Orthogonal multiple access
OSRPA	:	Optimum sum-rate power allocation
PA	:	Power allocation

P_c	:	Dissipated power in the transmitter operation circuit
P_m	:	Allocated power to the user *m*
P_{out}	:	The outage probability
PPO	:	Proximal policy optimization
P_t	:	Total transmission power of the transmitter
QoS	:	Quality of service
R_m	:	Data rate of the user m
R_{sum}	:	Sum data rate in the cell
SC	:	Single-carrier
SE	:	Spectrum efficiency
SINR	:	Signal to interference and noise ratio
SIC	:	Successive interference cancellation
SISO	:	Single input single output
STAR-RIS	:	Simultaneous transmission and reflection reconfigurable intelligent surface
Tbps	:	Tera bits per second
TDMA	:	Time-division multiple access
U_b	:	Upper bound of the optimization problem in genetic algorithm
UE	:	User equipment
U_m	:	User utility function
x(t)	:	Superposed transmitted signal
y(t)	:	Received signal

CHAPTER 1: INTRODUCTION

1.1 Background

A state-of-the-art wireless communication technology called Non-Orthogonal Multiple Access (NOMA) allows multiple users to share a time-frequency resource, like a channel or sub-channel, simultaneously. Using power domain multiplexing, NOMA enables various users to share the available resources concurrently, in contrast to traditional OMA schemes where users are assigned separate and non-overlapping resource blocks. This enables more effective use of the available spectrum by allocating various power levels to users within the same time-frequency resource. Users in NOMA are assigned power levels based on their channel conditions; users in poorer channel conditions are assigned lower power levels. NOMA breaks the conventional rule of exclusive resource allocation to a single user in the power domain by using non-orthogonal superposition coding to transmit signals from multiple users and using Successive interference cancellation (SIC) at the receiver to eliminate interference, proposing a new idea of multi-user G. Wu, Chen, and Chen (2023). This increases system capacity and spectral efficiency by enabling the base station to transmit and receive multiple signals simultaneously (Qi, Xie, & Liu, 2022). When it comes to improving the functionality of next-generation wireless communication systems, like the fifth generation (5G) and beyond, NOMA is especially promising (Kumar, Hanif, Juntti, & Tran, 2023).

However, the deployment of NOMA technology comes with its own set of challenges, particularly in the domain of energy-efficient power allocation. First, it is questionable whether it is fair to assign users different power levels based on their channel conditions and whether sufficient Quality of Service (QoS) is provided for each user. Resolving power disparities while upholding equity is a crucial obstacle in NOMA energy-efficient power allocation. Second, NOMA needs complex resource allocation algorithms in order to figure out what each user's ideal power level is (Aghdam, Tazehkand, & Abdolee, 2022). One major challenge is to design scalable and effective algorithms that can adjust to changing user requirements and dynamic channel conditions. Moreover, interference is considered an issue since there is a chance that users who are sharing the same resources could interfere with one another when multiple signals are transmitted simultaneously in NOMA. To lessen the effects of interference and guarantee dependable communication, effective interference management techniques are crucial (L. Xu, Cai, Chang, Fang, & Li, 2022).

In addition, achieving perfect channel state information is difficult in real wireless communication systems where wireless channels can experience changes and oscillations over time. To continuously optimize performance, NOMA energy-efficient power allocation systems need to be able to dynamically adapt to shifting channel conditions (Ihsan, Chen, Zhang, & Xu, 2022). Therefore, advanced front and back-haul infrastructure may be needed for NOMA to facilitate the simultaneous transmission and reception of multiple signals. There are additional challenges in maintaining the network infrastructure's dependability and managing the increased data rates. Finally, even though NOMA can increase spectral efficiency (Budhiraja et al., 2021), it is crucial to take the system's energy efficiency (EE) into account, particularly when raising power levels for users with better channel conditions. An essential component of energy efficient power allocation in NOMA is striking a balance between power consumption and efficiency.

It will take a combination of sophisticated algorithms, flexible systems, and strong network infrastructure to overcome these obstacles. To ensure that NOMA's potential benefits are realized in realistic wireless communication scenarios, ongoing research and development efforts are concentrated on optimizing it for real-world deployment (Kebede, Wondie, Steinbrunn, Kassa, & Kornegay, 2022; Shah, Qasim, Karabulut, Ilhan, & Islam, 2021).

The size of the transmitted data in the sixth generation (6G) is expected to be doubled ten to hundred times as compared to the 5G (S. Chen et al., 2020). Although many challenges appeared in 5G, such as energy-saving, (Souza, Vieira, Seruffo, & Cardoso, 2020; Zekri & Jia, 2018), the critical issues and challenges in 6G seem to be higher, such as attaining an improvement in system throughput, optimizing the spectrum efficiency (SE), reducing the time delay, and wider coverage (S. Chen et al., 2020). It is crucial to develop creative solutions that can improve the utilization of network resources as the demand for wireless services keeps rising, particularly in the context of NOMA, which is a crucial technology for 5G and beyond (Z. Wei, Yang, Ng, Yuan, & Hanzo, 2020). By allowing non-orthogonal sharing of the same time-frequency resources, NOMA could improve spectral efficiency. However, in NOMA networks, efficient resource allocation, energy saving, and data rate maximization present challenging optimization problems (Zamani, Eslami, Khorramizadeh, & Ding, 2019).

With the growing Internet of Things (IoT) and cloud-based applications, the demand for new services and data traffic for wireless communications has increased tremendously. Thus, one of the expectations for 6G is to increase the transmission data rate to achieve a peak value of 1 Tbps to provide a massive number of users with the required service (T. Huang et al., 2019). The accessible spectrum resources are restricted since they serve tens of thousands of pieces of mobile communications equipment and therefore more techniques are required to guarantee the connection quality for each user (X. Liu, Ding, & Hu, 2021). NOMA is considered a very promising technique beyond 5G and 6G where it provides services to several users simultaneously at the same subcarrier and at the same time through the use of superposition coding in the power domain (L. Zhu, Z. Xiao, X. G. Xia, & D. O. Wu, 2019). NOMA has several advantages such as high SE, improved cell edge data rate, low latency, and good compatibility with other techniques such as orthogonal multiple access (OMA) (Wan, Wen, Ji, Yu, & Chen, 2018).

Moreover, considerable improvements in SE, EE, and outage probability are achieved in Multiple Input Multiple Output (MIMO) NOMA -based communications compared to MIMO-OMA when an appropriate resource allocation is implemented (Ghosh, Sharma, Haci, Singh, & Ra, 2021). However, channels in massive MIMO systems exhibit a high degree of spatial correlation. Information that describes the present state or condition of a communication channel in a wireless communication system is referred to as channel state information (CSI). A communication channel's properties can change as a result of things like obstructions, interference, signal reflections, and other external factors. By offering insightful information about the channel's current condition, channel state information enables the communication system to adjust and perform at peak efficiency. CSI facilitates intelligent resource allocation in wireless networks. The system can maximize network performance by allocating resources like time slots, frequency bands, or power levels efficiently by knowing the channel conditions for various users or devices. In (Chopra, Murthy, Suraweera, & Larsson, 2019), a large-system analysis is applied to the covariance-aided CSI acquisition strategy in the MIMO system, which exploits the individual covariance matrices for channel estimation when non-orthogonal pilot sequences are used. The analysis shows that the training overhead can be reduced when a covariance-aided strategy is implemented compared to the conventional CSI acquisition, where no knowledge of the user spatial co-variance matrices is known.

The number of connected equipment massively increased in 5G compared to the previous fourth generation (4G) networks (Agiwal, Roy, & Saxena, 2016; Andrews et al., 2014). By 2030, the density of connected devices is expected to reach 10^7 devices/km^2, and multimedia applications will be the most popular applications for users, such as mobile video calls, streaming videos, and online conferences. As a result, the required data rate will rise about 10 times more than that in 4G, and the peak transmitted data in the 5G is expected to be about 20 Gbps (Bai, Yao, Zhang, & Leung, 2019; Z. Zhang et al., 2019). On the other hand, the SE and the EE should be enhanced in 5G by x5 and x100 times, respectively (Z. Zhang et al., 2019). Therefore, satisfying the requirements of a massive number of users within the network's limited resources is considered a challenge in 5G.

1.2 Motivation of the study

In today's hyper-connected world, the demand for faster and more reliable wireless communication networks is insatiable. The emergence of 5G technology has promised to revolutionize the way people connect and communicate, offering unprecedented data rates and low latency. NOMA has emerged as a key technology in 5G networks, allowing multiple users to share the same time and frequency resources, thus significantly enhancing spectral efficiency. However, it is faced with the pressing need to ensure the sustainability and energy efficiency of these networks (Islam, Avazov, Dobre, & Kwak, 2017). Despite the promises of 5G technology and the potential benefits of NOMA in enhancing SE, its integration into 5G networks poses several challenges. Sophisticated algorithms are needed to dynamically adapt to changing user conditions to ensure fairness and quality of service due to the complex resource allocation required by NOMA. To reduce the inter-user interference caused by multiple simultaneous transmissions, effective interference management becomes essential. Significant challenges also include addressing the dynamic nature of wireless channels, the requirement for sophisticated front- and back-haul infrastructure, and striking a balance between EE and higher power levels. In our hyper-connected world, standardization, security issues, and deployment costs highlight the complex terrain of NOMA implementation in the pursuit of faster and more dependable wireless networks.

Energy efficiency optimization and data rate optimization are critical issues in NOMA 5G networks, and this thesis aims to address these challenges using advanced techniques such as game theory and genetic algorithms. This research is motivated by several compelling reasons. Energy efficiency is one of the most important concerns. With the proliferation of wireless devices and increasing demand for data, the energy consumption of 5G networks is skyrocketing. Energy-efficient communication systems are imperative to reduce carbon footprints and operational costs. Game theory and genetic algorithms have shown promise in optimizing wireless communication systems. Game theory and genetic algorithms can provide novel solutions to optimize energy efficiency and data rate in NOMA-based 5G networks (R. Liu, Lee, Yu, & Li, 2020; Luo et al., 2019; K. Wang, Cui, Ding, & Fan, 2019). Secondly, improving the QoS by providing users with a high data rate is an essential challenge beyond 5G (B5G) where the explosive growth of data-hungry applications, including augmented reality, virtual reality, 4K video streaming, and IoT devices, has placed unprecedented pressure on 5G networks to deliver high data rates. NOMA, with its ability to enhance spectral efficiency, offers a promising solution. However, effective resource allocation and data rate optimization techniques are required to harness NOMA's full potential (P. Zhang, Yang, Chen, & Huang, 2019).

1.3 Problem statement

The optimization of resource allocation in the downlink (DL) is a challenging task in the context of NOMA systems, especially when there is imperfect CSI. This study tackles this important problem by exploring how game theory and genetic algorithms can be utilized to create novel approaches for data rate optimization and EE optimization in NOMA systems. Robust algorithms that strategically allocate power and optimize user pairings are imperative due to the inherent uncertainties introduced by imperfect CSI. Conventional algorithms may struggle to adapt to the dynamic and varying conditions in wireless channels, especially in NOMA systems with imperfect CSI. Furthermore, in situations where the communication environment is complex and prone to sudden changes, traditional algorithms may offer suboptimal solutions for user pairing and power allocation. The research aims to bridge this gap by proposing a novel framework that leverages game-theoretic principles and genetic algorithms to adapt to the challenges posed by imperfect channel information. It is anticipated that the results of this study will advance the field of wireless communication by adding to the theoretical underpinnings of NOMA systems and providing useful insights into optimizing downlink performance in imperfect CSI scenarios found in real-world settings.

The following explains the significance of these goals and how the proposed strategy utilizing genetic algorithms and game theory adds to the picture:

1. *The data rate*: As bandwidth-intensive applications like video streaming, virtual reality, Electronic learning (E-learning), online gaming, and augmented reality become more commonplace in our hyper-connected world, there is an unquenchable need for faster data rates. Applications requiring large data throughput can benefit from a more responsive and seamless user experience thanks to higher data rates, which also translate to faster upload and download. The game theory-based algorithm is proposed in this study to solve the data rate optimization problem in several scenarios where the effect of the error in the channel state information is considered.
2. *Energy efficiency*: In wireless communication systems, energy efficiency is crucial because it affects the network infrastructure's environmental sustainability and operational costs. In order to meet the increasing demand for high-performance wireless communication, NOMA systems must maximize data rate and EE.
3. *The cooperation between NOMA and other technologies*: The effect of jointing mmWaves and user association technologies with the NOMA system to improve the system performance will be proved. Hence, there is a need for an efficient resource allocation method which considered the mentioned challenges to improve the performance of DL NOMA system.

1.4 Research objectives

The main aim of the research is to investigate the resource allocation in the DL NOMA cellular systems. The research addresses various performance for NOMA systems, for example, optimizing the sum data rate and the energy efficiency of the DL NOMA system. The research also covered many scenarios such as single-cell and multi-cell networks for both: perfect CSI and imperfect CSI cases. Moreover, this thesis investigates user association for the NOMA-millimeter Waves (mmWaves) system. The objectives of the research are:

1. The first objective focuses on developing advanced power allocation strategies for DLNOMA systems. Game theory is employed to model and resolve strategic user interactions, ensuring equitable and efficient resource distribution in a multi-user environment. Genetic algorithms (GAs), known for their robustness in exploring large, complex solution spaces, are integrated to overcome the limitations of traditional optimization methods. These methods are particularly suited to address constrained system resources and maintain user terminal threshold levels while optimizing system performance.
2. The second objective addresses the significant challenge of optimizing non-concave data rate and EE problems in NOMA systems. Game theory provides a theoretical framework to represent user interactions and develop strategic decision-making models. Genetic algorithms are utilized as an AI-based approach to navigate the complexity of non-concave optimization, efficiently searching for near-optimal solutions by simulating the process of natural evolution. This combined approach ensures the practicality and scalability of the optimization process, bridging a key gap in existing methodologies.

3. This objective evaluates the robustness and effectiveness of the proposed power allocation schemes in both perfect and imperfect Channel State Information (CSI) scenarios. A comprehensive analysis of key performance metrics, including sum data rate, energy efficiency, and outage probability, is conducted to validate the algorithm's practicality in real-world conditions. The evaluation highlights the adaptability of the proposed methods to dynamic network environments, further reinforcing their suitability for next-generation wireless communication systems.

The objectives of the research are successfully achieved through the proposed methodologies and comprehensive evaluations. The developed power allocation mechanisms based on game theory and genetic algorithms effectively optimize the data rate and energy efficiency in both single-cell and multi-cell NOMA networks, demonstrating superior performance under perfect and imperfect CSI conditions.

1.5 Research scope

This research explores resource management in NOMA networks, emphasizing the application of game theory and genetic algorithms. The study addresses challenges related to energy efficiency, data rate optimization, and resource allocation under both perfect and imperfect CSI. The scope of the research is defined as follows:

1. Context and problem area: The research investigates the optimization of power allocation strategies in NOMA-based wireless communication networks, which are critical for addressing the growing demand for energy efficiency and high data rates in 5G and beyond networks. The study accounts for complex challenges, such as dynamic user conditions, interference management, and the inherent uncertainties of imperfect CSI.
2. Core objectives: The research is structured to achieve the following objectives:

- Develop power allocation mechanisms utilizing game theory and genetic algorithms to enhance energy efficiency and data rate performance in DL NOMA systems.
- Analyze non-convex optimization problems related to energy efficiency and data rates, particularly in scenarios involving imperfect CSI.
- Evaluate the performance of proposed resource management algorithms through simulation, focusing on metrics such as energy efficiency, outage probability, and average data rate.

3. Methodological framework: Two approaches are utilized in this study:

- Game Theory: The study employs game-theoretic models to formulate resource allocation as strategic user interactions. These models address fairness and efficiency in power distribution, ensuring that all users achieve satisfactory QoS.
- Genetic algorithms: Genetic algorithms are applied to solve complex, non-linear optimization problems. The research leverages these algorithms to optimize power allocation and user clustering in NOMA systems, especially under asymmetric user requirements and limited resources.

4. Technical scope: The study examines:

- Single-cell and multi-cell NOMA networks.
- Scenarios integrating NOMA with advanced technologies such as Millimeter-Wave (mmWave).
- The effects of imperfect CSI on resource allocation strategies and system robustness.

- Comparative analyses between NOMA and conventional OMA systems to highlight performance improvements.

5. Expected Contributions: The research aims to provide:

   - Enhanced power allocation strategies for improving energy efficiency and reducing outage probabilities.
   - Advanced algorithms that balance resource utilization and QoS, ensuring scalable solutions for future wireless communication networks.
   - Insights into the integration of NOMA with other emerging technologies, such as mmWave, to maximize system capacity and efficiency.

By addressing these aspects, this research contributes to advancing resource management strategies in next-generation wireless communication systems, supporting the evolution from 5G to 6G networks.

1.6 Thesis overview

This thesis consists of five chapters. Chapter 1 presents the background of the optimization problems in NOMA-based networks, the motivation of the study, the problem statement, and the objectives of the study. Chapter 2 presents a concise literature review concerning data rate optimization and EE in NOMA-based systems. Besides that, recent research is critically reviewed and discussed to provide a brief knowledge of the importance of energy-efficient power allocation in NOMA and the related challenges. Chapter 3 comprehensively describes the methodologies proposed in the study starting with the game theory and the role of the power allocation (PA) in optimizing data rate and EE in the CSI DL NOMA system. Then, the proposed genetic algorithm is described in detail. Chapter 4 critically analyses and discusses the results obtained by implementing game theory and GA to optimize the data rate and energy efficiency in the CSI DL NOMA system. Chapter 5 summarizes the research results and findings and drives the overall thesis conclusions. The chapter also provides recommendations for further improvement in the future.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a review of data rate optimization and EE optimization problems in NOMA-based networks and discusses the related works. This chapter is structured as follows. Section 2.1 presents the concept of NOMA and its advantages compared to OMA. Section 2.2 presents the PA and its role in source management in the NOMA system. Section 2.3 reviews the data rate optimization in NOMA systems while Section 2.4 reviews the energy efficiency in NOMA systems.

2.1 Multiple Access Techniques

2.1.1 Orthogonal Multiple Access (OMA)

Generally, multiple access techniques can be categorized into orthogonal and non-orthogonal techniques. The signals in the first classification are made to be orthogonal to their counterparts to avoid the cross-correlation between the signals, such as Orthogonal Frequency Division Multiple Access (OFDMA) which is the multiuser extension of Orthogonal Frequency Division Multiplexing (OFDM) and is widely used in 4G networks.

The advantage of orthogonality is that it allows simultaneous transmission over the subcarriers through a restricted frequency space with no interference. It is achieved among the OFDM subcarriers by a careful selection of the subcarrier spacing depicted in Figure 2.1, in which in some cases, the subcarrier spacing is set to be equal to the symbol rate. OFDMA is used for downlink in 4G and long-term evolution (LTE) where the inter-cell interference is avoided and the receiver design is relatively simple (Lei, Yuan, Ho, & Sun, 2016). OFDM allocates one subcarrier to one user at the same time, and therefore the information carried on all the subcarriers belongs to that user only. If several users intend to transmit by OFDM, they have to queue for their turns in time. This problem is solved in OFDMA by directly allocating the subcarriers in the frequency domain to different users. OFDMA robustness against inter-symbol interference (ISI) is the reason that this technology is considered suitable as the air interface of 4G communication systems. OFDMA allows multi-user communications through its technique in which subcarrier frequencies are chosen so that the subcarriers are orthogonal to each other (Dulout, Mendiboure, Pousset, Deniau, & Launay, 2023; Islam et al., 2017).

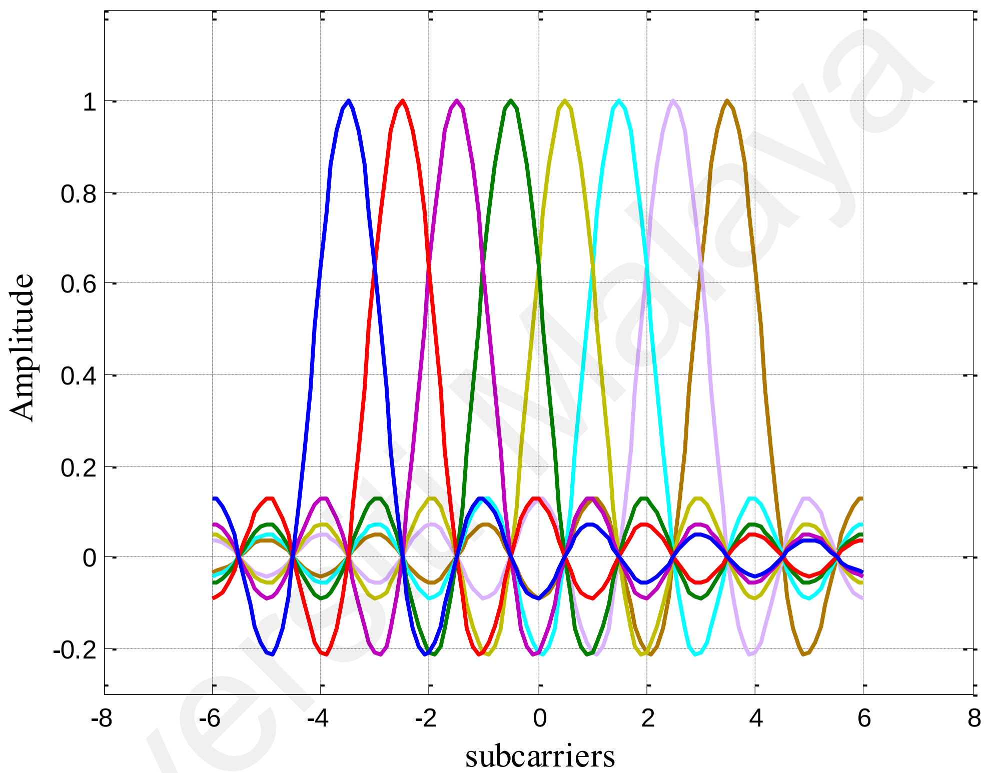

Figure 2.1: Illustration of the orthogonality of OFDM spectrum of eight different carrier frequencies

Under the orthogonal technology category, time-division multiple access (TDMA) is considered a conventional OMA (K. S. Ali, Haenggi, ElSawy, Chaaban, & Alouini, 2019; Mokhtari et al., 2019; Zamani et al., 2019). The total base station (BS) power is utilized to transmit each signal in the TDMA within a time slot T_i (K. S. Ali et al., 2019). TDMA is a technology used in communications that allows several users to share a communication channel effectively. At its core, TDMA assigns each user-specific time slot for transmissions by partitioning the channel into discrete time slots, usually arranged into frames. Throughout their allotted time slots, users alternately access the channel; the duration of the communication period is organized into repeating segments to enable uninterrupted engagement. For users to be temporally aligned with the base station or access point and to avoid interference and collisions, synchronization is essential in TDMA technology. TDMA and ODFMA are some examples of OMA schemes. In TDMA, several users share the same frequency channel on a time-sharing basis. The users communicate in rapid succession, one after the other, each using their assigned time slots. The BS in the TDM-OMA system allocates the total transmission power to m-*th* user during the m-*th* time slot (Arzykulov, Tsiftsis, Nauryzbayev, & Abdallah, 2019; Z. Wei et al., 2020).

Implementing OMA algorithms in 5G will not be adequate due to the limited number of simultaneously transmitted signals within the orthogonal resources (Y. Wang, Ren, Sun, Kang, & Yue, 2016). On the other hand, NOMA is considered a high-potential technique to provide an increasing number of users in 5G by the required quality of service.

2.1.2 Non-Orthogonal Multiple Access (NOMA)

The ambitious aims of Next Generation Mobile Networks (NGMN) include providing extremely fast connections and enormous data for billions of different users' equipment in all areas. In recent years, there has been a rapid proliferation of innovative cyber habits (Abozariba et al., 2019). People can now participate in cutting-edge activities like monitoring and managing different areas of their homes and getting real-time data from smart city applications thanks to IoT technology. This development points to a move toward a more technologically advanced and networked way of living, where IoT devices are essential for improving efficiency, security, and convenience in homes and cities alike (Kunst, Avila, Pignaton, Bampi, & Rochol, 2018). The explosion of new IoT applications is growing in tandem with the growth of online business, resulting in a transformative shift across multiple domains. A few examples of the growing electronic landscape influenced by IoT innovations are health, navigation, transportation, and security (Aloqaily, Elayan, & Guizani, 2023; Joshi et al., 2023; J. Zhang, Wang, Li, & Shi, 2021). Consequently, the proliferation of IoT applications has placed mobile communications technology in the position of facilitating a hyper-connected society (Derawi, Dalveren, & Cheikh, 2020; Santos, Perkusich, & Almeida, 2014). This fast-paced development affects traditional e-commerce and new IoT applications, ushering in a time when networked gadgets and services transform how people interact with and perceive the digital world. From the next-generation radio access technology viewpoint, an exponential increase in data speed and required capacity for high data–rate applications are major concerns for 5G. In particular, many of the industry initiatives that have progressed with work on 5G declare that the network-level data rate in 5G should be 10-20 Gbps (10-20 times the peak data rate in 4G), and the user-experienced data rate should be 1 Gbps (100 times the user-experienced data rate in 4G) (P. Zhang et al., 2019).

5G is expected to provide a higher data rate and higher capacity to a massive number of users at lower power consumption and latency. One of the key techniques to meet these requirements in mobile communication systems is using NOMA where one frequency channel is allocated to several users within the cell at the same time (Budhiraja et al., 2021). Several advantages are offered by NOMA, compared to OMA, such as improved spectral efficiency, higher cell-edge throughput, relaxed channel feedback (only the received signal strength, not exact CSI, is required), and low transmission latency (no scheduling request from users to base station is required) (Alsabah et al., 2021; Wan et al., 2018).

NOMA techniques are divided into two classifications, namely, power-domain and code-domain NOMA (Islam et al., 2017). In wireless networks, code-domain NOMA is a communication technique that uses distinct code-domain signatures to let multiple users share the same time-frequency resource blocks. Unlike traditional OMA schemes, where users are assigned separate and non-overlapping resource blocks, code-domain NOMA enables users to share the same resource blocks simultaneously. A distinct spreading code or signature identifies each user and permits signal separation between them during transmission and reception. In power-domain NOMA, which is the focus of this study, multiple users are superposed in the power domain at the transmitter (BS) in the downlink transmission and the difference in the channel gain is exploited among the multiplexed users' power (Z. Ding, Fan, & Poor, 2016), while multiuser detection algorithms such as the SIC could be used at the receiver (the mobile user device) to decode the desired signals. Signal interference between users can occur in multi-user communication systems, particularly in NOMA scenarios where users share a time-frequency resource. The SIC technique works by trying to decode each user's signal one at a time and canceling the interference that corresponds to that user as it is decoded (Ihsan et al., 2022). By using SIC, users with relatively high received signal-to-noise and interference ratios (SINR) decode the interfering signals before decoding their signal while users with lower SINR levels would treat the interference as noise (Alsabah et al., 2021). Thus, power-domain NOMA guarantees flexible resource allocation that improves the NOMA performance (Kassir, Dziyauddin, Kaidi, & Izhar, 2018) and increases the sum data rate (M. S. Ali, Hossain, Al-Dweik, & Kim, 2018).

Figure 2.2 presents the principal comparison between the NOMA system model and the conventional OMA system model. From Figure 2.2, the user equipment (UE_1) is the farther user from the BS; this means that channel h_1 is the weakest channel. However, that does not imply that the signal strength at UE_1 is the weakest since a higher power level is assigned for that user. On the other hand, a lower power level is allocated for the nearest user to the BS that has the strongest channel. In other words, for the ordering users from the BS according to their channel gains ($|h_M^2| > \cdots > |h_2^2| > |h_1^2|$), the allocated power to these users in the NOMA system should be $P_M < \cdots < P_2 < P_1$. Therefore, NOMA is in line with the SIC principle when the strongest signal is decoded first. Moreover, the effect of the inter-cell interference is more significant on the farther user who gets relatively high allocated power while this interference is negligible at the nearest user with the weakest signal since it decodes all the higher power allocated to the next users (Islam et al., 2017). In contrast to OMA, NOMA exploits the power domain to simultaneously serve multiple users at different power levels, where the PA for each user plays a key role in determining the overall performance of the system. DL NOMA combines superposition coding at the BS and SIC decoding at the user (Islam, Zeng, Dobre, & Kwak, 2018).

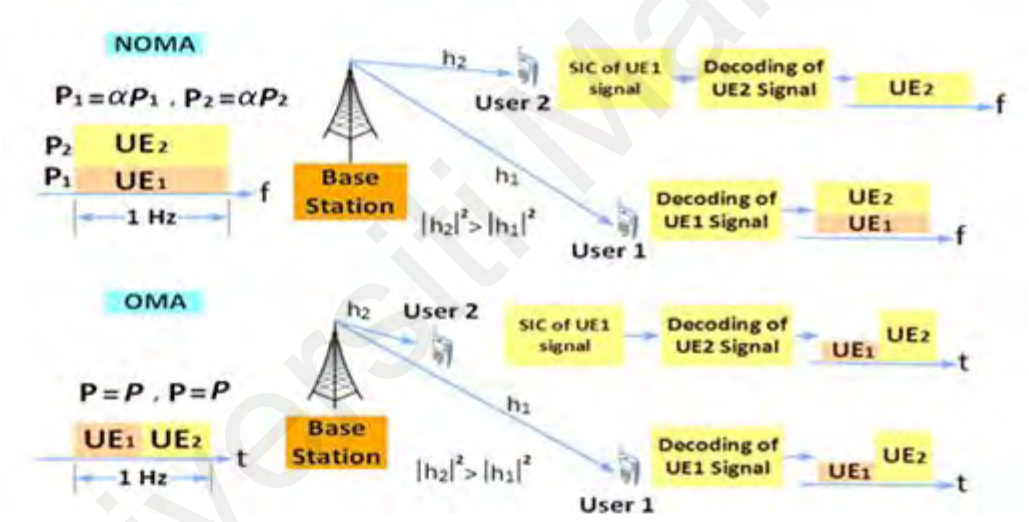

Figure 2.2: A comparison between the OMA and the NOMA system models.

Practically, it is a challenge to obtain perfect CSI. To enable the NOMA users to perform SIC and to detect the signals of the lower-order users, BS allocates the power levels according to their channel gains. That is, each receiver will eliminate the signals of other combined users on the same carrier which have weaker channel gain. On the other hand, the signals of the higher-order users with stronger channel gains will represent interference signals. To maximize the data rate, the effect of this interference should be minimized, and this could be ensured when the allocated power to the stronger channel user is lower than the allocated power to the weaker channel user (M. S. Ali, Hossain, Al-Dweik, et al., 2018).

2.2 Power Allocation for NOMA-based Systems

Figure 2.3 illustrates the hierarchical framework for resource allocation in NOMA systems, highlighting key components such as PA strategies, optimization objectives, and methodologies, as well as the various techniques used to achieve efficient resource management and system performance.

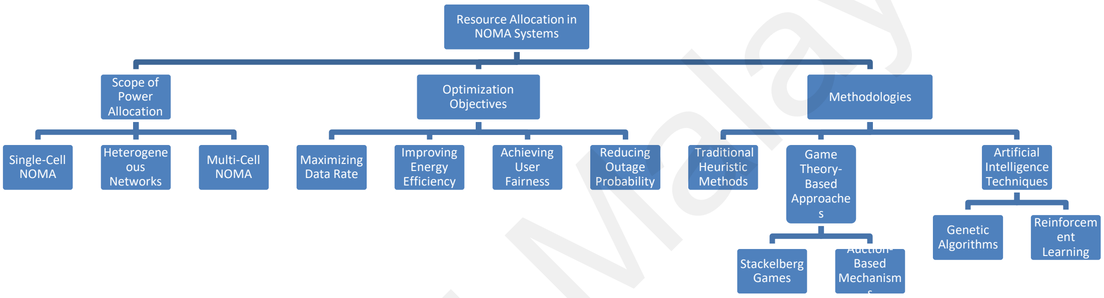

Figure 2.3: The hierarchical framework for literature review of resource allocation in NOMA systems

Power allocation in NOMA attracted the attention of the researchers who proposed different strategies and targeted different aspects of PA in NOMA. Many studies have been made on PA in NOMA system either in single cell or multi cells scenarios, one operating technology or heterogeneous network, maximization of the sum data rate or achieving higher fairness, and other schemes. To maximize the performance of a device to device (D2D) communication system based on NOMA for imperfect Successive SIC decoding, an efficient power allocation scheme is proposed in(G. Wu et al., 2023). An alternative optimization algorithm was presented to find the best solution using Lagrange duality analysis and the sub-gradient descent method to address the non-convexity of the problem caused by integer constraints and coupling variables. The numerical simulation results show how the suggested joint optimization algorithm for channel resource allocation and power control performs better in terms of energy efficiency. Elbakry, Amer, and Ismail (2023) presented a dynamic power allocation scheme and optimal user pairing for the NOMA system to increase the system's performance. The algorithm precisely pinpoints the locations of dispersed users and ascertains the necessary power levels for every user by considering their position and channel conditions. By ensuring that every user receives the ideal power level, this precise power allocation maximizes the efficiency of data transmission.

Power allocation is considered an essential method to raise the data rate and the energy efficiency in the NOMA system, where various powers are assigned to the cell's users and combined on the same subcarrier at the same time (Yang, Hussein, Xu, Ding, & Wu, 2018). PA depends on various factors in NOMA such as the channel conditions, the required QoS, total power restriction, and the system requirements. If power allocation is performed inappropriately, then the users will have an unfair rate distribution and the system outage will fail (Fang, Cheng, & Ding, 2019; Q. Wang, Zhang, Yang, & Hanzo, 2018; H. Zhang, Fang, et al., 2018; Zhu et al., 2017). Power allocation is evaluated by different performance metrics such as the number of admitted users, the system fairness, the total power consumption, the sum data rate, and the outage probability. In general, power allocation in NOMA aims to achieve a higher number of admitted users and a higher sum data rate or to achieve more fairness between users at a limited consumed power (Nain, Das, & Chatterjee, 2018; H. Zhang, Fang, et al., 2018; Zheng, Liang, & Yu, 2018). The complexity of power allocation is a measure of the computational resources needed to figure out the best power levels to assign to various users who share the same time-frequency resources. With consideration for each user's channel conditions and quality of service requirements, power allocation in NOMA seeks to optimize the overall system performance. Several factors can impact this process's complexity such as the number of users, QoS constraints, and interference management. In (Nain et al., 2018), a low complexity method to remove users who do not fit with the derived condition is presented where the proposed power allocation scheme offers nearly equal cell throughput and user fairness to the optimal scheme utilizing exhaustive user search. The power allocation scheme has a closed-form solution, which reduces complexity, whereas the suggested user selection method finds an efficient user set by verifying users through basic conditions based on their SINR and weights.

There are studies done on a Single-Carrier (SC) (Chraiti, Ghrayeb, & Assi, 2018), which is the focus of this study, while others considered Multi-Carrier (MC) (Al-Abbasi & So, 2017; M. S. Ali, Hossain, Al-Dweik, et al., 2018; Fu, Salaün, Sung, & Chen, 2018; Ni, Hao, Tran, & Qian, 2018; H. Zhang, Fang, et al., 2018). By allocating more power to the weak user in SC systems, better fairness is accomplished as well as more balanced system throughput could be achieved. This is because the strong user is capable of handling the interference due to the weak user by using the SIC technique (Islam et al., 2018).

Chraiti et al. (2018) proposed an efficient PA technique that does not require CSI at the BS and applied it to two users Multi Input Single Output (MISO) downlink channels. CSI refers to the information that characterizes the current state or condition of a communication channel between a transmitter and a receiver. Instead of draining the system bandwidth for feeding the BS with the CSI, the authors proposed a nonlinear interference alignment technique to enable the BS to communicate with the users simultaneously and keep the signals separated at their respective receivers. This technique enables each user to detect its signal without any interference from the other user's signal while achieving better outage probability and data rate per user.

Perfect CSI is challenging to achieve because of channel estimation errors, feedback, and quantization errors. It is requisite to search for novel solutions that address the imperfect CSI in wireless communication systems (X. Song, Dong, Wang, Qin, & Han, 2019). Moreover, energy efficiency receives significant attention from both academia and industry researchers since the information and communication sector consumes 5% of the total global energy consumption (Y. Zhang, Wang, Zheng, & Yang, 2017). Hence, many researchers have concentrated on energy efficiency in the NOMA system (Shi et al., 2019; Vien, Le, Barn, & Phan, 2016; H. Zhang, Wang, et al., 2018). An energy-efficient novel power allocation algorithm is presented in (X. Song et al., 2019) where the optimization problem is formulated based on imperfect CSI with outage probability constraints and then it is relaxed to a non-probabilistic problem. The results obtained for a small cell of one BS and 2 users showed that the performance of the proposed algorithm is better than the conventional algorithms.

Optimizing the energy efficiency in the single input single output NOMA (SISO-NOMA) system has been studied in (Y. Zhang et al., 2017) where the proposed power allocation algorithm for 2 users in a single cell shows superior behavior compared to the traditional algorithms. However, more investigation is still required on this algorithm in the imperfect CSI case. Distance between the receiver and the BS has been used for power allocation in (Glei & Chibani, 2019; Y. Zhang et al., 2017). On the other hand, joint optimization algorithm has been proposed in (X. Chen, Jia, & Ng, 2019) where power allocation is utilized to minimize the transmitted power which is required to attain the minimum required rate. Optimizing energy efficiency for imperfect CSI case with two secondary users is studied in (Arzykulov et al., 2019). Zamani et al. (2019) studied energy efficiency optimization and proved that NOMA outperforms conventional OMA schemes under low user's quality of service constraint.

There have been a number of studies applying game theory in power allocation for the NOMA systems. A Stackelberg game is used in (C. Li, Zhang, Li, & Qin, 2016) to model the interaction between BS and multiple users in the cellular network where the BS acts as a team leader and set the transmitted power price to each user to ensure maximum revenue is achieved. In (Z. Wang, Wen, Fan, & Wan, 2018), a price-based PA algorithm based on Stackelberg game is presented for DL NOMA cellular system which shows better performance in terms of BS revenue and sum data rate. Lamba, Kumar, and Sharma (2019) proposes an auction-based mechanism to determine the allocated power by the BS to each user in the DL NOMA system. Each user attempts to maximize the utility by offering a price bid. The simulation results show an increase in the average sum rate of the users compared to that in (Z. Wang et al., 2018). In (Zamani et al., 2019), a state of high CSI error variance values was investigated and the results show that NOMA is recommended for a special case of only two users to achieve the user data rate requirement. The energy efficiency concerning various transmission power levels and channel estimation error have been evaluated in (Zamani et al., 2019), and the proposed algorithm performed better compared to OMA. However, the performance of the proposed algorithm for high traffic should be considered.

2.3 Data Rate Optimization in NOMA-Based Systems

Figure 2.4 provides an overview of the data rate optimization challenges and solutions in NOMA systems, highlighting key research contributions and optimization techniques. It encompasses the complexities of non-convex optimization problems arising from interference control, power allocation, and non-linear constraints, as well as the methods used to address these challenges. The chart also reflects the advancements in throughput-optimal scheduling, network utility maximization, hybrid relay-RIS systems, and game-theory-based power allocation mechanisms, with an emphasis on overcoming the limitations of traditional approaches and improving the applicability of NOMA systems in real-world scenarios.

In NOMA systems, the challenge of optimizing the aggregate data rates of multiple users sharing the same time-frequency resource blocks is known as the data rate optimization problem. This problem is formulated as a non-convex optimization problem. Efficient spectrum utilization is made possible by NOMA, which permits users to concurrently occupy the same resource at different power levels (Y. Song, Xu, Sun, & Ai, 2023). Because the optimization problem is non-convex, it becomes more complex and calls for specialized methods to solve. The inherent non-linearity brought about by the interference control, power distribution, and possibly non-convex constraints make the optimization problem non-convex where the power allocation variables for different users and potentially non-linear power constraints contribute to the non-convexity and the interference management aspect, which aims to minimize interference among users, often leads to non-convex formulations due to the non-linear nature of interference terms (Liesegang, Zappone, Muñoz, & Pascual-Iserte, 2023).

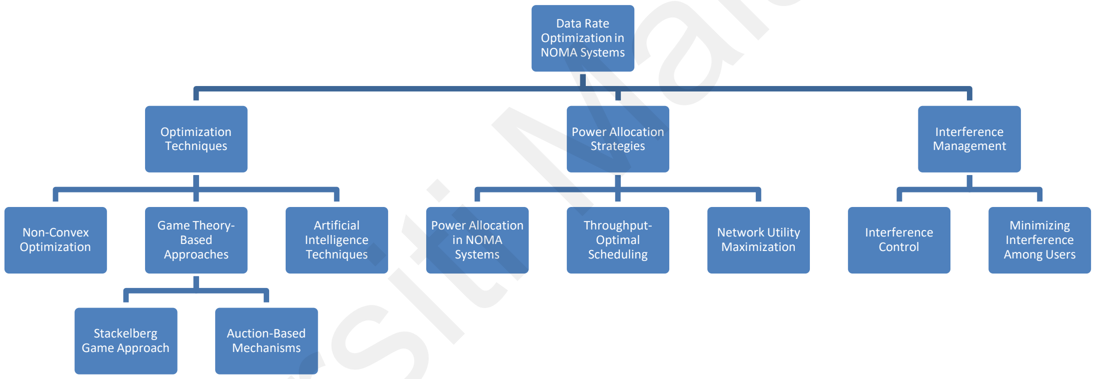

Figure 2.4: The hierarchical framework for data rate optimization in NOMA systems

(Y. Chen, Zhu, Guo, Yuan, & Feng, 2023) contributes significantly to the field by addressing the dual objectives of throughput-optimal scheduling and network utility maximization in DL NOMA systems with flow-level dynamics. This study is pioneering in investigating a DL NOMA system with flow-level dynamics, where both long-lived and short-lived flows coexist. This is a significant departure from traditional models, which often assume static traffic conditions. Although the proposed suboptimal algorithm demonstrates practical applicability and strong performance, addressing the limitations related to scalability, parameter dependence, and multi-subchannel allocation could enhance its impact and utility further. The paper formulates an optimization problem that jointly addresses user selection and power allocation. It aims to maximize network utility while ensuring throughput-optimality under QoS constraints. The proposed algorithm successfully achieves throughput-optimal scheduling and network utility maximization, addressing two critical challenges in wireless networks. The study restricts itself to a single subchannel allocation per user. This constraint simplifies the problem but limits its applicability to real-world networks with more dynamic and diverse requirements. Moreover, the proposed model assumes perfect CSI and fixed QoS constraints, which may not hold in practical deployment scenarios. Thus, incorporating mechanisms to handle imperfect CSI and other uncertainties, makes the solution more practical for real-world deployment.

Kan, Chang, Chien, Chen, and Poor (2023) present a significant step forward in the design of hybrid relay–RIS systems, demonstrating their potential to enhance sum rate and energy efficiency in next-generation wireless networks. The paper explores a hybrid relay–RIS system integrating a half-duplex decode-and-forward (DF) relay and a full-duplex RIS. This hybrid architecture leverages the strengths of both technologies, making it a novel contribution to next-generation wireless networks. The simultaneous design of active beamforming at the BS and DF relay, as well as passive beamforming at the RIS, addresses the complexity of multiuser MISO systems and maximizes system performance. The alternating optimization (AO)-based algorithm proposed in the paper effectively tackles the non-convex joint optimization problem, ensuring a practical solution. The gap here is assuming ideal conditions, such as perfect CSI and no hardware impairments may limit its applicability in real-world scenarios. Thus, addressing practical deployment challenges, full-duplex RIS limitations, and extending the energy efficiency analysis would further strengthen the research and its applicability.

Maximization of the total cell data rate and fairness for N PD-NOMA users in Poisson distribution BSs is the objective of the study in (K. S. Ali et al., 2019) where the authors applied two efficient algorithms to find the feasible resource allocation, namely; mean signal power-based and instantaneous signal-to inter cell-interference-and-noise-ratio-based. This maximization problem is subject to two constraints, which are the lower boundary of throughput for each user and identical throughput for all users. The results show that under a specific set of network parameters, there is an optimal number of served users in the cell. In addition, the effect of choosing the network parameters and the ordering technique on the data rate and fairness has been highlighted and the results show the necessity of a critical level of SIC to outperform the OMA. Choi (2016) focuses on the fairness in the DL NOMA system when power allocation is considered a key role in achieving proportional fairness scheduling and providing multiple users with positive transmission data rates simultaneously. The study shows that the required fairness could be acquired by maximizing the minimum normalized rate.

Game theory has been applied in a wide range in NOMA systems' power allocation. For instance, a Stackelberg game is used in (C. Li et al., 2016) to model the interaction between the BS and multiple users in the cellular network where the BS plays as the team leader and sets the transmitted power price to each user to ensure that it gets the maximum revenue. After that, as a secondary player in this game, each user chooses an optimal power to maximize its utility. To solve this non-convex optimization problem, the authors decoupled it into three optimization problems and then used an alternating optimization algorithm to solve them. Although the results show outperforming of the proposed algorithm over the uniform power allocation scheme, another price-based PA algorithm based on the Stackelberg game is presented in (Z. Wang et al., 2018) for DL NOMA cellular system which shows better performance in terms of BS revenue and sum data rate. It presents a closed-form solution for two users' cases when the total transmission power could be allocated to either the strong user or both users. For the M -users case, an iterative algorithm is proposed and the results show that the number of iterations to find the optimal solution is less than that in (C. Li et al., 2016). Lamba et al. (2019) propose an auction-based mechanism to compute the allocated power by the BS to each user in the DL NOMA system. Each user attempts to maximize his utility by putting in a price bid. The authors prove theoretically the existence of Nash equilibrium of the given model and the simulation results show an increase in the average sum rate of the users compared to that in (Z. Wang et al., 2018).

A novel fast-learning machine-based extreme learning user cluster scheme is proposed in (Kumaresan, Tan, & Ng, 2021). A faster learning rate is achieved because the input weights and bias for the extreme learning machine hidden layer nodes are randomly generated and do not require parameter tuning. The modified architecture functions in NOMA environments, where it is possible to quickly predict the ideal cluster formation depending on the channel gains and powers of the users. Extensive simulations show better performance compared to the most advanced user cluster schemes.

However, all the above-mentioned studies aiming to achieve maximum EE and data rate in practical wireless systems, while considering imperfect channel estimation, have encountered significant challenges with one-stage algorithms. These approaches often rely on simplistic assumptions and do not fully account for the complexities and uncertainties inherent in real-world wireless environments (Mokhtari et al., 2019). The presence of imperfect channel estimation can lead to inaccurate transmission decisions, reducing the overall system performance and hindering the ability to achieve optimal EE and data rate. In contrast, this thesis offers a compelling solution by incorporating a multistage mechanism. Adaptively address the imperfections in channel estimation of the communication process ensuring superior performance in real-world wireless systems compared to traditional one-stage algorithms (L. Xu et al., 2022). Table 2.1 summarizes the contributions, strengths, weaknesses, insights, suggestions for improvement, and the approaches used in each of the data rate optimization problems in the NOMA system's studies within this section.

Table 2.1 : Summary of literature review of data rate optimization problem in NOMA systems

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
Y. Song, Xu, Sun, & Ai (2023)	Efficient spectrum utilization in NOMA, power allocation optimization	Non-convex optimization solved, improves system throughput	Complex due to non-convexity and interference management	Solves non-convex optimization in NOMA systems	Develop more robust methods for real-world non-ideal conditions	Non-convex optimization, Power allocation
Liesegang, Zappone, Muñoz, & Pascual-Iserte (2023)	Interference control and power allocation optimization in NOMA	Addresses non-linear power and interference management	Non-convex due to interference terms and power distribution	Provides approach to handle interference in NOMA	Explore alternative interference management techniques	Power allocation, Interference management
Y. Chen, Zhu, Guo, Yuan, & Feng (2023)	Throughput-optimal scheduling, network utility maximization in DL NOMA	Focus on flow-level dynamics, practical applicability	Limited by single subchannel allocation, assumes perfect CSI	Optimizes scheduling and network utility	Consider multi-subchannel allocation and imperfect CSI	Scheduling optimization, Flow-level dynamics
Kan, Chang, Chien, Chen, & Poor (2023)	Hybrid relay–RIS system for sum-rate and energy efficiency	Integrates relay and RIS for system enhancement	Assumes ideal conditions, limited real-world applicability	Hybrid relay-RIS approach improves efficiency	Address practical deployment challenges, including hardware impairments	Hybrid relay-RIS, Energy efficiency
K. S. Ali et al. (2019)	Maximization of cell data rate and fairness in N PD-NOMA systems	Effective resource allocation algorithms, fairness considered	Assumes specific network parameters, limiting generality	Optimizes throughput and fairness for NOMA users	Broaden parameter set and extend to dynamic networks	Resource allocation, Fairness, NOMA

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
Choi (2016)	Fairness in DL NOMA systems via power allocation	Fairness achieved with proportional fairness scheduling	Limited to downlink, assumes ideal conditions	Maximizes minimum normalized rate	Explore fairness in uplink and real-world conditions	Power allocation, Fairness
C. Li et al. (2016)	Stackelberg game for power allocation in NOMA	Game-theory-based power allocation, optimal user interaction	Non-convexity makes the solution challenging	Optimal power allocation via game theory	Further refine solutions for multi-user systems	Stackelberg game, Power allocation
Z. Wang et al. (2018)	Price-based power allocation in DL NOMA	Closed-form solution for two-user cases, iterative algorithm for M-users	Relies on ideal conditions and assumptions	Price-based PA improves BS revenue and data rate	Extend to more dynamic user and network models	Stackelberg game, Price-based power allocation
Lamba et al. (2019)	Auction-based mechanism for DL NOMA power allocation	Increases average sum rate for users	Relies on idealized auction assumptions	Auction mechanisms improve power allocation	Extend to practical scenarios with imperfect CSI	Auction-based mechanism, Power allocation
Kumaresan, Tan, & Ng (2021)	Extreme Learning Machine (ELM) for user clustering in NOMA	Fast learning rate for user clustering, no parameter tuning	Limited scalability in complex environments	ELM optimizes clustering in NOMA environments	Test with larger and more dynamic networks	Extreme Learning Machine (ELM), User clustering
Mokhtari et al. (2019)	Challenges with one-stage algorithms in imperfect channel estimation	Highlights flaws in one-stage optimization approaches	Simplistic assumptions reduce real-world accuracy	One-stage algorithms struggle with real-world complexities	Explore multistage algorithms and dynamic channel estimation	One-stage algorithms, Imperfect channel estimation

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
L. Xu et al. (2022)	Multistage mechanism for addressing imperfect channel estimation	Better performance in real-world systems with imperfections	More complex than one-stage algorithms	Multistage solutions outperform one-stage algorithms	Further optimize for larger networks and dynamic environments	Multistage mechanism, Channel estimation

2.4 Energy Efficiency Optimization in NOMA-Based systems

The hierarchical structure in Figure 2.5 organizes the complex topics in a logical flow, focusing on methods, metrics, applications, and challenges. You can use this framework for your diagrams or summaries to illustrate the relationships between techniques, performance measures, and the challenges in applying NOMA-based EE and throughput optimization in real-world networks.

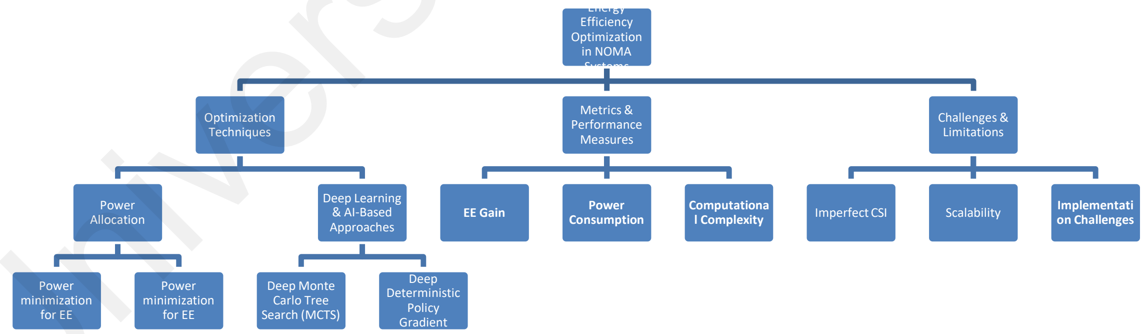

Figure 2.5: The hierarchical framework for EE optimization in NOMA systems

The EE optimization and throughput optimization problems in NOMA have been studied under various constraints such as the total power, interference, and/or the minimum QoS of the users. A code reuse scheme in the downlink MIMO-NOMA system which separates active users into groups based on their channel quantity and inner interference is proposed in (Gkonis, Trakadas, & Sarakis, 2020). The transmitted data correlation matrix is constructed at the transmitter using only the primary eigenvector and eigenvalue of the corresponding correlation matrix as the input via feedback, deducted by principal component analysis. The performance of this scheme is evaluated, in terms of code assignment gain and bit error rate. The results show that employing the SIC technique at the receivers can achieve an improvement over the conventional OMA. On the other hand, the same SINR level is assumed for all users in (L. Chen, Hu, Xu, & Chen, 2021). Similarly, minimizing the total power consumption of the whole network under the constraint of all users' long-term rate requirements is assumed in (Zhai, Zhang, Cai, Li, & Jiang, 2018). However, applications that require high QoS can drain network resources (Ahn, Kim, Park, & Cho, 2021).

Y. Y. Guo, Tan, Gao, Yang, and Rui (2023) introduce a novel methodology for EE optimization in cooperative non-orthogonal multiple access (CNOMA) networks using a deep Monte Carlo Tree Search (MCTS) framework. This combination of artificial intelligence (AI) and optimization represents a creative application in wireless networks. The use of a "Go game" analogy to model the optimization problem provides a structured and intuitive framework for joint user pairing, subchannel assignment, and power control. The derivation of optimal closed-form expressions for power control provides a foundational mathematical basis for the proposed optimization framework. The deep MCTS approach combines neural networks and tree search for efficient exploration and decision-making, which is particularly advantageous for large-scale problems with complex constraints. The paper provides simulation results comparing the proposed method with existing NOMA schemes, demonstrating its superiority in terms of energy efficiency. The negligible computational overhead highlighted in the results strengthens the practicality of the proposed approach for real-time systems. However, while computational overhead is claimed to be negligible, the implementation of deep MCTS with neural networks may require significant resources, especially in training the neural network with large datasets. The effectiveness of the approach in scenarios with a significantly larger number of users and subchannels is not explicitly discussed. This paper proposes a significant methodological advancement in CNOMA networks by leveraging AI techniques for energy-efficient optimization. However, further work is needed to address practical implementation challenges and validate the results in real-world scenarios.

In (Y. Guo, Fang, Cai, & Ding, 2023), the use of a Deep Deterministic Policy Gradient (DDPG) algorithm for solving EE optimization problem is innovative. DDPG is well-suited for continuous action spaces, making it an apt choice for this optimization problem. In addition, the joint optimization of transmission beamforming at the base station and simultaneous transmission and reflection reconfigurable intelligent surface (STAR-RIS) coefficient matrices represents a holistic approach to addressing the EE challenge, as both components significantly impact network performance. The computational complexity of the DDPG algorithm might increase significantly as the number of users, antennas, or STAR-RIS elements grows. This scalability concern is not thoroughly addressed. Moreover, similar to other deep reinforcement learning approaches, the performance of DDPG is heavily dependent on the quality of training and hyper parameter tuning. The paper does not discuss potential challenges in training the algorithm or mitigating issues like overfitting. While the paper claims that the DDPG-based method outperforms traditional approaches, it does not provide sufficient details about the benchmarks used for comparison, making it difficult to assess the magnitude of improvement. This study presents a significant contribution by leveraging STAR-RIS and DDPG for energy efficiency optimization in NOMA-assisted networks. While the proposed solution shows promise in simulation, addressing the highlighted weaknesses and incorporating real-world validation would strengthen its impact and applicability.

(Cao & Hou, 2023) addresses EE in the context of massive machine-type communications (mMTC), which is a cornerstone of 5G and beyond. This focus on a critical application is both timely and relevant. The discovery of a "hidden feature" in the NOMA SIC process is a significant contribution. This feature simplifies the analytical complexity of EE analysis in Carrier-sense multiple access (CSMA) NOMA networks. The use of Markov chains and Q-function approximations to model the system is a robust choice. These methods provide a solid foundation for deriving precise closed-form expressions for EE. However, the models assume ideal conditions such as perfect SIC and accurate Markov chain representations, which may not fully capture real-world complexities like noise, interference, or imperfect channel conditions. While the paper highlights the interactions among transmission probability, power, and data rate, it does not provide a comprehensive sensitivity analysis to explore how variations in one parameter influence the others. Moreover, although the approach ensures fast convergence, the computational overhead for large-scale systems with numerous devices is not discussed, leaving uncertainty about its practical implementation. Although this paper makes a substantial contribution by simplifying the analytical complexity of EE optimization in CSMA-NOMA networks and proposing an efficient optimization framework, addressing the limitations through real-world validation and scalability analysis would strengthen its impact and applicability in practical mMTC scenarios.

(Muhammed, Chen, Seid, Han, & Yu, 2023) introduces a novel framework combining mmWave communications with NOMA in a two-tier heterogeneous network (HetNet) comprising macro-cells and small cells connected via wireless backhaul. The integration leverages the massive bandwidth of mmWave and the spectral efficiency of NOMA, enabling efficient resource utilization. A unique user grouping algorithm simplifies clustering by grouping highly correlated users, reducing inter-cluster interference. The framework incorporates hybrid analog/digital precoding at the macro base station and jointly optimizes hybrid precoding, power allocation, and bandwidth partitioning to maximize system EE. The authors transform the non-convex optimization problem into a quasi-convex equivalent and propose an iterative algorithm for solution derivation. Extensive simulations validate the framework, demonstrating significant performance gains in EE and spectral efficiency compared to traditional OMA systems. Despite its strengths, the study has limitations that impact its practicality. The assumption of perfect CSI oversimplifies real-world scenarios where CSI estimation errors are prevalent, particularly in mmWave environments with high mobility and frequent blockages. Additionally, the impact of limited backhaul capacity on performance is not addressed, potentially overlooking a critical bottleneck in practical deployments. While the hybrid precoding approach is computationally efficient, the paper lacks a detailed analysis of its hardware implementation feasibility, including cost and energy consumption. Furthermore, the iterative algorithm may face scalability issues in dense network scenarios with a high number of users and cells. Benchmarking against more advanced NOMA and mmWave systems and accounting for dynamic factors like user mobility and interference would provide a more comprehensive evaluation of the proposed framework.

The proposed framework in (Alajmi, Fayaz, Ahsan, & Nallanathan, 2023) strikes a balance between centralized and distributed approaches, leveraging their respective advantages while mitigating shortcomings such as high complexity and long convergence times. The use of Proximal Policy Optimization (PPO) for grant-based clients and a multi-agent deep Q-network (DQN) for grant-based clients reflects a well-thought-out approach to tackling different optimization problems efficiently. These algorithms are suitable for handling the complexity and dynamics of resource allocation in NOMA IoT networks. The framework achieves notable improvements in energy efficiency: A 6% and 11.5% increase for grant-based clients compared to fixed and random power allocation strategies, respectively, and a 47.4% increase for GF clients over the benchmark scheme.

The study includes an analysis of how an increase in the number of grant-based clients affects the energy efficiency of both grant-based and GF clients, providing insights into the system's scalability and interdependence. However, the findings are based solely on numerical simulations, with no experimental validation or testing in real-world IoT environments. This limits the practical applicability of the results. In addition, although the framework demonstrates improvements over fixed and random power allocation methods, it lacks a comprehensive comparison with other advanced state-of-the-art algorithms for NOMA IoT networks and the simulations likely operate under idealized conditions (e.g., perfect channel state information), which may not account for real-world factors like channel estimation errors, interference, or hardware limitations. Thus, addressing the highlighted weaknesses through real-world validation, scalability analysis, and benchmarking would significantly enhance its impact and applicability.

Many prior works have studied power allocation in NOMA as the key role to optimize EE in perfect CSI case (Khazali, Bozorgchenani, Tarchi, Shayesteh, & Kalbkhani, 2023; G. Liu et al., 2018; Rezvani, Jorswieck, Joda, & Yanikomeroglu, 2022; J. Wang, Xu, Fan, Zhu, & Zhou, 2018; H. Zhang, Fang, et al., 2018). In a real cellular system, it is a challenge to obtain a full CSI at the BS because of the channel estimation error and the quantization error (Fang, Zhang, Cheng, Roy, & Leung, 2017; X. Song et al., 2019; Zamani et al., 2019). However, channel estimation errors in the imperfect CSI DL NOMA system could cause user ordering ambiguities (Z. Ding et al., 2017). The pilot transmission design for power-domain NOMA and the influence of the inaccurate channel estimation on power-domain NOMA have been investigated in (Ma, Liang, Xu, & Ping, 2017). Previous studies proved that NOMA technology has better performance than OMA in the imperfect CSI case. Resource allocation has been investigated in (Z. Wei, Ng, & Yuan, 2016) for multi-carrier NOMA depending on the available statistical CSI at the transmitter. Moreover, partial CSI has been used in (Hou et al., 2020; P. Xu, Yuan, Ding, Dai, & Schober, 2016; Y. Xu, Cai, Ding, Shen, & Zhu, 2018) to determine the order of the user equipment, where CSI feedback has been mainly considered a potential improvement to support the BS in sorting user equipment. For example, one-bit feedback from the user to the transmitter scheme is proposed in (P. Xu et al., 2016) to indicate whether the sending bit is below or above a specific power level.

Nooh et al. (2024) present a significant advancement in reducing power consumption and improving energy efficiency in 2-user NOMA downlink systems through an optimal user pairing strategy and tackles the computationally challenging problem of joint user pairing and power allocation in 2-user NOMA downlink systems, formulating it as a mixed-integer programming problem aimed at minimizing power consumption. The power minimization approach achieves an EE gain by a factor of 4.5 over OMA, outperforming the sum-rate maximization approach, which achieves a gain of 2.4. However, addressing the highlighted limitations, particularly in real-world scenarios and multi-user configurations, would further enhance its applicability and impact since the study focuses exclusively on 2-user NOMA systems, limiting its applicability to scenarios with larger or more dynamic user groupings, such as multi-user NOMA or heterogeneous IoT networks. The analysis relies on idealized assumptions, such as perfect CSI and a specific propagation model. Real-world factors like imperfect CSI or interference are not considered.

In (Zamani et al., 2019), the impact of the CSI error levels on the system performance was investigated and the energy efficiency at various transmission power levels and the channel estimation error were evaluated. Results show that the system performance has been improved compared to OMA. Thus, NOMA is recommended for only two users in the cluster to achieve the user's required data rate. The probabilistic problem is converted to a non-probabilistic version in (X. Song et al., 2019) to maximize EE in imperfect CSI DL NOMA system under outage probability constraints. Since outage probability is one of the maximization problem constraints in (X. Song et al., 2019), the number of served equipment in the cell has to be evaluated. A simple suboptimal user device scheduling mechanism is presented to maximize the system EE and a closed-form formula of the assigned power for two or more users is derived in (Fang et al., 2017). Q. Zhao, Yang, and Zhang (2022) presented how NOMA technology can allow multiple kinds of mine smart devices to share subchannel resources for data transmission, thereby enhancing the Mine Internet of Things (MIoT) system's spectrum utilization and device access, realizing the state perception and information interaction by connecting massive smart sensing devices deployed in mine. Through power and subchannel assignment, the energy efficiency of small cell networks is maximized. An iterative algorithm for joint power allocation and subchannel assignment is proposed under the imperfect CSI. First, the EE optimization problem is formulated as a mixed integer nonlinear fractional programming problem by taking into account the cross-layer interference power constraints, maximum power constraints, and QoS constraints. Second, the original problem is converted into an equivalent convex optimization form by applying an elliptical uncertainty set to represent the uncertain CSI.

Tackling the optimization problem becomes more challenging and complicated especially when dealing with a massive number of users in the beyond 5G and 6G networks. Solving the non-convex EE maximization by traditional approaches suffers from poor resource utilization while some advanced techniques that involve fractional programming and sequential convex optimization or heuristic algorithms target are unable to find effective solutions to large-scale wireless networks because of the complexity of the wireless communication systems (Spantideas et al., 2021). This has motivated the use of AI-based methods to satisfy these massive wireless connectivity requirements and solve power allocation and subchannel problems in the mmWave systems. Machine Learning techniques can provide new ideas for intelligent energy-efficient algorithms in wireless networks due to the fast adapting to environmental changes (Q. Ding, Zhu, Liu, & Ma, 2021). R. Liu et al. (2020) adopted the machine learning approach to decide the best user association in the mmWave NOMA system that maximizes EE. To maximize the EE under the constraints of QoS, interference, and transmission power in (H. Zhang, Zhang, Long, & Karagiannidis, 2020), the authors propose a machine learning framework to deal with the user association, subchannel and power allocation problems in the NOMA mmWave heterogeneous networks to meet the various requirements of users in different applications. Deep learning trained by GA is proposed in (Pan, Yang, & Li, 2021) to make benefits of the advantages of deep learning and genetic algorithm where combining GA with deep learning significantly reduces the computation time of complicated optimization problems in various scenarios. Moreover, the combined algorithm is advisable for solving complicated optimization problems and problems with high required timeliness.

Forming clusters for different channel gain users in mmWave NOMA system is one of the aspects of achieving a good performance in NOMA. However, an excessive overhead is required to enable the BS to the users' state information to form the clusters and allocate the power to each cluster's member to improve the system performance (Celik, Tsai, Radaydeh, Al-Qahtani, & Alouini, 2019). In (K. Wang et al., 2019), Stackelberg game-based algorithm is proposed to design the user clustering and power allocation that maximizes the sum rate of the mmWave-NOMA system where the CSI of all cluster users is assumed to be perfectly known at the BS. More approaches are required to optimize the EE of the mmWave-NOMA system with a massive number of users considering the imperfection in the channel state.

However, the CSI imperfection effect on optimizing the EE in NOMA systems has been not addressed (Glei & Chibani, 2019; G. Liu et al., 2018; J. Wang et al., 2018; H. Zhang, Fang, et al., 2018). The channel estimation error and the quantization error are among the possible causes of imperfect CSI at the BS in the real wireless system (Fang et al., 2017) and this leads to user ordering ambiguities (Z. Ding et al., 2017).

In (Asif et al., 2023), the EE maximization problem was reformulated as several sub-problems, and an iterative method was used to find the optimal solutions that optimize the transmit power of the BS and power allocation coefficients under the imperfect SIC decoding at the receiver. The proposed algorithm shows an improvement in the system EE in perfect CSI condition. The probabilistic problem is converted to a non-probabilistic version in (X. Song et al., 2019) to maximize EE in imperfect CSI DL NOMA system under outage probability constraints. Since outage probability is one of the maximization problem constraints in (X. Song et al., 2019), the number of the served devices in the cell has to be evaluated. Similarly, Qiu, Gao, Chen, and Tu (2022) proposed an energy-efficient rate allocation algorithm to minimize the energy in NOMA-assisted mobile edge computing under latency and outage constraints when only statistical channel state information is available. An iterative water-filling-based rate allocation algorithm is utilized to solve the EE problem. However, the effect of the channel estimation error existence on the EE, the data rate, and the outage probability need to be investigated when these algorithms are implemented.

Previous studies proposed schemes to handle the imperfection of CSI to improve the performance of the NOMA system. In this context, pilot transmission design for power-domain NOMA and the influence of the inaccurate channel estimation on power-domain NOMA have been investigated in (Klimentyev & Sergienko, 2016; Ma et al., 2017). The key findings show the advantages of NOMA in scenarios with imperfect channel estimation. Thus, NOMA is a promising multiple-access technique for future wireless communication systems, particularly in real-world environments with challenging channel conditions. Thus, improving the EE in an imperfect CSI DL NOMA system is still an open issue and needs deeper investigation. Table 2.2 summarizes the contributions, strengths, weaknesses, insights, suggestions for improvement, and the approaches used in each of the data rate optimization problems in NOMA system's studies within this section.

Table 2.2: Summary of literature review of energy efficiency optimization problem in NOMA systems

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
Gkonis, Trakadas, & Sarakis (2020)	Code reuse in downlink MIMO-NOMA, SIC at receivers	Uses SIC for improved performance over OMA, PCA for channel information	Assumes ideal SIC, performance heavily dependent on system conditions	Performance improvement using SIC	Further validation in realistic scenarios with imperfect SIC	MIMO-NOMA, SIC
L. Chen, Hu, Xu, & Chen (2021)	Energy and throughput optimization with constant SINR	Simplified assumptions	Doesn't account for varying SINR among users	Focus on energy efficiency	Consider dynamic SINR levels across users	SINR-based optimization
Zhai, Zhang, Cai, Li, & Jiang (2018)	Power minimization in NOMA networks with long-term rate constraints	Addresses power consumption in large networks	High QoS requirements may drain resources	Energy-efficient network design	Explore resource constraints in high-QoS environments	Power minimization, NOMA
Ahn, Kim, Park, & Cho (2021)	NOMA power optimization under high QoS requirements	Identifies impact of QoS on resources	High QoS may be inefficient	QoS optimization for energy	Investigate optimal QoS allocation strategies	Power optimization, QoS constraints
Y. Guo, Tan, Gao, Yang, and Rui (2023)	EE optimization using Deep MCTS	Novel AI-based optimization framework	Heavy computational requirements,	Innovative AI techniques in NOMA	Validate scalability for large networks	Deep Monte Carlo Tree Search (MCTS), AI-based

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
			scalability concerns			optimization
Y. Guo, Fang, Cai, & Ding (2023)	EE optimization with DDPG, STAR-RIS	Suitable for continuous spaces, comprehensive approach	Training and hyperparameter tuning challenges	DDPG for EE optimization	Address training challenges and provide more detailed benchmarks	Deep Deterministic Policy Gradient (DDPG), Reconfigurable Intelligent Surfaces (STAR-RIS)
Cao & Hou (2023)	EE optimization in mMTC networks, hidden feature in SIC	Simplifies EE analysis, efficient approach	Assumes ideal conditions like perfect SIC	EE simplification in mMTC	Address real-world conditions like interference and noise	EE optimization, SIC
Muhammed, Chen, Seid, Han, & Yu (2023)	mmWave-NOMA integration in HetNets, user grouping	Efficient hybrid precoding and resource allocation	CSI errors and backhaul impact not considered	Hybrid precoding boosts performance	Consider practical backhaul and mobility effects	mmWave-NOMA, Hybrid precoding
Alajmi, Fayaz, Ahsan, & Nallanathan (2023)	Energy-efficient strategies using PPO and DQN	Suitable for complex, dynamic systems	Limited by numerical simulations, idealized conditions	Effective for NOMA IoT networks	Real-world testing and more algorithm comparisons needed	Proximal Policy Optimization (PPO), DQN
Khazali, Bozorgchenani, Tarchi, Shayesteh, & Kalbkhani (2023)	Power allocation optimization in NOMA	Optimizes EE under ideal CSI	Real-world challenges like imperfect CSI not addressed	EE gains in ideal conditions	Investigate CSI imperfections and their impact	Power allocation, NOMA
Nooh et al. (2024)	User pairing and power allocation for 2-user NOMA	EE gain by 4.5x over OMA	Limited to 2-user systems, ideal assumptions	Efficiency in small-scale systems	Extend to multi-user configurations and real-world settings	User pairing, Power allocation

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
Zamani et al. (2019)	CSI error impact and EE maximization in NOMA	Shows improvements over OMA despite CSI errors	Ideal conditions assumed	CSI error tolerance in NOMA	Address real-world CSI errors and interference	CSI error mitigation, EE maximization
Q. Zhao, Yang, and Zhang (2022)	EE optimization in Mine IoT	Improves EE by optimizing power and subchannel	Limited to specific IoT networks	EE maximization in IoT systems	Expand to diverse IoT scenarios and consider more dynamic parameters	Power and subchannel optimization, IoT
Spantideas et al. (2021)	AI for EE optimization in large-scale networks	Tackles large-scale issues with AI	Complexity limits large network scalability	AI-based optimization approach	Further exploration into scalability and real-time applications	AI-based optimization, Large-scale networks
R. Liu et al. (2020)	ML for user association in mmWave-NOMA	Maximizes EE using ML techniques	Doesn't address channel uncertainty	ML-driven user association	Validate in larger, real-world mmWave networks	Machine Learning (ML), User association
H. Zhang, Zhang, Long, & Karagiannidis (2020)	ML framework for EE in mmWave-NOMA	Addresses user association, power allocation	Doesn't address mobility and interference	ML-based resource allocation	Include real-time mobility and interference considerations	Machine Learning (ML), Power allocation
Pan, Yang, & Li (2021)	Combining deep learning with GA for EE optimization	Reduces computation time for complex problems	Requires substantial resources for training	Efficient ML approach to EE	Improve computational efficiency in larger networks	Deep Learning, GA
Celik, Tsai, Radaydeh,	User clustering	Efficient clustering	Excessive overhead	Performance in	Reduce overhead	User clustering,

Ref.	Key Contributions	Strengths	Gaps	Key Insights	Improvement Suggestions	Approach Used
Al-Qahtani, & Alouini (2019)	for mmWave-NOMA	and power allocation	for channel state info	clustered mmWave systems	in large user networks	mmWave-NOMA
K. Wang et al. (2019)	Stackelberg game for user clustering and power allocation	Optimizes sum rate in mmWave-NOMA	Relies on perfect CSI assumptions	Game-theoretic clustering and power allocation	Consider imperfect CSI and practical deployment conditions	Stackelberg game, User clustering
Glei & Chibani (2019)	CSI imperfection in EE optimization	NOMA outperforms OMA in imperfect CSI	Doesn't explore real-world factors	Imperfect CSI tolerance	Address more real-world CSI imperfections	CSI imperfection, EE optimization
Asif et al. (2023)	EE maximization under imperfect SIC decoding	Improves EE in perfect CSI conditions	Needs more testing for imperfect conditions	EE gains with SIC	Validate with imperfect SIC and dynamic user scenarios	SIC, EE maximization
X. Song et al. (2019)	EE optimization with outage constraints	Maximizes EE under outage probability	Outage impacts not fully explored	EE with outage constraints	Explore real-world outage scenarios and interference	Outage constraints, EE optimization
Qiu, Gao, Chen, and Tu (2022)	Rate allocation for NOMA mobile edge computing	Minimizes energy in NOMA	CSI errors and latency not fully explored	Effective for latency and QoS constraints	Address more complex real-world scenarios like latency and interference	Rate allocation, Mobile edge computing

CHAPTER 3: METHODOLOGY

This chapter is structured to address the core objectives of the research and provide a logical progression from theoretical frameworks to practical implementation. This chapter is organized into four sub-sections, each detailing a critical aspect of the proposed approach for optimizing energy-efficient power allocation in NOMA systems. By leveraging game theory and genetic algorithms, the methodology systematically tackles challenges related to resource allocation, data rate maximization, and energy efficiency in both perfect and imperfect CSI scenarios. Each sub-section builds upon the insights and outcomes of the preceding one, creating a cohesive narrative that aligns with the overall research objectives.

3.1 Game-Theoretic Power Allocation (GTPA) Algorithm for Downlink NOMA System

This section lays the groundwork for the proposed methodology by introducing the application of game theory in optimizing power allocation. The focus is on modeling resource distribution as a strategic interaction among users, ensuring fairness and efficiency in allocation. The insights gained from this analysis form the basis for addressing more complex scenarios, including imperfect CSI and advanced optimization strategies discussed in subsequent sections.

A field of mathematics called "game theory" examines how rational decision-makers interact with one another. It was created to simulate strategic interactions and has applications in computer science, biology, and even economics and political science. This paper explores the basic ideas of game theory, including its criteria, rules, and proofs that influence choices made in competitive situations. The core idea of game theory is that players make choices based on what other people do. Information, players, strategies, and payoffs are among the essential components (Fei et al., 2021). The foundation for comprehending strategic interactions is the interaction of these components. In most game theories, there are two or more players, each of whom can employ a variety of strategies.

Gamers make decisions based on the tactics that other players have selected. A payoff matrix shows the game's results for every combination of strategies. The utility or satisfaction that each player obtains from their chosen strategies is reflected in the payouts. Game theory can be represented in two ways: normally (a matrix) or extensively (a tree). The extended form captures sequential decision-making, while the normal form simplifies games with simultaneous moves (Tim, 2020). A key idea in game theory, the Nash Equilibrium is a collection of strategies in which no player has a reason to unilaterally change their preferred course of action. It symbolizes a steady state in which every player's plan is the best one in light of the other players' choices. The games are classified mainly into two types: zero-sum games and cooperative games. In zero-sum Games games, the victory of one player equals the defeat of another such as Chess and poker. On the other hand, participants can establish legally binding coalitions and agreements and the joint payoff distribution is the main topic of interest in cooperative games (Jinho, 2022). In many different domains, game theory is an effective tool for comprehending strategic decision-making. It offers a framework for examining interactions and making predictions thanks to its criteria, proofs, and rules.

In this thesis, a new power allocation mechanism is proposed that can allocate power to the users in fewer simple steps than (Lamba et al., 2019; Z. Wang et al., 2018) which makes the proposed model simpler. Also, most of the previous studies focus on maximizing the BS revenue (Lamba et al., 2019; Z. Wang et al., 2018), while in the proposed power allocation algorithm studied here, the sum data rate will be maximized by maximizing the utility function of the served users as players in a Glicksberg game. Besides, the SIC condition is also considered here. In this study, a price-based utility function of the user is proposed and its convexity is proven. Then, the effectiveness of the proposed utility function is also proven. Subsequently, a new Glicksberg game-theoretic model is proposed to distribute the power in the DL NOMA cellular network. The existence and the uniqueness of the Nash equilibrium of the proposed model are proven. Moreover, a mathematical expression of power price is derived. The proposed algorithm outperforms the algorithm proposed in (Lamba et al., 2019; Z. Wang et al., 2018) in terms of sum data rate and average data rate of users. The following subsection describes the system model for the proposed game-theoretic power allocation algorithm..

3.1.1 System Model

A cellular DL NOMA transmission system is considered, which is equipped with a set of M user equipment (UE), $m = \{1, 2, \dots, M\}$ which is being served by the BS on the same channel is considered. Here, the BS and all UEs are equipped with a single antenna. The BS in the NOMA system uses superposition coding techniques to serve multiple users simultaneously. The received signal at the m-th UE terminal is given by

$$\boldsymbol{y_m(t) = h_m x(t) + n_m} \,, \tag{3.1}$$

where h_m is the m-th channel gain from the BS to the m-th user, n_m is the additive white Gaussian noise (AWGN) at the m-th UE, n_m rrepresents a complex Gaussian distribution noise CN(0,σ^2) and $x(t)$ is the superposed transmitted signal by the BS that could be expressed as

$$\boldsymbol{x(t) = \sum_{m=1}^{M} \sqrt{\alpha_m P_m} x_m(t)} \tag{3.2}$$

where $x_m(t)$ is the individual OFDM signal, P_t is the total transmitted power from the BS and α_m is the power coefficient allocated to the m-th UE, where it satisfies

$$\sum_{i=1}^{M} \alpha_i = 1, \tag{3.3}$$

The SIC technique will be used to exclude interference from other users who multiplexed on the same bandwidth. The nearest UE to the BS, with the strongest channel h_M, is defined as UE_M while the farthest user, with the weakest channel h_1, is noted as UE_1. Thus, the BS transmits M different signals over the same frequency resource while every user receives the desired signal combined with the interferences due to the other users' signals on the same radio signal (M. S. Ali, Tabassum, & Hossain, 2016). It is assumed that the users are being sorted according to their channels' strengths, such as $|h_M| \geq |h_{M-1}| \geq \ldots \geq |h_2| \geq |h_1|$. Thus, a user with a higher order (stronger channel) can decode the lower order users' signals before decoding its desired signal. Thus, the SINR at the m-th user can be expressed as

$$\boldsymbol{SINR_m} = \frac{\boldsymbol{P_m |h_m|^2}}{\boldsymbol{|h_m|^2 \sum_{i=m+1}^{M} P_i + \sigma^2}}, \tag{3.4}$$

where P_m is the allocated power to the m-th user, and the summation term in the denominator represents the remaining undesired signals from the users with stronger channels (higher order than m). The allocated power for any user P_m should be greater than the allocated power for the next user in the sequence ($P_m \geq P_{m+1}$). This indicates the importance of different power levels for the multiplexed signals to decode the desired signal and therefore maximize the data rate (M. S. Ali, Hossain, Al-Dweik, et al., 2018). The achieved data rate of the m-th user is given by

$$\boldsymbol{R_m} = \boldsymbol{\log_2}(\boldsymbol{1} + \frac{\boldsymbol{P_m |h_m|^2}}{\boldsymbol{\sigma^2 + |h_m|^2 \sum_{i=m+1}^{M} P_i}}). \tag{3.5}$$

It is worth noting that fairness among users in the NOMA system is not the focus of this study. Since PA plays a vital role in maximizing the sum data rate, R_{sum} in the cell, this study focuses on the maximization of R_{sum} in the DL NOMA system. R_{sum} per each 1

Hz spectrum, of a BS serving M multiplexed users on the same bandwidth can be defined as

$$\boldsymbol{R_{sum}} = \sum_{\boldsymbol{m-1}}^{\boldsymbol{M}} \mathbf{log_2}\left(\mathbf{1} + \frac{\boldsymbol{P_m}|\boldsymbol{h_m}|^2}{\boldsymbol{\sigma^2} + |\boldsymbol{h_m}|^2 \sum_{\boldsymbol{i=m+1}}^{\boldsymbol{M}} \boldsymbol{P_i}}\right). \tag{3.6}$$

Assuming the total transmission power of the BS is limited to P_t, the maximization problem could be formulated as

$$\max_{P_m} R_{sum} = \sum_{m-1}^{M} \log_2\left(1 + \frac{P_m|h_m|^2}{\sigma^2 + |h_m|^2 \sum_{i=m+1}^{M} P_i}\right)$$
$$subject\ to \sum_{i=1}^{M} P_i \leq P_t$$
$$\forall\, \boldsymbol{P_i} \geq \mathbf{0} \tag{3.7}$$

The

3.1.2 Game-Theory and Power Allocation

It can be seen from Equation $\forall\, \boldsymbol{Pi} \geq \mathbf{0}$ (**3**.**7**) that this is a non-convex optimization problem. The number of served users and their allocated power should be determined carefully to ensure the QoS of the cellular systems. Furthermore, the difference in the allocated power levels should be compatible with SIC conditions so that each receiver would be able to extract the desired signal (M. S. Ali et al., 2016). The user utility function, U_m is defined as

$$\boldsymbol{U_m} = \frac{\boldsymbol{P_m^2}}{\boldsymbol{SINR_m}} - \boldsymbol{B^{P_m}} = \frac{\boldsymbol{P_m}}{|\boldsymbol{h_m}|^2}\left(\boldsymbol{\sigma^2} + |\boldsymbol{h_m}|^2 \sum_{\boldsymbol{i=m+1}}^{\boldsymbol{M}} \boldsymbol{P_i}\right) - \boldsymbol{B^{P_m}} \tag{3.8}$$

where B is the price of the allocated power P_m collected by the BS. It describes the behavior of the player and sets the strategy for each user in the game. Based on (3.8**Error! Reference source not found.**, an increase in the allocated power to the user will raise its SINR, but at the same time will cause more interference on the higher order users. Therefore, higher power will be needed to maintain the required SINR. Thus, the proposed U_m reflects the idea of the utility function, in which the positive effect (benefit) is represented by the SINR of the user while the second term (B^{P_m}) represents the negative side (detriment) of increasing the allocated power to the m-th user.

The increase in P_m will cause a rise in U_m until a maximum point, and then the negative effect of the price will lead to a decrease in the utility function. Figure 3.1 illustrates the effect of increasing P_m on this utility function and its effect on the SINR.

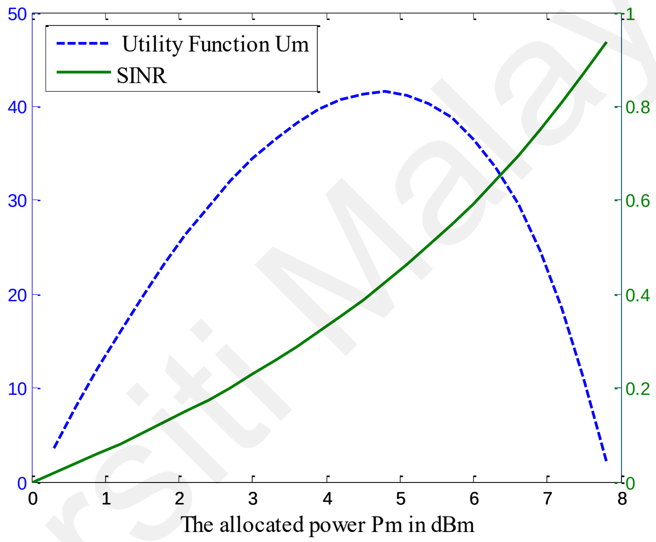

Figure 3.1: Comparison between the effect of P_m on U_m and $SINR_m$

Lemma 1: U_m given in Equation (3.8**Error! Reference source not found.** is effective and restrictive.

Proof. U_m is considered an effective utility function if an increase in the allocated power to any user causes an increase in the utility value. On the other hand, it is restrictive if the allocated power beyond a threshold value causes a decrease in the utility value. In other words, restrictiveness ensures that the strategy adopted by the user to set its allocated power will be limited to control the interference on other users. The effectiveness and restrictiveness features of the utility function could be ensured by satisfying the following condition:

$$\frac{\partial^2 U_m}{\partial P_m^2} < 0 \tag{3.9}$$

From Equation (3.8**Error! Reference source not found.**, this condition is satisfied since

$$\frac{\partial^2 U_m}{\partial P_m^2} = -B^{P_m}(lnB)^2 < 0 \tag{3.10}$$

Glicksberg game is proposed to solve the optimization problem discussed earlier. The selection of the Glicksberg game in the proposed method to ensure the existence of a Nash equilibrium, which is crucial for achieving stable and efficient power allocation in a game-theoretic context. The Glicksberg game allows users (players) to iteratively adjust their strategies to maximize their utility, ensuring that the total power allocation is optimized while maintaining fairness and satisfying SINR constraints. This method is particularly suitable because it guarantees that each user's strategy is optimal given the strategies of others, leading to a stable and efficient outcome. Compared to existing studies such as (J. Huang, Huang, Xing, & Qian, 2018), the main difference lies in the use of a more structured utility function and a clear derivation of Nash equilibrium conditions, which enhances the model's stability. While both methods use game theory, the proposed method's focus on utility and price dynamics introduces additional complexities in the implementation, not seen in simpler versions. Therefore, it is not a direct adaptation but rather an extension that refines the game-theoretic approach for better network optimization. The strongest user reveals its required SINR, and then the power price and the number of users will depend on the total transmission power, based on the required $SINR_M$. Secondly, all players (users) set their power to maximize the total users' utility function. Proof of the existence of Nash equilibrium for the proposed power allocation algorithm is shown below.

Theorem 1: The proposed game theoretic power allocation model satisfies Nash equilibrium.

Proof: The allocated power to each user is limited to $P_i \geq 0$. Thus, the strategy space of the downlink is nonempty, compact, and convex. Also, the utility function, U_m in Equation (3.8) is continuous. In addition, for any BS-user link, Equation (3.10) is verified. This implies that U_m is quasi-concave with respect to P_m. The allocated power among the users in a cellular system is limited to the total power of the BS, such that $\sum_{i=1}^{M} P_i < P_t$. Thus, the number of users is finite.

This completes the proof.

Theorem 2: If $\left|\frac{\partial^2 U_m}{\partial P_m^2}\right| \geq \sum_{i \neq j}^{M} \left|\frac{\partial^2 U_m}{\partial P_i \partial P_j}\right|$ for any user, the Nash equilibrium is unique.

Proof: The best response function for any user could be determined by solving the first derivative equation:

$$\frac{\partial U_m}{\partial P_m} = 0 \tag{3.11}$$

Thus, the optimal allocated power that maximizes the utility function of the m-th user is given by

$$P_m^* = (lnB)^{-1} ln\left(\frac{\sigma^2 + |h_m|^2 \sum_{i=m+1}^{M} P_i}{|h_m|^2 lnB}\right). \qquad 3.12)$$

Also, from the proposed utility function U_m,

$$\left|\frac{\partial^2 U_m}{\partial P_i \partial P_j}\right| = \begin{cases} -B^{P_m}(lnB)^2 & j = i \\ 1 & j > i \\ 0 & j < i \end{cases} \tag{3.13}$$

Using Equation (3.13), the Hessian matrix for M users can be represented as

$$H = \begin{bmatrix} -B^{P_1}(lnB)^2 & 1 & \cdots & 1 \\ 0 & \ddots & 1 & 1 \\ \vdots & 0 & -B^{P_{M-1}}(lnB)^2 & 1 \\ 0 & \cdots & 0 & -B^{P_M}(lnB)^2 \end{bmatrix}. \tag{3.14}$$

The best response function must be contractive to guarantee a unique Nash equilibrium. Thus,

$$\left|\frac{\partial^2 U_m}{\partial P_m^2}\right| \geq \sum_{i\neq j}^{M} \left|\frac{\partial^2 U_m}{\partial P_i \partial P_j}\right| \tag{3.15}$$

In the proposed game theoretic model, the PA aims to maximize $\sum_{i=1}^{M} U_m$. Based on Equation (3.15), the following equalities can be obtained

$$B^{P_m}(lnB)^2 \geq M - m \tag{3.16}$$

$$B^{P_M}(lnB)^2 \geq 0 \xrightarrow{yields} \begin{cases} B > 1 \\ P_M \geq 0 \end{cases} \tag{3.17}$$

It can be seen that Equation (3.16) corresponds to the requirement of the SIC principle. Moreover, Equation (3.17) represents the negative effect of the utility function. The crucial step in PA mechanism is to determine the power price, *B*. To derive *B*, the allocated power to the M-th user based on the required SINR needs to be determined, which is given by

$$P_M + \sum_{i=1}^{M-1} P_i \leq P_t \tag{3.18}$$

Substituting Equation (3.16) into Equation (3.18),

$$P_M + \sum_{i=1}^{M-1} \frac{\ln\left(\frac{M-i}{(lnB)^2}\right)}{lnB} \leq P_t. \tag{3.19}$$

Thus, Equation (3.19) could be re-written as

$$P_M + \frac{\ln(M-1)! - 2(M-1)\ln(lnB)}{lnB} \leq P_t. \tag{3.20}$$

This shows the relation between power price and the number of served users in the cell. Once M and *B* are determined, the minimum allocated power to each user is determined according to Equation (3.16). Then, Equation (3.12) is used to find the optimal allocated power that maximizes U_m. The leader reveals its required SINR, and thus, the power price and the number of possible served users are determined depending on the limited total transmission power. Then, power is assigned to each user to maximize the overall cell utility function. The flowchart in Figure 3.2 illustrates the steps of the Game-theoretic power allocation algorithm. It simplifies the complex process into clear, sequential steps, making it easier to understand and follow the algorithm effectively.

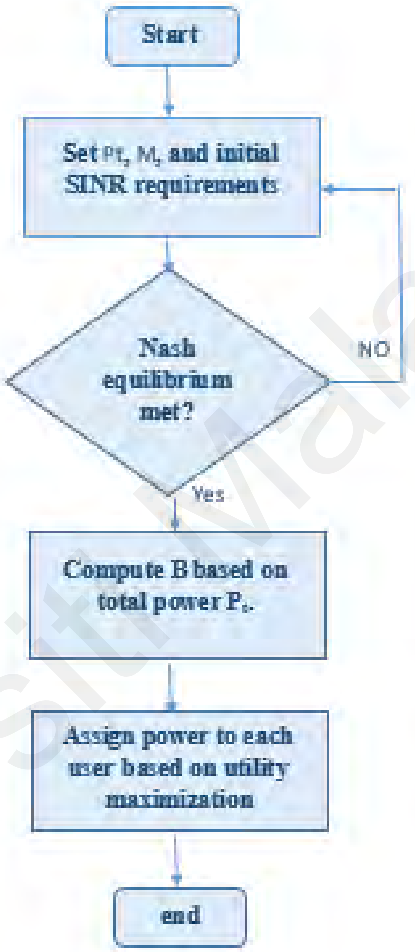

Figure 3.2: Game-theoretic power allocation algorithm flowchart.

Ignoring fairness in the design of the proposed method can lead to significant issues such as unequal resource allocation, where some users receive excessive power, resulting in high data rates, while others suffer poor service. This imbalance can degrade user experience, violate QoS requirements, and cause instability in the network, as users adjust their power allocations to maximize personal utility, leading to interference and inefficient resource usage. Moreover, it could create economic disparities, with some users generating higher revenue for the base station than others. Overall, neglecting fairness undermines network efficiency, user satisfaction, and regulatory compliance, potentially destabilizing the system and reducing its overall performance.

Maximizing the sum data rate instead of the BS's revenue prioritizes system efficiency, user satisfaction, and overall throughput. While this leads to better user performance and fairness, it may not align with the BS's financial goals. Balancing the need for revenue generation with data rate optimization is essential for designing a sustainable business model for cellular networks. In practice, a hybrid approach that optimizes both revenue and data rate while managing user interference and satisfaction would be more practical in achieving a balance between performance and profit.

The practicality of the proposed GTPA algorithm lies in its ability to model the dynamic interactions between users and the BS, ensuring that the system remains efficient even under varying network conditions. However, one of the main challenges in applying game-theoretic approaches in real-time cellular systems is the high computational complexity, especially when the network conditions are constantly changing due to factors like user mobility, varying traffic loads, and interference. These factors require the system to re-compute the optimal power allocation regularly, which can result in significant computational overhead. To address this challenge, the proposed method likely includes mechanisms for simplifying the computation, such as approximating the Nash equilibrium or using iterative algorithms that converge quickly. For example, using a distributed approach where each user only updates its power allocation based on local information could reduce the computational burden on the BS and speed up convergence. Furthermore, the method could incorporate adaptive strategies, allowing it to adjust the frequency of power updates based on the rate of change in network conditions, thus balancing between computational efficiency and system performance. Additionally, while game-theoretic models can be computationally expensive, advances in hardware and software, such as parallel processing and machine learning optimization techniques, can make the implementation more feasible in practical scenarios. These methods could be further refined to limit the number of iterations or to use approximations that maintain system stability without the need for exhaustive computations. As the network conditions change, a real-time adjustment of the power allocation could be carried out in a way that does not significantly disrupt ongoing communication, ensuring that the BS can react quickly while maintaining overall system fairness and performance.

3.2 Energy-Efficient Power Allocation for Imperfect CSI DL NOMA System

Building on the game-theoretic approach, this section expands the methodology to consider the challenges posed by imperfect CSI. The proposed algorithm integrates error modeling and robustness analysis to ensure reliable performance under realistic conditions. This section bridges the gap between theoretical constructs and practical challenges, setting the stage for leveraging genetic algorithms in more dynamic scenarios.

The main goals and approaches of energy-efficient PA algorithms for maximizing EE and game-theoretical PA algorithms for maximizing data rate differ significantly. When utilizing game theory to maximize data rates, user-centric strategies are the main focus. This can lead to a competitive environment where users try to maximize their own data rates without necessarily taking the efficiency of the system as a whole into account. On the other hand, a comprehensive strategy is given priority by an energy-efficient power allocation algorithm, which seeks to maximize the total EE of the communication system. These algorithms take into account striking a balance between obtaining acceptable data rates and reducing power consumption, promoting user cooperation, and a communication network that is more globally optimized, environmentally friendly, and sustainable. While energy-efficient power allocation tackles the larger issue of resource utilization and environmental impact in the pursuit of sustainable telecommunications, data rate maximization emphasizes individual gains.

In communications networks, EE is crucial for several strong reasons. Above all, the effects of these systems on the environment are enormous, especially considering how frequently data centers and mobile networks are used. In keeping with international efforts to mitigate climate change, energy-efficient practices greatly lower the carbon footprint of telecommunications operations. EE, above and beyond environmental concerns, is essential to the long-term financial viability of telecom networks. Operators can save significant operating expenses, improve network reliability, and guarantee continuous service, particularly in times of emergency, by optimizing their energy consumption. Adopting energy-efficient technologies also becomes a catalyst for innovation as technology continues to change the sector, guaranteeing that telecom networks will continue to be both commercially and environmentally sustainable in the future. Energy efficiency receives significant attention from both academia and industry researchers since the information and communication sector consumes 5% of the total global energy consumption (Y. Zhang et al., 2017). Hence, energy efficiency is crucial in NOMA systems.

In this study, a simple PA algorithm among M users is proposed for a DL NOMA system with imperfect CSI where the allocated power to each channel in the cell depends on channel strength. The performance of the proposed algorithm in a single cell is investigated in terms of EE and outage probability and compared with the conventional OMA. The following subsection describes the system model of the proposed PA algorithm to maximize EE.

3.2.1 System Model

A single cellular cell of the DL NOMA system with M users' equipment (UEs), which share the same resources is considered. Here, the transmitter and each UE are provided by a single antenna, and superposition coding techniques are used to serve all users at the same time. The received signal at UE_m is defined as,

$$\boldsymbol{y_m(t) = (h_m + e_h)x(t) + n_m}, \qquad \boldsymbol{m \in \{1, 2, \ldots, M\}}. \tag{3.21}$$,

where h_m is the channel gain from the BS to UE_m, e_h is the channel estimation error, $n_m \sim CN(0,\sigma^2)$ represents the AWGN at UE_m, and $x(t)$ is the transmitted signal from BS which is given as

$$\boldsymbol{x(t) = \sum_{m=1}^{M} \sqrt{\alpha_m P_m} x_m(t)}, \tag{3.22}$$

where $x_m(t)$ is the individual OFDM signal, P_t is the total BS's transmission power, and α_m is the power coefficient of UE_m, which verifies:

$$\sum_{m=1}^{M} \alpha_m = 1. \tag{3.23}$$

M different signals are combined on the same carrier, transmitted by the BS, and then, are received by all users (M. S. Ali et al., 2016). These users have been ordered depending on their channels' strength such that $|h_M| \geq |h_{M-1}| \geq \ldots \geq |h_2| \geq |h_1|$. The closest user to BS is denoted as UE_M and the farther user, which has the weakest channel h_1, is denoted as UE_1. The SIC technique could be utilized to extract a specific signal from superposed signals on a single carrier. Thus, a higher-order user can decode signals of the lower-order users before decoding its signal. The system model is shown in Figure 3.3.

Practically, it is a challenge to obtain perfect CSI. Thus, an error in the channel estimation is considered as shown in Equation (3.21). To implement the SIC method in the NOMA system at the receivers, the allocated power to every user has to be less than the allocated power to the farther user within the cell ($P_m \geq P_{m+1}$) (M. S. Ali, Hossain, Al-Dweik, et al., 2018). In this case, the SINR at UE_m is expressed as

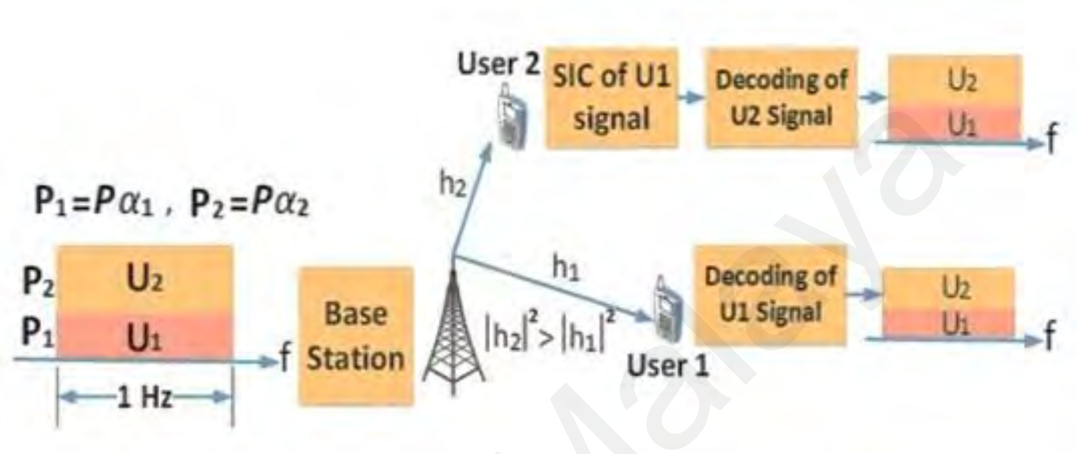

Figure 3.3: DL NOMA cellular system

$$\boldsymbol{SINR_m} = \frac{\boldsymbol{P_m |h_m|^2}}{\boldsymbol{|h_m|^2 \sum_{i=m+1}^{M} P_i + \sigma_\epsilon^2 \sum_{i=1}^{M} P_i + \sigma^2}} \tag{3.24}$$

where P_m is the allocated power to UE_m, $\sum_{i=m+1}^{M} P_i$ represents undesired signals from the higher-order users, and σ_e^2 represents the power fraction due to the channel estimation error. Thus, the data rate of UE_m is defined as

$$\boldsymbol{R_m} = \boldsymbol{\log_2}\left(\boldsymbol{1} + \frac{\boldsymbol{P_m |h_m|^2}}{\boldsymbol{|h_m|^2 \sum_{i=m+1}^{M} P_i + \sigma_\epsilon^2 \sum_{i=1}^{M} P_i + \sigma^2}}\right). \tag{3.25}$$

The total data rate, R_{sum} of a cell of a single BS that serves M multiplexed users on the same carrier is expressed as

$$\boldsymbol{R_{sum}} = \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \boldsymbol{R_m}. \tag{3.26}$$

The system's EE is defined as the total data rate (throughput) to the total consumption power ratio, which is expressed as

$$EE = \frac{R_{sum}}{P_t + P_c}$$

$$= \frac{\sum_{m=1}^{M} \log_2 \left(1 + \frac{\boldsymbol{P_m |h_m|^2}}{\boldsymbol{|h_m|^2 \sum_{i=m+1}^{M} P_i + \sigma_\epsilon^2 \sum_{i=1}^{M} P_i + \sigma^2}} \right)}{\sum_{i=1}^{M} \boldsymbol{P_i + P_c}}, \qquad (3.27)$$

where P_c is the BS's dissipated power in the operation circuit.

The objective of this study is to maximize the system's EE under a restriction of limited total consumption power. To implement SIC for extracting the desired signals at the receivers, the allocated power to the users should be ordered according to their channels' strength (M. S. Ali et al., 2016). Hence, the problem could be formulated as

$$\max_{P_m} \quad EE = \frac{R_{sum}}{P_t + P_c}$$

$$subject\ to \sum_{i=1}^{M} P_i \leq P_t$$

$$\forall\, P_i \geq 0$$

$$\boldsymbol{P_m \leq P_{m+1}} \qquad (3.28)$$

It can be seen from Equation (3.28) that maximizing EE requires maximizing the sum rate at a certain power consumption level.

3.2.2 Energy-Efficient Power Allocation Algorithm

The flowchart in Figure 3.4 illustrates the steps of the Energy-efficient power allocation algorithm. It simplifies the complex process into clear, sequential steps, making it easier to understand and follow the algorithm effectively.

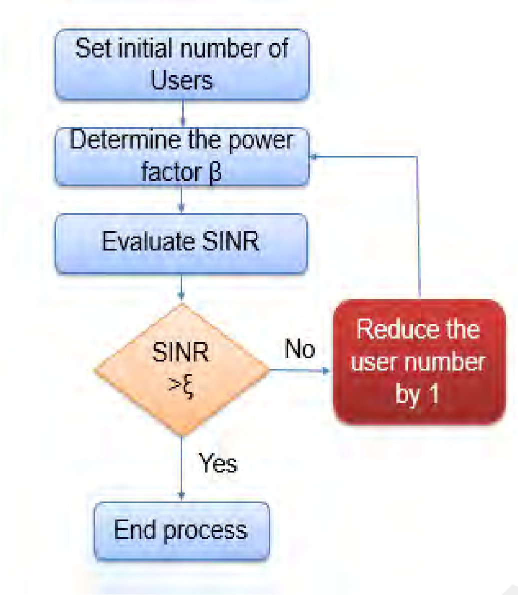

Figure 3.4: Energy-efficient power allocation algorithm flowchart

In the DL NOMA system, a higher power level should be set to the weaker user and a lower power level will be allocated to the strongest user. Based on this fact, a PA algorithm for the NOMA system in the imperfect CSI case is proposed. For simplicity, the channel estimation error is assumed to be constant for all users in the cell. The allocated power P_m to the m–th user is inversely proportional to the channel strength as follows

$$\boldsymbol{P_m} = \frac{\boldsymbol{\beta P_t}}{|\boldsymbol{h_m}|^2 + \boldsymbol{\sigma_h^2}}, \tag{3.29}$$

where β is the power factor which has to guarantee that Equation (3.23) is verified. Hence

$$\boldsymbol{\beta} = \left[\sum_{i=1}^{M} \frac{\mathbf{1}}{|\boldsymbol{h_i}|^2 + \boldsymbol{\sigma_h^2}}\right]^{-1}. \tag{3.30}$$

By substituting Equation (3.30) in Equation (3.29), P_m can be re-written as

$$\boldsymbol{P_m} = \frac{\boldsymbol{P_t}}{\left(|\boldsymbol{h_m}|^2 + \boldsymbol{\sigma_h^2}\right)\sum_{i=1}^{M} \frac{\mathbf{1}}{|\boldsymbol{h_i}|^2 + \boldsymbol{\sigma_h^2}}}, \tag{3.31}$$

From Equation (3.31), the allocated power to a user will decrease when the user's number rises. This will affect the SINR of the user at the cell edge and consequently, the coverage of the BS will degrade. The proposed algorithm has been summarized in Algorithm 1.

Algorithm 1: Energy Efficient Power Allocation Algorithm of Imperfect CSI DL NOMA System

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1: Initiate l=M,

2.Determine β based on Equation (3.30),

3. **For** m=1:l, do:

 3.1 Evaluate the allocated power P_m based on Equation (3.31),

 3.2 Evaluate $SINR_m$ based on Equation (3.24)

4. **If** $SINR_m$<threshold level

 4.1 $l=l-1$

 4.2 Repeat steps 2 to 4

5. **End If**

6. **End For**

One important outcome of this approach is that it guarantees fairness in power distribution since weaker users get more power, which helps meet the required SINR for each user. However, as the user number increases, the allocated power for each user decreases, which could lead to coverage degradation, especially for users at the cell's edge. The algorithm dynamically adjusts the number of users served based on their SINR, ensuring that the SINR threshold is met while maintaining energy efficiency. Thus, this method is important because it provides an energy-efficient solution for power allocation under the assumption of perfect CSI, allowing for optimal system performance and power distribution across users. The downside is that this assumes perfect knowledge of the channel, which may not be feasible in practical systems due to the challenges of obtaining perfect CSI in real-world environments. This limitation should be addressed in future work focusing on imperfect CSI.

3.3 Genetic Algorithm for Optimizing Energy Efficiency in Downlink mmWave NOMA System with Imperfect CSI

To address the limitations of traditional methods in dynamic environments, this section introduces GA as an advanced optimization tool. The GA-based framework enhances the adaptability and performance of power allocation mechanisms, especially under multi-user and multi-cell scenarios. The results from this section are core of the finding of this study, where optimizing EE in imperfect CSI NOMA system is a main objective, while GTPA aims to achieve the maximum data rate in the NOMA system.

This study focuses on user clustering to maximize the EE in the DL mmWave NOMA imperfect CSI system subjected to the asymmetric users' data rate requirement using one of the AI methods, which is a genetic algorithm for light traffic and heavy traffic cases. GA are selected to solve the non-convex problem in the proposed method due to their ability to efficiently navigate complex solution spaces with multiple local optima, which is a common characteristic of non-convex problems like PA in NOMA systems. Unlike traditional gradient-based methods that require differentiable objective functions and can be prone to getting stuck in local optima, GA uses a population-based approach that explores multiple solutions simultaneously, increasing the chances of finding a global optimum. Additionally, GA does not rely on initial guesses, making it more robust and adaptable to large, complex problems with many variables and constraints, such as power limits, SINR requirements, and fairness considerations in resource management. Its flexibility in handling non-smooth objective functions and the ability to incorporate multiple constraints make GA a practical and effective choice for optimizing resource allocation in NOMA systems.

In the field of artificial intelligence, GA has arisen as a powerful tool to solve the non-convex optimization problem to determine the minimum solutions when the level of quality of service is constrained and the resources are limited especially when no full information about the users' states is available. In this study, firstly, the EE optimization problem for the DL mmWave NOMA system with user clustering under total power and specific required SINR for each user depending on the users' application is formulated. Then, the role that PA can play in maximizing the EE in DL mmWave NOMA system with clustering where the users' applications impose asymmetric SINR requirements is Investigated. For this purpose, the EE of a two-member cluster system is evaluated at asymmetric users' requirements scenarios where the cell-edge user and the nearby BS user require different data rates. Next, a mixed-integer GA problem is converted to an integer GA problem for solving EE optimization problems by determining the best clusters. The performance of the proposed GA and its convergence is evaluated in the case of light traffic and heavy traffic. The performance of the proposed GA is compared with the optimal solution and the conventional OMA at different users' SINR requirements scenarios. The impact of estimation error in CSI at BS on the system performance is evaluated based on the proposed GA and the optimal NOMA. Table 3.1 shows the list of parameters of the NOMA mmWave system model that is described in the following subsection.

Table 3.1: List of parameters

Notation	Parameters
θ_m^b	The beam width of the mmWave BS *b to user m*
φ_m^b	The boresight angle from mmWave BS *b* to user *m*
γ_m^b	The spatial angle from user *m* to mmWave BS *b*
g_m^b	The gain of the directivity between the beam from mmWave BS *b* to user *m* and the beam from device *m* to mmWave BS *b*
θ_m^u	The beam width of the user *m* to mmWave BS *b*
φ_m^u	The boresight angle from device *m* to mmWave BS *b*
γ_m^u	The spatial angle from mmWave BS *b* to user *m*
g_m^u	The gain of the directivity between the beam from user *m* to mmWave BS *b* and the beam from mmWave BS *b* to user *m*
g_m^c	The gain of the channel linked the user *m* to the mmWave BS *b*
ϵ	Side lobe
h_m	The complete representation of the channel between BS ***b*** and user *m*
p_m	The allocated power to the user *m* from the mmWave BS *b*

3.3.1 System Model

A single-cell cellular NOMA mmWave system is considered as illustrated in Figure 3.5, which includes the beamforming-based directional links (L. Li, Ota, Dong, & Verikoukis, 2018; R. Liu et al., 2020). The central BS is equipped with multiple antennas whereas each user is equipped with a single antenna. Without losing generality, the users are assumed to be uniformly allocated (R. Liu et al., 2020). The set of users within the cell boundary is $\mathcal{M} = \{1, 2, 3, \dots, M\}$. The set of the clusters is denoted as $\mathbb{C} = \{1, 2, 3, \dots, C\}$, where one subchannel is dedicated for each cluster. The user association state between every user and BS is represented by $\mathrm{X}^{M\times B}$matrix as follows:

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{1,1}} & \cdots & \boldsymbol{x_{1,B}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{M,1}} & \cdots & \boldsymbol{x_{M,B}} \end{bmatrix} \tag{3.32}$$

where $x_{m,b} = 1$ when the user m is a member of cluster b, and $x_{m,b} = 0$ when it is not. Due to the complexity of SIC decoding, it is assumed that each cluster can support two members simultaneously on one subchannel (Xie, 2019).

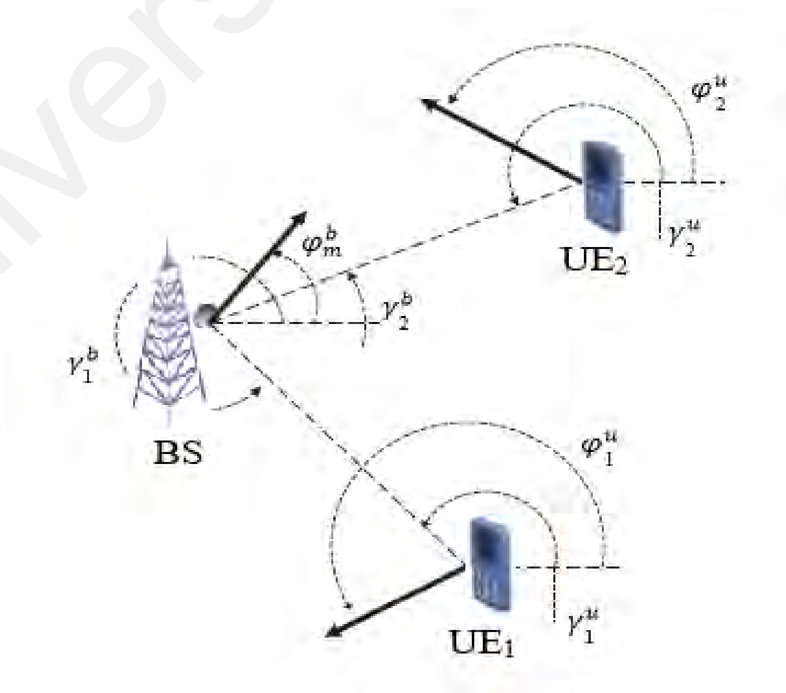

Figure 3.5: The proposed DL mmWave NOMA system.

The gain of the directivity between the beam from mmWave BS to user m and the beam from user m to mmWave BS is given by

$$\boldsymbol{g_m^b\left(\theta_m^b, \varphi_m^b, \gamma_m^b\right) = \begin{cases} \epsilon, & if\ \frac{\theta^b}{2} < \left|\varphi_m^b - \gamma_m^b\right| < 2\pi - \frac{\theta^b}{2} \\ \frac{2\pi-(2\pi-\theta^b)\epsilon}{\theta^b}, & otherwise \end{cases}} \tag{3.33}$$

Similarly, the gain of the directivity between the beam from the user m to the mmWave BS and the beam from the mmWave BS to the user m is given as

$$\boldsymbol{g_m^u({\theta_m}^u, \varphi_m^u, \gamma_m^u) = \begin{cases} \epsilon, & if\ \frac{{\theta_m}^u}{2} < |\varphi_m^u - \gamma_m^u| < 2\pi - \frac{{\theta_m}^u}{2} \\ \frac{2\pi-(2\pi-{\theta_m}^u)\epsilon}{{\theta_m}^u}, & otherwise \end{cases}} \tag{3.34}$$

The cluster users are supported at the same time and at the same subchannel by utilizing superposition coding techniques. The channel gain from the BS to every user is given by $g_m^c = c_m d_m^{-\frac{\delta}{2}}$, where $c_m \sim CN(0,1)$ is a Rayleigh fading factor, d_m denotes the distance from each UE to the transmitter, and δ refers to the path loss exponent (Zamani et al., 2019). In practice, it is difficult to attain perfect channel state information due to various reasons such as channel estimation errors, feedback delays, and quantization errors. Here, a NOMA system with imperfect CSI is considered in which the channel estimation is given by $g_m^c = \widehat{g_m^c} + \varepsilon$, where $\varepsilon \sim CN(0, \sigma_\varepsilon^2)$ is the error of the channel estimation with variance σ_ε^2, and $\widehat{g_m^c}$ is the estimated channel gain $\widehat{g_m^c} \sim CN(0, \sigma_{g_m}^2)$ which is uncorrelated with ε (Zamani et al., 2019). Thus, the complete representation of the channel between BS and user m is given by:

$$h_m = g_m^b g_m^u g_m^c \tag{3.35}$$

In the DL NOMA system, the users equipment are ordered according to their channels' strength ($|h_M| \geq |h_{M-1}| \geq \dots \geq |h_2| \geq |h_1|$) (Z. Ding et al., 2017). Thereby, the SIC technique could extract a specific signal from the superposed signals on a single carrier. The strongest user device is indicated as UE_M and the weakest user device is indicated as UE_1. The BS transmits M different messages on the same carrier within the same bandwidth. On the other side, each user receives a composition of its message with the interferences from the signals of other users (M. S. Ali et al., 2016).

Figure 3.6 illustrates the SIC technique in the mmWave-NOMA system where each cluster consists of two members and is carried on a specific subchannel. The mmWave BS in the NOMA system utilizes superposition coding techniques to serve several users simultaneously. A superposed transmitted signal by the mmWave BS can be expressed as (Zamani et al., 2019):

$$f = \sum_{m=1}^{M} \sqrt{\alpha_m P_{tot}}\, f_m(t) = \sum_{m=1}^{M} \sqrt{p_m}\, f_m \tag{3.36}$$

where f_m is the individual signal dedicated to the m-th user and $E\{|f_m|^2\}$=1, before transmission, M is the number of the UEs supported by the mmWave BS, P_{tot} is the total transmitted power of the mmWave BSs and α_m is the power coefficient allocated to the m-th UE where:

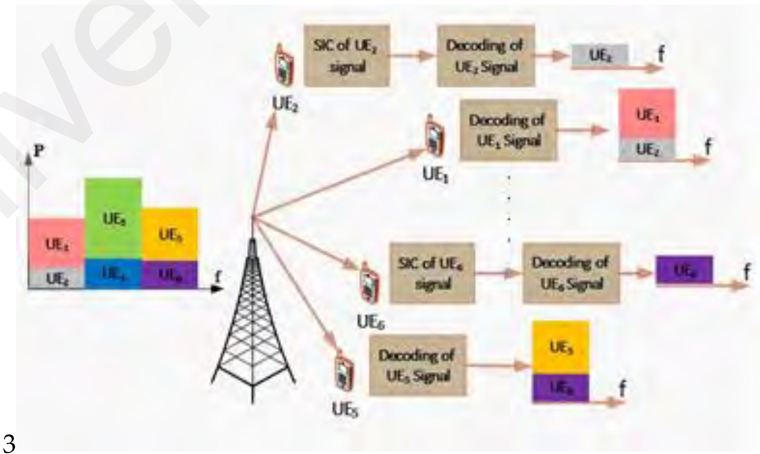

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Figure 3.6: SIC technique to decode signals for two members' clusters in DL mmWave-NOMA system.

3.3.2 Problem Formulation

The variation in the power levels of the composed signals plays an important role in maximizing the cell throughput and EE (M. S. Ali, Hossain, Al-Dweik, et al., 2018). The mmWave BS transmits different signals over the same frequency resource while every user receives its desired signal combined with the interferences due to the other users' signals on the same radio signal (M. S. Ali et al., 2016). Each one of the DL NOMA's users undergoes a different attenuation according to its channel gain with the mmWave BS. The user with the strongest channel has the capability to decode the signals of the remaining users before decoding its own signal. On the other hand, the user with the weakest channel can't eliminate the signals of the other strong channel UEs. The received signal at the m-th UE terminal before applying the SIC technique is given by (Zamani et al., 2019).

$$y_m = \sum_{\forall l \in M, b \in B} \sqrt{x_{m,b} g_m^b g_m^u g_m^c p_l} f_l + w_m \tag{3.37}$$

where p_l is the allocated power to the l-th user and w_m represents the additive white Gaussian noise (AWGN). In general, the signal after applying SIC technique at the m-th user can be expressed as (Zamani et al., 2019)

$$y_m = \sqrt{x_{m,b} g_m^b g_m^u g_m^c p_m} f_m + \underbrace{\sum_{\forall l \in M} \sqrt{x_{m,b} g_m^b g_m^u g_m^c p_l}\, f_l}_{l>m} + \sum_{\forall l \in M} \sqrt{\varepsilon x_{l,b} p_l}\, f_l + w_m \tag{3.38}$$

where in Equation (3.39), the dedicated signal for the m-th UE is represented by the first term, while the second term is the inter-channel interference due to decomposed signals on the same subchannel of other users and the third term is due to the estimation error of the CSI. It is worth mentioning that the interference due to the signals of the other clusters will be eliminated by filtration where other clusters are on different subchannels.

It is assumed that all users utilize the mmWave spectrum resources completely to achieve full employment of the directional gain of the mmWave system. Thus, the communication link between the mmWave BS and the m-th user is subjected to interference given by

$$I_m = \underbrace{\sum_{\forall l \in M} x_{m,b} p_l g_m^b \, g_m^u g_m^c}_{l<m} + \sigma_\varepsilon^2 \sum_{l=1}^{M} x_{l,b} p_l \tag{3.39}$$

This is considered a commonly used interference model in mmWave PA systems (Y. Liu, Fang, Xiao, & Mumtaz, 2018). Based on the interference model, the SINR at the m-th user is given as

$$SINR_m = \frac{x_{m,b} p_m g_m^b g_m^u g_m^c}{I_m + BN_o} \tag{3.40}$$

where B represents the utilized bandwidth and N_o represents the power spectrum density of the AWGN at the user terminal. Thereby, the obtained data rate at the m-th user from the mmWave BS could be expressed as

$$R_m = Blog_2(1 + SINR_m) \tag{3.41}$$

The improved throughput is an advantage of the NOMA over the conventional OMA. For a more specific comparison, conventional frequency division multiple access (FDMA) will be considered in this thesis. For a fair comparison with the NOMA, the bandwidth dedicated for each cluster is divided equally among its members so that the cluster will support the same number of users within the same dedicated bandwidth in both systems: NOMA and OMA. Thus, the data rate of the m-th user from the mmWave BS in OMA system is determined as

$$R_m^{OMA} = \frac{B}{M} log_2\left(1 + \frac{\sum_{n\in N} P_m g_m^b g_m^u g_m^c}{\sigma_\varepsilon^2 P_m + \frac{B}{M} N_o}\right) \tag{3.42}$$

The advantage of NOMA over OMA in increasing the data rate could be illustrated by taking an example of a cell with only two users where the first is at the cell edge, which is far from the BS while the second is near the BS. Although low power will be allocated to the nearest user who has the strongest channel, its *SINR* will be high since no inter-cell interference significantly affects it.

Due to the system's resource constraints, the number of served users and their allocated power should be determined carefully to ensure the QoS of wireless systems. Furthermore, the difference in the allocated power levels should be verified so that each receiver would be able to perform SIC and extract the desired signal (M. S. Ali et al., 2016). The sum data rate of the NOMA mmWave downlink system is expressed as

$$R_{sum} = \sum_{m\in M} R_m \tag{3.43}$$

Based on the given data rate, the EE of the user association NOMA mmWave DL system would be written as (Zhou et al., 2019)

$$EE = \frac{R_{sum}}{\sum_{m\in M} p_m + P_c} \tag{3.44}$$

where P_c represents the circuit power dissipation for SIC detection at the mmWave BSs with the assumption that it is fixed for all users. In this work, the objective is to maximize the non-concave EE optimization problem of the NOMA mmWave with clustering. The allocated power by the mmWave BS to each user depends on the required QoS by that user within the limited total BS transmission power. Each cluster is assumed to consist of two members while each user is supported by one cluster (subchannel). Finding the optimal cluster composition that maximizes the EE of the mmWave system subjected to the required QoS and limited transmission power. This EE optimization problem could be formulated as

$$\underbrace{\max}_{x_{m,b},p_m} \quad EE = \frac{R_{sum}}{\sum_{m\in M}\sum_{b\in B} x_{m,b}\, p_m + P_c}$$

$$subject\ to \quad C1: x_{m,b} \in \{0,1\}, \qquad \forall m \in M, \forall b \in B,$$

$$C2: \sum_{m\in M, b\in B} x_{m,b} = 1, \qquad \forall m \in M,$$

$$C3: \sum_{m\in M, b\in B} x_{m,b} = 2, \qquad \forall b \in B,$$

$$C4: \sum_{m\in M}\sum_{b\in B} x_{m,b}\, p_m \leq P_{tot},$$

$$C5: SINR_m \geq \delta_m, \forall m \in M \tag{3.45}$$

where $C1$ refers to the association of each user m with a cluster b. $C2$ states that each user should be supported by one cluster while $C3$ defines that every cluster consists of two members. The limited transmission power of the mmWave BS is represented in $C4$ while $C5$ is to ensure that the minimum QoS requirements for all users in the DL mmWave NOMA system are satisfied. It is worthy to mention that the design that allows only two users per cluster is likely a simplification for analytical purposes rather than a strict implementation of NOMA. In reality, NOMA systems are designed to accommodate multiple users in a cluster, where power allocation and SIC are applied to a larger set of users. Limiting the number of users per cluster to just two simplifies the problem by reducing the complexity of power allocation and interference management. This simplification allows for easier mathematical analysis and clearer insights into the system's performance, but in practical NOMA implementations, there would typically be more than two users in each cluster, depending on the system's design and resource constraints. Therefore, the two-user assumption is a modeling choice to facilitate the study, not a direct reflection of actual NOMA deployment.

It is obvious the difficulties and complexity of finding all x_{mn} and p_m that maximize the data rate in the downlink user association mmWave NOMA system. Besides, the relation between the data rate and the transmitted power makes this problem a non-convex optimization problem that is difficult to solve using classical methods. Therefore, a genetic algorithm is employed in this study to solve the subchannel association problem. Based on the GA scheme, the optimization problem in Equation (3.46) is a mixed integer nonlinear problem.

Genetic Algorithms are often considered a complex optimization technique with a relatively low convergence rate, but they are still suitable for solving power allocation problems in non-convex scenarios like those encountered in NOMA systems. The primary advantage of GA lies in its ability to explore a wide solution space and handle complex, non-linear, and non-convex problems that traditional optimization methods might struggle with. Power allocation in NOMA, especially when considering factors like imperfect CSI, interference, and fairness, introduces a high level of complexity that requires a global search for an optimal or near-optimal solution. GA's stochastic nature, which mimics the process of natural evolution, allows it to efficiently navigate through multiple local optima without being trapped in suboptimal solutions. Although GA may have a slower convergence rate compared to some more specialized algorithms, its robustness in handling diverse problem constraints, its ability to work with noisy or incomplete data, and its flexibility in dealing with complex system models make it highly effective in power allocation. Additionally, techniques like elitism, mutation, and crossover can be applied to enhance GA's convergence rate over time, allowing it to converge to a suitable solution while avoiding computationally expensive methods. Given these characteristics, GA is well-suited for resource management problems where conventional methods may fail or become computationally prohibitive.

The GA method can be extended to a multi-cell scenario, though it requires additional considerations to account for inter-cell interference, coordination between cells, and the complexity of managing resources across multiple cells. Here's how it can be extended:

1. Inter-cell Interference Management: In a multi-cell scenario, the interference between cells becomes a critical factor in power allocation. GA can be extended by including inter-cell interference as part of the fitness function. The fitness function would then need to incorporate the total interference from neighboring cells and penalize solutions that result in high interference levels. This encourages solutions that optimize power allocation not just within a single cell but across multiple cells, reducing the overall interference and improving the system's performance.
2. Resource Sharing: In a multi-cell system, power allocation across multiple cells might need to be coordinated. GA can be extended to handle resource sharing between cells. Each cell can be treated as a separate agent or player, and GA can optimize the power allocation by considering the overall network's objectives (such as total sum rate, fairness, or EE) rather than focusing on individual cells. The interactions between cells can be modeled as a multi-agent system, where the power allocation in each cell depends on the decisions made by neighboring cells.
3. Multiple Objectives: In a multi-cell system, the goals of optimization are more complex, often involving a trade-off between sum data rate, fairness, energy efficiency, and interference management. GA can be extended to a multi-objective optimization problem, where multiple objectives are simultaneously optimized. For instance, the fitness function could be designed to balance the total data rate with fairness across cells or minimize the total interference

across the network. Multi-objective GA techniques, such as Pareto-based approaches, could be employed to find a set of optimal solutions.

4. Population Representation: In a multi-cell system, the population in the GA could represent the power allocation across all cells. Each chromosome could encode the power allocation decisions for all users in all cells, and crossover and mutation operations could be designed to exchange power allocation information between different cells. The algorithm would then search for the optimal distribution of power across the entire network.
5. Cooperation or Competition Between Cells: Depending on the network architecture, GA can be adapted to either coordinate the power allocation between cells (cooperative case) or have each cell independently optimize its power allocation based on local objectives and constraints (non-cooperative case). In the cooperative case, a centralized GA approach can be used where the cells exchange information to jointly optimize the system's performance. In the non-cooperative case, the GA can be used to find Nash equilibria, where each cell independently maximizes its performance given the strategies of other cells.
6. Additional Constraints: In a multi-cell system, there might be more constraints, such as the backhaul capacity, cell-specific power limits, and the quality of service requirements for users in different cells. These constraints would be incorporated into the fitness function and the genetic operators to ensure that the solutions are feasible in the context of the entire multi-cell network.

By extending GA to handle these additional factors, the power allocation problem in a multi-cell NOMA system can be effectively addressed. The flexibility of GA in handling complex, non-convex optimization problems, coupled with its ability to incorporate various network-wide constraints, makes it a promising tool for solving power allocation in multi-cell scenarios.

3.3.3 Power Allocation and GA Scheme

3.3.3.1 Power Allocation

To propose a mechanism to allocate the power to cluster members of various required data rates, first, investigate the assumption the assumption of allocating higher power to the weaker-channel state user in the cluster as well as the assumption of allocating the lower power to the stronger-channel state user is required to ensure higher EE can be achieved (Vaezi, Schober, Ding, & Poor, 2019). For simplicity, a simple scenario is considered where the mmWave has complete CSI information of all users. Thus, for a two members-cluster, the SINR of the strong-channel user (SINR_1) and the SINR of the weak-channel user (SINR_2) are given as:

$$SINR_1 = \frac{p_1 g_1^b g_1^u g_1^c}{p_2 g_1^b g_1^u g_1^c + BN_o} \tag{3.46}$$

and

$$SINR_2 = \frac{p_2 g_2^b g_2^u g_2^c}{BN_o} \tag{3.47}$$

where the SIC technique is used at the UE_2 to eliminate the interference due to the weaker-channel user UE_1.

3.3.3.2 Genetic Algorithm

The GA is one of the classical heuristic algorithms that successfully implemented to solve non-convex optimization problems (H. Wei et al., 2021). In this section, the components of the GA to solve the EE optimization problem in DL mmWave NOMA with clustering will be described.

GA is one of the evolutionary algorithms that is inspired by the biological selection process and follows similar operators. Goldberg's GA was inspired by Darwin's evolution theory, which says that an organism's survival is determined by the criterion "the strongest species survive". Based on Darwin's theory, an organism's survival can be ensured by the processes of reproduction, crossover, and mutation (Sai et al., 2020). Darwin's principle about evolution is utilized later in a computational algorithm to solve a problem called an objective function. The solution found by GA is indicated by a chromosome whereas a collection of chromosomes represents a population. A chromosome comprises genes, and the value of each chromosome can be numerical, binary, or character depending on the nature of the problem. These chromosomes pass through a series of steps starting with a fitness function process to evaluate the suitability between the solution provided by GA and the problem. Through another process called a crossover, new offspring of chromosomes are generated by mating some chromosomes in the population. The genes carried by the new offspring are a mixture of their parents (X. Sun, Yang, & Cai, 2020). On the other hand, some chromosomes in the generation will undergo gene mutation. The crossover rate and mutation rate values determine the number of chromosomes that will undergo crossover and mutation, respectively. According to Darwin's rule of evolution, the chromosome with the highest fitness value will have a larger chance of being selected again in the future generation. The chromosomal value will converge over numerous generations to a specific value which is the optimal solution for the problem (Ahn et al., 2021).

By utilizing GA to solve the problem in Equation (3.46), repetitively assigning cluster members and determining their power allocation process should be performed to determine the maximum EE. Based on the known CSI of the users at mmWave NOMA BS, the allocated power to the weaker-channel user and the allocated power to the strongest user depends on their inquired QoS to attain $C5$. To solve the non-convex optimization problem in Equation (3.46) using GA, a reformulation was conducted to achieve a minimization problem, which can be written as

$$\underbrace{\min}_{x_{m,b}} - \frac{R_{sum}}{\sum_{m\in M}\sum_{b\in B} x_{m,b}\, p_m + P_c}$$

$$subject\ to \quad C1: x_{m,b} \in \{0,1\}, \qquad \forall m \in M, \forall b \in B,$$

$$C2: \sum_{m\in M, b\in B} x_{m,b} = 1, \qquad \forall m \in M,$$

$$C3: \sum_{m\in M, b\in B} x_{m,b} = 2, \qquad \forall b \in B,$$

$$C4: \sum_{m\in M}\sum_{b\in B} x_{m,b}\, p_m \le P_{tot},$$

$$C5: SINR_m = \delta_m, \forall m \in M \tag{3.48}$$

Integer GA is utilized to determine the best cluster combination that maximizes EE. The GA process to solve the optimization problem in Equation (3.49) consists of sequential stages, that begin with a determination of the chromosome number, maximum number of generations, mutation rate, and crossover rate. Initial values of x_{mb} will be assumed then sequences of selection and mutation will be performed. The evolution starts with random individual elements $x_{m,b}$ of the generation that satisfies *C1, C2*, and *C3*. Based on *C2*, the sum of each row in the matrix X in Equation (3.32) should be equal 1, which indicates that each user is supported by only one subchannel via one cluster in the cell. On the other hand, based on *C3*, the sum of each column in X should be equal to 2 since each cluster supports 2 members. Because these are integer constraints, the linear equality constraints of the optimization problem in Equation (3.49) should be reformulated to inequality constraints. Generally, the vector form for linear inequality constraints of GA problem is given as

$$\boldsymbol{AX} \leq \boldsymbol{b} \tag{3.49}$$

For a problem of n_c linear inequality constraints and n_{vars} variables, A is a matrix of size n_c-by-n_{vars} and b is a vector of length n_c. Thus, $C2$ and $C3$ could be reformulated as

$$C2: \begin{cases} \sum_{b=1}^{B} x_{m,b} \leq 1 \\ \sum_{b=1}^{B} x_{m,b} \geq 1 \end{cases}, \qquad \forall m \in M, \tag{3.50}$$

$$and, \qquad C3: \begin{cases} \sum_{m=1}^{M} x_{m,b} \leq 2 \\ \sum_{m=1}^{M} x_{m,b} \geq 2 \end{cases}, \qquad \forall b \in B \tag{3.51}$$

Since each cluster is assumed to support 2 users ($B = \frac{M}{2}$), the number of variables n_{vars} would be $\frac{M^2}{2}$ and the number of linear inequality constraints n_c would be $3M$. It is worth mentioning that the initial population created by GA contains several individuals that lie within the preset initial range. For the concerned GA problem, all individuals should lie within the range [0; 1]. Because of the massive number of users in the real wireless system, the population size will contain thousands of potential solutions and the initial population will be randomly selected. The population size of the integer GA problem should be higher than the double GA problem to ensure a feasible solution can be obtained (Mircea, Chen-Ching, & Abdel-Aty, 2016).

These generation elements are reproduced iteratively within a maximum number of generations. Providing lower and upper bounds for all $x_{m,b}$ elements is necessary to find the best solution to the integer GA problem. Thus, the lower bound L_b and the upper bound U_b of the problem in Equation (3.49) are given by:

$$L_b = [0 \quad \dots \quad 0]_{1 \times n_c} \tag{3.52}$$

and

$$U_b = [1 \quad \dots \quad 1]_{1 \times n_c} \tag{3.53}$$

Some genes of selective individuals in the current population (parents) are passed on to the next generation (children). Usually, the selected individuals are those who have the best fitness values. The other individuals pass through crossover and mutation processes that are illustrated in Figure 3.7. Thus, the next generation is classified into three types:

- Elite children: Individuals that attain the best fitness values and therefore have a higher probability to appear in the next generation. In the concerned GA problem, the elite group is selected as the individual clustering groups $x_{m,b}$ that attain the maximum EE among the whole population. The percentage of the elite to the total individual is set to 2% to pass completely to the next generation.
- Crossover children: Individuals that are created by mixing the vectors of a pair of parents.
- Mutation children: Individuals that are created by applying random changes, or gene mutations, to individual parents to produce children. The mutation rule applies to the individual with a lower probability of attaining maximum EE.

The flowchart of the proposed GA is illustrated in Figure 3.8 where the fitness of the population units is assessed by the objective function value of the optimization problem in every generation. However, the integer genetic algorithm seeks to minimize a penalty function instead of the objective function. The penalty function adds a term for solution infeasibility to the original objective function (Deb, 2000). The penalty function consists of weighted penalty parameters to estimate the infraction of the constraints. Thus, the constrained problem is converted to a series of unconstrained problems where their solutions are converged to the potential solution of the original problem. The penalty function represents the fitness function if the candidate solution is feasible. Otherwise, the sum of the constraint violations of the (infeasible) point is added to the objective function (Deep, Singh, Kansal, & Mohan, 2009). Thus, the penalty function of the EE optimization problem in Equation (3.49) is given as:

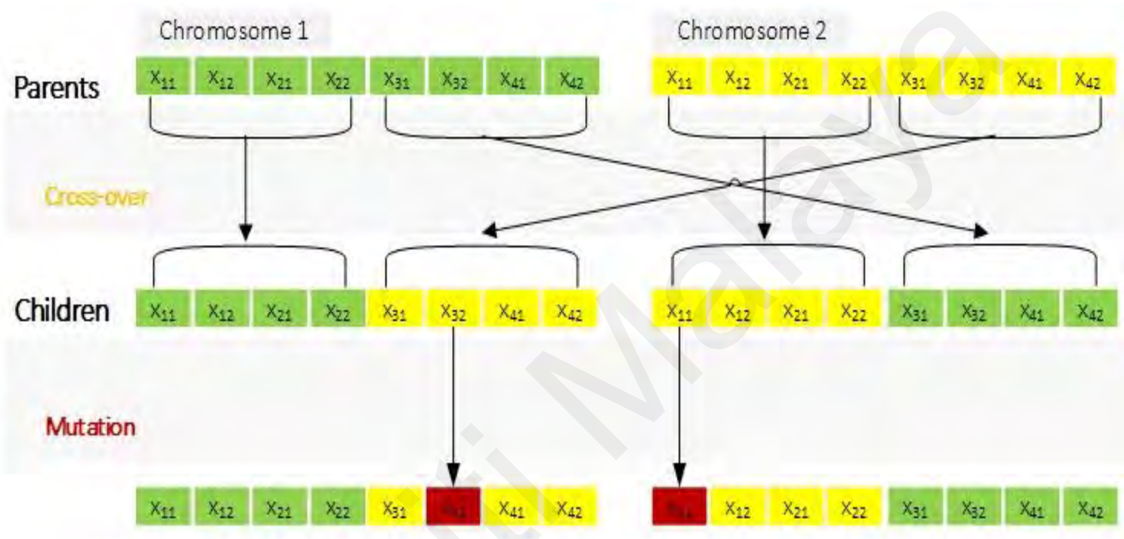

Figure 3.7: Three classifications of the next generations (children) created by GA.

$$\underbrace{\min}_{x_{m,b}} - \frac{R_{sum}}{\sum_{m\in M}\sum_{b\in B} x_{m,b}\, p_m + P_c} + \rho_k \sum_{i=1}^{2} g_i(x), \qquad (3.54)$$

where ρ_k is the penalty factor and the second term in Equation (3.55) represents the penalty function which could be represented as

$$g_1(x) = \max\left(1, \sum_{b=1}^{B} x_{m,b}\right), \quad \forall m \in M \qquad (3.55)$$

and

$$g_2(x) = \max\left(2, \sum_{m=1}^{M} x_{m,b}\right), \quad \forall b \in B \qquad (3.56)$$

Initially, the penalty factor is set to a small value and, then it is increased in the next iterations. The penalty function converges to the fitness function when the penalty function attains the constraints. Eventually, the solutions of the successive unconstrained problem will meet the solution of the original constrained problem.

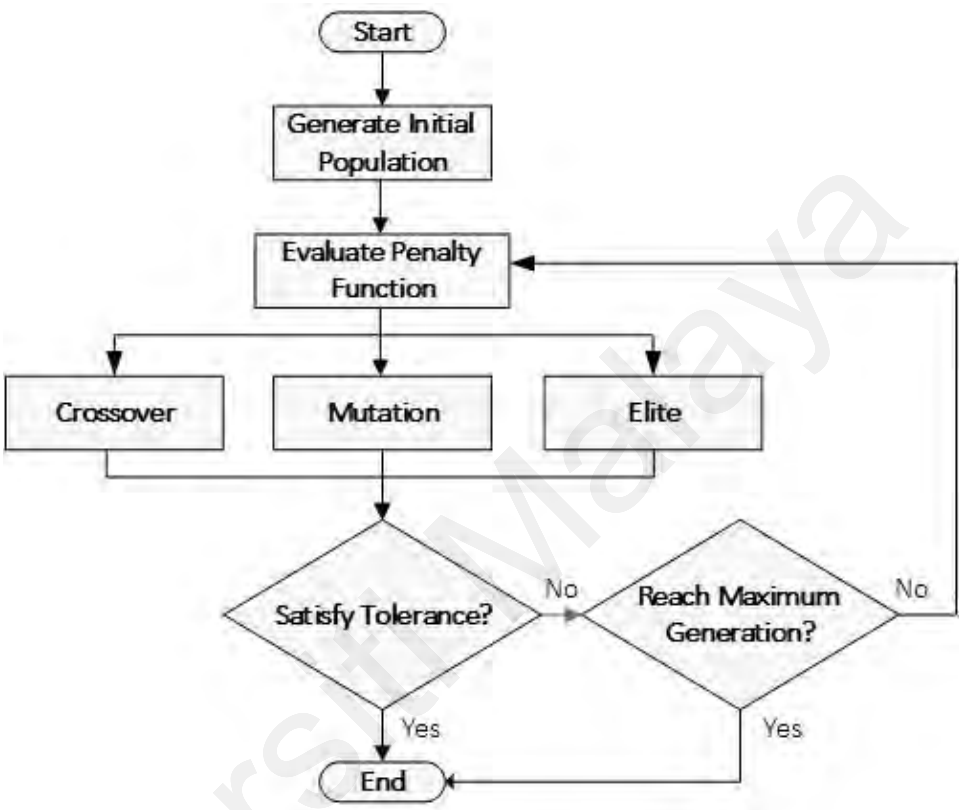

Figure 3.8: The flowchart of the proposed genetic algorithm

The computational complexity of the proposed GA-based method has been analyzed to evaluate its feasibility for real-world applications, particularly in large-scale networks. The complexity primarily depends on the population size (P), the number of generations (G), and the constraints incorporated within the fitness function evaluation. For a single iteration, the complexity is proportional to $O(P\cdot F)$ where F represents the time required to compute the fitness value for each solution. Over G generations, the total complexity becomes $O(P\cdot G\cdot F)$. In the context of the optimization problem addressed in this study, the constraints (e.g., user and cluster assignments, power allocations) increase the evaluation time due to additional penalty calculations. However, integer GA has been chosen for its ability to handle these constraints efficiently while ensuring convergence to a near-optimal solution. While the method demonstrates scalability to moderate problem sizes, further optimizations (e.g., parallel processing or hybrid techniques) can enhance its applicability to large-scale networks. Additionally, reference to the mechanism described in (Ruochen Liu, Yang, & Liu, 2021) provides insights into analyzing complexity and optimizing GA performance under large-scale scenarios. This analysis will be explored further in future work to refine the algorithm and enhance its practical deployment in real-world NOMA networks.

3.4 Multi-Stage Mechanism for Optimizing EE in Imperfect CSI DL NOMA System

The final section synthesizes the insights and techniques from previous sections into a comprehensive, multi-stage mechanism. This approach ensures iterative refinement and robust optimization of energy efficiency and data rates in complex network environments. The multi-stage methodology proposes a trade-off between EE and data rate in the imperfect CSI NOMA systems, highlighting their synergistic potential in addressing the challenges of next-generation wireless networks.

In this thesis, a multi-stage mechanism is proposed to optimize the EE under the imperfect CSI condition. In the proposed technique, game theory is utilized in the first stage to maximize the data rate, and an iterative method is incorporated in the second stage so that the EE can be optimized. Imperfect CSI at the BSs is also considered in this study and the effect of the channel estimation error on the system performance is evaluated. In this study:

- Based on the game theory, a PA algorithm that maximizes the system data rate is derived. Firstly, a user utility function based on the power cost in an imperfect CSI scenario is derived and its convexity will be proved. Next, a theoretical model of the Glicksberg game is presented to assign powers to users in the DL NOMA system under the maximum transmitted power and SINR constraints. Besides that, a mathematical proof of unique Nash and the mathematical relation between the power cost and users' number for the proposed model are also presented.

- An iterative method is utilized to find the optimal transmission power that maximizes the EE. Based on the proposed game strategy, power is allocated to the users to maximize the data rate.
- A closed-form expression for the outage probability of the user device at the cell edge is derived based on the adopted channel model.
- Finally, the performance of the proposed multi-stage algorithm is evaluated by simulation in terms of EE, average data rate, and outage probability in the case of perfect CSI and imperfect CSI.

The algorithm is referred to as multi-stage because it involves multiple iterative stages in which the PA and EE are updated step by step until a convergence criterion is met. Each "stage" corresponds to one iteration of evaluating and adjusting the power allocation for each user, followed by an assessment of the energy efficiency. The process is repeated (in stages) until the difference in energy efficiency between the upper and lower bounds becomes sufficiently small (i.e., the convergence criterion is satisfied). The following subsection describes the system model of the proposed multi-stage power allocation algorithm and the outage probability of the edge user based on the proposed algorithm.

3.4.1 System Model

A DL multi-cell NOMA system consisting of K cells is considered. In the NOMA system, one carrier has been dedicated to every cell $k = \{1, 2, , \dots, K\}$ that is equipped with a central BS to provide service to M user equipment (UEs), where $m = \{1, 2, , \dots, M\}$. The BS and each user device are assumed to be equipped with a single antenna. Every BS serves numerous users at the same time with the same carrier by utilizing superposition coding techniques. The channel gain from the BS k to the user m is given by $h_{m,k} = g_{m,k} d_{m,k}^{-\delta/2}$, where $g_{m,k} \sim CN(0,1)$ is a Rayleigh fading factor, $d_{m,k}$ denotes the distance from each UE$_{(m)}$ to the BS$_{(k)}$, and δ refers to the path loss exponent (Zamani et al., 2019). Here, a NOMA system with imperfect CSI is considered, in which the channel estimation is given by $h_{m,k} = \hat{h}_{m,k} + \varepsilon$, where $\varepsilon \sim CN(0, \sigma_{\varepsilon}^2)$ is the error of the channel estimation with variance σ_{ε}^2, and $\hat{h}_{m,k}$ is the estimated channel gain $\hat{h}_{m,k} \sim CN(0, \sigma_{\hat{h}_{m,k}}^2)$ which is uncorrelated with ε (Zamani et al., 2019). The system architecture is illustrated in Figure 3.9.

In the DL NOMA system, the user devices within every cell are ordered according to their channels' strength $(|h_M| \geq |h_{M-1}| \geq \dots \geq |h_2| \geq |h_1|)$ for perfect CSI and imperfect CSI cases (Z. Ding et al., 2017). Thus, SIC technique could be utilized to extract a specific signal from the superposed signals on a single carrier. The strongest user device associated with the k BS is denoted as UE$_{M,k}$ while the weakest user device is indicated as UE$_{1,k}$. The BS k transmits M different messages on the same carrier within the same bandwidth. On the receiver side, each user receives a composition of its message with inter-cell interference from the signals of other users associated with the same BS (M. S. Ali et al., 2016).

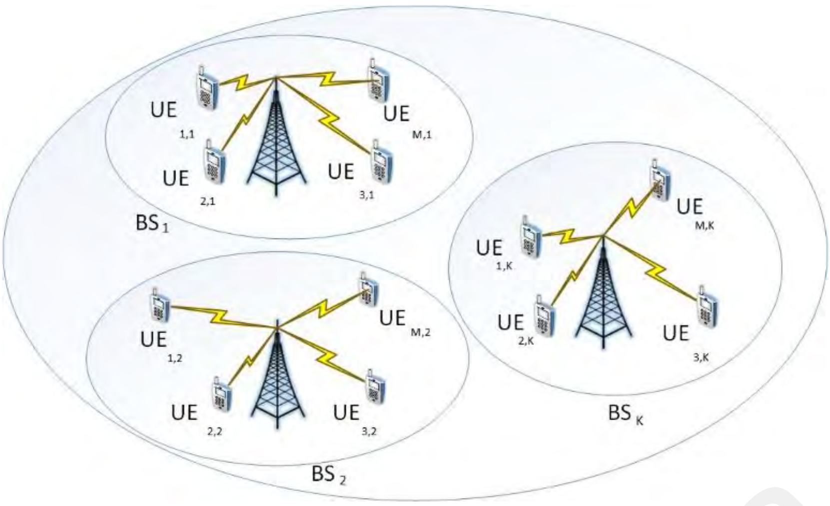

Figure 3.9: The multi-cell DL NOMA system.

It is worth noting that the BS is assumed to have a full CSI knowledge of all user devices (Khan, Yu, Yu, Sidhu, & Liu, 2019). However, because of the channel estimation error and the quantization error, these CSIs might be imperfect (Zamani et al., 2019). Moreover, imperfect SIC could happen due to an error in the SIC procedure where the users of stronger channels imperfectly eliminate the interference that results from the weaker users' signal. This remaining interference degrades the system's performance (Saetan & Thipchaksurat, 2019). To facilitate the performance analysis, this study focuses on the effect of the imperfect CSI while the influence of imperfect SIC is beyond the scope of this thesis. The analytical framing of this study could be expanded in future work to study the impact of both imperfect SIC and imperfect CSI in a straightforward manner where the imperfect SIC changes the system model by adding one independent noise part (Y. Sun, Ding, Dai, & Dobre, 2019).

In general, the signal at the receiving terminal m in cell k before applying the SIC technique is given by (Khan, Li, Zeng, & Dobre, 2021; Zamani et al., 2019)

$$y_{m,k}(t) = \hat{h}_{m,k}\sqrt{\alpha_{m,k}P_k}x_{m,k}(t) + \hat{h}_{m,k}\sum_{\substack{j=1\\j\neq m}}^{M}\sqrt{\alpha_{j,k}P_k}x_{j,k}(t)$$
$$+ \varepsilon\sum_{j=1}^{M}\sqrt{\alpha_{j,k}P_k}x_{j,k}(t) + w_m, \qquad (3.57)$$

where in Equation (3.58), the dedicated signal for a user device m in cell k is represented by the first term, while the second term represents the inter-cell interference due to the decomposed signals on the same carrier of other devices within cell *k*. The third term in Equation (3.58) represents the interference due to the error in the channel estimation, and w_m is the AWGN at the m-th user with zero mean and density and variance σ^2. P_k is the total power of the k-th BS, $x_{m,k}$ refers to the individual OFDM signal, and $\alpha_{m,k}$ represents the assigned power coefficient of $\mathrm{UE}_{m,k}$, which satisfies:

$$\sum_{m=1}^{M}\alpha_{m,k} \leq 1. \qquad (3.58)$$

In general, the received signal at the user device terminal after performing the SIC technique is given as:

$$y_{m,k}(t) = \hat{h}_{m,k}\sqrt{\alpha_{m,k}P_k}x_{m,k}(t) + \hat{h}_{m,k}\sum_{j=m+1}^{M}\sqrt{\alpha_{j,k}P_k}x_{j,k}(t)$$
$$+ \varepsilon\sum_{j=1}^{M}\sqrt{\alpha_{j,k}P_k}x_{j,k}(t) + w_m, \qquad (3.59$$

Consider the case where the allocated power to the m-th UE in the k-th cell is $P_{m,k} = \alpha_{m,k}P_k$. Then the *SINR* at $\mathrm{UE}_{m,k}$ in the NOMA system when CSI is imperfect can be derived as:

$$SINR_{m,k} = \frac{P_m|\hat{h}_m|^2}{|\hat{h}_{m,k}|^2\ \sum_{j=m+1}^{M}P_{j,k} + \sigma_\epsilon^2\sum_{j=1}^{M}P_{j,k} + \sigma^2}, \qquad (3.60)$$

where the noise due to all undesired signals from the stronger channel users is represented by the first term in the denominator, and the second term represents the inter-cell interference resulting from the composed messages due to the error in the channel estimation. Based on the SIC process, $SINR_{M,k}$ will be relatively high despite its low allocated power since no inter-cell interference will influence it. On the other hand, the highest power level should be assigned to the weakest device to compensate for the inter-cell interference and maintain the required $SINR_{1,k}$. However, the presence of channel estimation errors adversely impacts the *SINR* for all users, leading to a reduction in both individual and overall achieved data rates within the cell.

The throughput of $UE_{m,k}$ in the case of imperfect CSI NOMA of this thesis case can be written as

$$\boldsymbol{R_{m,k}}^{\boldsymbol{NOMA}} = \mathbf{log_2}\left[\mathbf{1} + \frac{\boldsymbol{P_m}|\widehat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^{\mathbf{2}}}{|\widehat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^{\mathbf{2}}\ \sum_{\boldsymbol{j=m+1}}^{\boldsymbol{M}} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma_\epsilon^2} \sum_{\boldsymbol{j=1}}^{\boldsymbol{M}} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma^2}}\right], \tag{3.61}$$

TDMA is commonly used to compare the performance of NOMA to OMA (Y. Wu, Zhang, & Rong, 2020; L. Zhu, Z. Xiao, X. Xia, & D. O. Wu, 2019). Hence, to evaluate the proposed mechanism, TDMA is adopted here where the total BS power is assigned to an individual user during its block time. Thus, the data rate of m-th user in the downlink OMA cellular system with a central BS serving *M* users on a single carrier per each 1 Hz spectrum for the imperfect CSI case is given by:

$$\boldsymbol{R_{m,k}}^{\boldsymbol{OMA}} = \frac{\mathbf{1}}{\boldsymbol{M}}\mathbf{log_2}\left[\mathbf{1} + \frac{\boldsymbol{P_m}|\widehat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^{\mathbf{2}}}{\boldsymbol{\sigma_\epsilon^2}\boldsymbol{P_k} + \boldsymbol{\sigma^2}}\right]. \tag{3.62}$$

On the other hand, the sum data rate, R_{sum} of DL NOMA system with *K* cells where every central BS serving *M* users on a single carrier per each 1 Hz spectrum in imperfect CSI case can be expressed as:

$$\boldsymbol{R_{sum}}^{\boldsymbol{NOMA}} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}}\sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \mathbf{log_2}\left[\mathbf{1} + \frac{\boldsymbol{P_m}|\widehat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^{\mathbf{2}}}{|\widehat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^{\mathbf{2}}\ \sum_{\boldsymbol{j=m+1}}^{\boldsymbol{M}} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma_\epsilon^2} \sum_{\boldsymbol{j=1}}^{\boldsymbol{M}} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma^2}}\right], \tag{3.63}$$

The importance of EE as a performance metric lies in its ability to optimize resource utilization, minimize energy consumption, and promote the sustainability of the system. Energy efficiency is defined as the ratio of the total network throughput to the total consumed power (Luong et al., 2018), and it is expressed as

$$EE = \frac{R_{sum}}{P_t + P_c}$$

$$= \frac{\sum_{k=1}^{K} \sum_{m=1}^{M} \log_2 \left[1 + \frac{P_m |\hat{h}_{m,k}|^2}{|\hat{h}_{m,k}|^2 \sum_{j=m+1}^{M} P_{j,k} + \sigma_\epsilon^2 \sum_{j=1}^{M} P_{j,k} + \sigma^2} \right]}{\sum_{k=1}^{K} \sum_{j=1}^{M} P_{j,k} + P_t}, \quad (3.64)$$

where P_c represents the fixed transmitter circuit dissipation power (Zeng, Hao, Dobre, & Poor, 2019). This thesis focuses on maximizing the EE of DL NOMA systems within limited total power consumption subject to the QoS requirements. Utilizing power allocation plays a key role in optimizing the total EE in wireless systems. Hence, to extract the desired signals at the receivers using SIC, the assigned power to the user devices should be based on their channel's strength (M. S. Ali et al., 2016). Thus, the EE optimization problem could be formulated as:

$$\max_{P_{m,k}} \quad EE = \frac{R_{sum}}{P_t + P_c}$$

$$subject\ to \sum_{m=1}^{M} P_{m,k} \le P_k \quad \forall k \in K$$

$$P_{m,k} \ge P_{m+1,k} \ge 0, \quad \forall k \in K$$

$$SINR_{m,k} \ge \zeta, \ \forall m \in M \quad (3.65)$$

where ζ is the *SINR* threshold value that ensures the minimum required data rate for all users (H. Zhang, Wang, et al., 2018). The number of users and their assigned powers must be determined carefully to verify the minimum boundary of the constraints. Moreover, variations in the levels of the assigned power must be verified to ensure that each UE is capable of performing SIC and extracting its signal (M. S. Ali et al., 2016). In this study, a multi-stage mechanism based on the game theory and PA is proposed to solve the EE optimization problem in Equation (3.66).

The QoS in your study is represented by ensuring that the required minimum SINR is achieved for each user, but it is treated as a constraint within the power allocation optimization problem, rather than being explicitly calculated. The algorithm ensures that the power allocation adheres to the minimum SINR requirement through constraints, which govern how the power is distributed among users to meet this threshold, thereby ensuring the desired QoS. This constraint is incorporated into the problem formulation and is not computed directly as a separate process.

3.4.2 Multi-Stage Power Allocation Algorithm

Game theory provides a robust tool for modeling discrepancies between communication system members such as BS and user devices. Every user requires high power to increase its data rate. On the other hand, the BS, which represents the communication utility, aims to minimize the consumed power and to provide all users with minimum QoS at the same time. In game theory, each player seeks to maximize his payoffs, where the benefit of each player relies on his playing strategy as well as other players' strategies. The result of the game represents a solution in which all players have no motive to change their actions to gain more benefit. This stable state where all the participants are in approval is known as Nash Equilibrium. In general, the strategic game involves a group of players (the users and the BS), strategies, and the declared benefit functions (utility functions) for every adopted action by the game player. In a non-cooperative game, such as the Glicksberg game, each user aims to increase his benefit, in terms of data rate, by requesting higher allocated power. The BS sets the power price to restrict the demanded power and to create a balance (Mohammadi, Mashhadi, & Shahidehpour, 2019). All players in this case, the users, use the game theory to decide intelligently how to achieve as maximum as possible benefits while maintaining the required quality of service at a minimum data rate level. Non-cooperative games, such as the Glicksberg game (J. Huang et al., 2018) and the Stackelberg game (Q. Wang, Wang, Jin, Zhu, & Zhang, 2015), have been utilized to solve data rate and EE optimization problems in 5G. Based on the Glicksberg-Fan fixed point theorem (Van Hung & Keller, 2021) , if a game consists of a delimited number of players where the space of the playing strategy of each player is not empty, is limited convex set in the Euclidian space and the utility function of each player is quasi-concave in its strategy space, then the game is expected to have at minimum one pure strategy Nash equilibrium.

Equation (3.61) shows that a larger $P_{m,k}$ results in a higher $SINR_{m,k}$ for the m-th user in the k-th cell. However, this increase leads to higher interference to other users. Thus, the relationship among the users at the time of allocating their powers could be described as a game. In this Glicksberg game, the user devices represent the game players, and the allocated power represents each player's action. By definition, let $G = (M, \{P_{m,k}\}, \{U_{m,k}\})$ a PA game in which $m = \{1, 2, \ldots, M\}$ represents the index of user devices in the cell $k = \{1, 2, \ldots, K\}, \{P_{m,k}\}$ represents the strategy set, and $U_{m,k}$ refers to the utility function. Up to a certain level of transmission power, maximizing the total data rate refers to the maximum EE that can be achieved at this level (Zamani et al., 2019). Maximizing the sum data rate is obtained when every user's data rate is maximized. Thus, the proposed approach will be to design a game to determine the power that maximizes the throughput. The utility function $U_{m,k}$ of each user device in every cell can be derived as:

$$U_m = \frac{P_{m,k}^2}{SINR_{m,k}} - B^{P_{m,k}}$$

$$= \frac{\boldsymbol{P_{m,k}}}{|\boldsymbol{h_{m,k}}|^2}\left(|\boldsymbol{h_{m,k}}|^2 \sum_{j=m+1}^{M} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma_\epsilon^2} \sum_{j=1}^{M} \boldsymbol{P_{j,k}} + \boldsymbol{\sigma^2}\right) - \boldsymbol{B^{P_{m,k}}}, \qquad (3.66)$$

where B represents the cost charged by the BS for the assigned power $P_{m,k}$. The first term $\frac{P_{m,k}^2}{SINR_{m,k}}$ represents the utility gained by the m-th user based on its power allocation $P_{m,k}$ and the SINR. The SINR measures the quality of the received signal, accounting for both the desired signal power and interference. The squared term in the numerator implies that higher power allocation increases the utility, but the SINR denominator ensures diminishing returns as power allocation grows due to increasing interference. The second term $B^{P_{m,k}}$ models the cost of allocating power to the user. This term penalizes the system for increasing the power, thus discouraging excessive power allocation. The function $B^{P_{m,k}}$ could be an increasing function of $P_{m,k}$ representing the price or cost associated with allocating more power to the user. This encourages efficient power distribution across users. The first term of the utility function encourages maximizing the SINR, which translates to better signal quality for the user. The second term penalizes excessive power allocation, helping prevent inefficiency and ensuring that power resources are not wasted. The utility function reflects a balance between maximizing user performance (through high SINR and power) and minimizing the associated cost of power usage. The utility function describes the player's reactions in playing. An increase in the assigned power to any device certainly enhances its *SINR*.

However, more interference will be seen by other users of a higher order (Z. Wang et al., 2018) where a greater power level is required to achieve the threshold *SINR*. Thus, $U_{m,k}$ in Equation (3.67) illustrates the utility function's conditions; where *SINR* represents the user's benefit while the price, $B^{P_{m,k}}$ represents a detriment resulting from the increment in the assigned power to $UE_{m,k}$. The rise in $P_{m,k}$ leads to a rise in $U_{m,k}$ until it reaches a peak value, and then it will start to decrease due to the negative effect of the price. Thus, the relation between the proposed utility function and $P_{m,k}$ is a convex function.

Firstly, the proposed utility function has proved to be effective. Then, a complete theoretic game mechanism to allocate the power is presented and the existence of the equilibrium is investigated.

Lemma 1. *The proposed $U_{m,k}$ in Equation* (3.67) *is effective and restrictive.*

Proof. The effectiveness of $U_{m,k}$ is achieved if a rise in the assigned power to $UE_{m,k}$ leads to an increase in the $U_{m,k}$ value. Besides, the utility function's restrictiveness is achieved when the assigned power beyond a specific threshold degrades the utility value (J. Huang et al., 2018). In other words, restrictiveness guarantees a limited level of the allocated power to every player, depending on the adopted game strategy. Therefore, its influence on other users can be controlled. The utility function is considered effective and restrictive if it satisfies the following condition:

$$\frac{\partial^2 U_{m,k}}{\partial P_{m,k}^2} < 0 \tag{3.67}$$

It can be seen that, Equation (3.67) fulfills the condition in Equation (3.68) if and only if $\sum_{i=1}^{M} P_{i,k} = P_k$, where:

$$\frac{\partial^2 U_{m,k}}{\partial P_{m,k}^2} = -B^{P_{m,k}}(lnB)^2 < 0 \tag{3.68}$$

Thus, the proposed $U_{m,k}$ is considered as a well-designed utility function. Moreover, the channel estimation error term does not affect the effectiveness and restrictiveness of the proposed $U_{m,k}$.

Glicksberg game is proposed for solving the optimization problem in Equation (3.66), where the leader in this game is the user with the strongest channel. This leader takes the first action in the game by choosing his minimum required *SINR*. The total transmission power and the required $SINR_{M,k}$ will determine the power cost and the number of users covered by service in the cell. Then, all players set their power level that maximizes $U_{m,k}$.

Next, the existence of the Nash equilibrium for the proposed algorithm will be proved (Vamvakas, Tsiropoulou, & Papavassiliou, 2019).

Theorem 1. *Nash equilibrium satisfies the proposed game theoretic power allocation.*

Proof: The assigned power to every user for the proposed game model is predefined as $P_{i,k} \geq 0$. For the DL system, the strategy space is nonempty, compact, and convex. Moreover, $U_{m,k}$ in Equation (3.67) is continuous and Equation (3.68) is verified for every link between BS and the user. Therefore, $U_{m,k}$ is a quasi-concave function depending on $P_{m,k}$. Every BS-transmitted power predefines the assigned power to all user devices within the cell ($\sum_{i=1}^{M} P_{i,k} = P_k$). Thus, the number of user devices will be limited due to the finite system resources.

This completes the proof.

Theorem 2. *If* $\left|\frac{\partial^2 U_{,km}}{\partial P_{m,k}^2}\right| \geq \sum_{i \neq j}^{M} \left|\frac{\partial^2 U_{m,k}}{\partial P_{i,k} \partial P_{j,k}}\right|$ *for any user who is involved in the proposed game model, the Nash equilibrium is unique.*

Proof: The result of the following first derivative Equation gives the best user response:

$$\frac{\partial^2 \boldsymbol{U}_{\boldsymbol{m,k}}}{\partial \boldsymbol{P}_{\boldsymbol{m,k}}^2} = \mathbf{0} \tag{3.69}$$

Hence, the optimal allocated power that maximizes $U_{m,k}$ in DL NOMA cellular system in the case of imperfect CSI is given by:

$$\boldsymbol{P}_{\boldsymbol{m,k}}^{*} = \frac{\mathbf{1}}{\boldsymbol{lnB}} \boldsymbol{ln} \left(\frac{\left|\boldsymbol{h}_{\boldsymbol{m,k}}\right|^2 \sum_{i=m+1}^{M} \boldsymbol{P}_{\boldsymbol{i,k}} + \boldsymbol{\sigma}_{\epsilon}^2 \sum_{j=1}^{M} \boldsymbol{P}_{\boldsymbol{j,k}} + \boldsymbol{\sigma}^2}{\left|\boldsymbol{h}_{\boldsymbol{m,k}}\right|^2 \boldsymbol{lnB}} \right). \tag{3.70}$$

Equation (3.71) shows that higher allocated power is required to obtain the same value of data rate compared to the perfect CSI case where $\sigma_{\varepsilon}^{2} = 0$. This is due to the effect of the inaccurate channel estimation value. Based on the given $U_{m,k}$,

$$\left|\frac{\partial^2 U_{m,k}}{\partial P_{i,k}\partial P_{j,k}}\right| = \begin{cases} -B^{P_{m,k}}(lnB)^2 & m = n \\ 1 & m > n \\ 0 & m < n \end{cases} \tag{3.71}$$

Based on Equation (3.72), the Hessian matrix is formulated as:

$$H = \begin{bmatrix} -B^{P_{1,k}}(lnB)^2 & 1 & \cdots & 1 \\ 0 & \ddots & 1 & 1 \\ \vdots & 0 & -B^{P_{M-1,k}}(lnB)^2 & 1 \\ 0 & \cdots & 0 & -B^{P_{M,k}}(lnB)^2 \end{bmatrix} \tag{3.72}$$

To ensure that the Nash equilibrium is unique, the response function should be contractive. Therefore,

$$\left|\frac{\partial^2 U_{,km}}{\partial P_{m,k}^2}\right| \geq \sum_{i\neq j}^{M} \left|\frac{\partial^2 U_{m,k}}{\partial P_{i,k}\partial P_{j,k}}\right|. \tag{3.73}$$

From Equation (3.74):

$$B^{P_{m,k}}(lnB)^2 \geq M - m \tag{3.74}$$

$$B^{P_{M,k}}(lnB)^2 \geq 0 \xrightarrow{yields} \begin{cases} B > 1 \\ P_{M,k} \geq 0 \end{cases} \tag{3.75}$$

It can be seen that Equation (3.75) matches the SIC requirements while Equation (3.76) illustrates the detriment of the $U_{m,k}$. Determining B is an essential stage in the PA algorithm. The strongest player, denoted by $UE_{M,k}$, has the top priority in the game and therefore its allocated power is set to meet the required *SINR*. Then the price B is determined once power has been assigned to $UE_{M,k}$. The total transmission power at the BS is allocated to the users to obtain the maximum data rate. Subsequently,

$$P_{M,k} + \sum_{i=1}^{M-1} P_{i,k} \leq P_t \tag{3.76}$$

Substituting Equation (3.75) into Equation (3.77),

$$P_{M,k} + \sum_{i=1}^{M-1} \frac{ln\left(\frac{M-i}{(lnB)^2}\right)}{lnB} = P_k. \tag{3.77}$$

Equation (3.78) could be expressed as

$$\boldsymbol{P_{M,k}} + \frac{\boldsymbol{ln(M-1)! - 2(M-1)ln(lnB)}}{\boldsymbol{lnB}} = \boldsymbol{P_k}. \tag{3.78}$$

The relationship between the cost and the number of user devices covered by the BS service and the BS power is apparent in Equation (3.79). First, M and B are predefined and the minimum assigned power to every UE in the cell is calculated by using Equation (3.75). Subsequently, the optimal power that maximizes $U_{m,k}$ could be determined based on Equation (3.71).

From Equation (3.79), all the allowable transmission power at the BS will be consumed to achieve the maximum data rate at the cell. However, maximizing the data rate does not ensure maximizing the EE at all transmission power levels. At high transmission power, EE tends to decrease rapidly although the data rate is high (Ihsan et al., 2022). In other words, providing a user with a high data rate exceeding its requirement will drain the system resources while a noteworthy data rate increment is required to attain the required QoS. Therefore, the second stage of the proposed multi-stage mechanism pursues a lower total transmission power that maximizes the EE while achieving the maximum data rate as well as meeting the minimum required SINR constraint.

A summary of the proposed algorithm is presented in Algorithm 2, where the false position method is utilized to evaluate the minimum transmission power to attain the maximum EE where the allocated power to all users is determined based on the proposed game theory. Comparing the False-position method to the other closed interval methods such as the bisection method, reveals several benefits. Its propensity to converge more quickly in many situations is a major benefit. The false-position approach uses linear interpolation based on the function values at the endpoints to improve the interval. In contrast, the bisection technique cuts the distance in half with each iteration. For non-linear functions, this often results in a more direct approach to finding the solution.

To solve the non-convex optimization problem in Equation (3.66) using the false position method, a reformulation was conducted to achieve a minimization problem, which can be written as:

$$\min_{P_{m,k}} \quad EE_{P_{kl}} - EE_{P_{ku}}$$

$$subject\ to \sum_{m=1}^{M} P_{m,k} \leq P_k \quad \forall k \in K$$

$$P_{m,k} \geq P_{m+1,k} \geq 0, \quad \forall k \in K$$

$$\boldsymbol{SINR_{m,k} \geq \zeta}, \ \forall \boldsymbol{m} \in \boldsymbol{M} \tag{3.79}$$

where P_{ku} is the total allowable transmission power and P_{kl} is the lower transmission power at the BS. To increase the EE, the total transmission power should be decreased. Thus, based on the false position method, the total transmission power in the next iteration, P_{kr} is determined as:

$$\boldsymbol{P_{kr} = P_{ku} \frac{EE_{P_u}(P_{kl} - P_{ku})}{EE_{P_{kl}} - EE_{P_{ku}}}} \tag{3.80}$$

$SINR_{M,k}$ is assigned initially in the process, so it does not change for the user with strongest channel condition within the next steps. The algorithm confirms that it is not stuck at a local maximum by leveraging the global search capability of the game-theoretic framework. The convergence to a Nash equilibrium, as guaranteed in the formulation, implies that the EE metric is optimized across all users, given the constraints and conditions of the system. This equilibrium inherently avoids local maxima by ensuring that no individual user can unilaterally improve their utility. To address the possibility of infinite iterations, a predefined convergence threshold (Δ) is used. The algorithm stops when the change in energy efficiency $|EE_{P_{kl}} - EE_{P_{ku}}|$ falls below Δ, which is a small, positive value chosen to balance computational complexity and accuracy. This ensures that the iterations terminate after a finite number of steps while achieving a sufficiently high EE. Furthermore, practical constraints such as a maximum iteration count or a timeout can be imposed to safeguard against excessive runtime in edge cases.

Algorithm 2: Multi-stage game-theoretic power allocation algorithm for maximizing EE and data rate in imperfect CSI DL NOMA system

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Require: P_c, $SINR_{M,k}$,
Ensure: $P_{ku} = P_k$, $P_{kl} = 0$,
$EE_{kl} \Leftarrow 0$,
Determine B based on Equation (3.79),
$m \Leftarrow M$,
while m $\neq$ 0 do,
Evaluate P_m, $\forall m \in$ M based ((Equation (3.61))
$m \Leftarrow m - 1$,
end while
Evaluate EE_{ku} based on Equation (3.65),
while $|EE_{ku} - EE_{kl}| \geq \triangle$ do
P_{kr} based on Equation (3.65),
if $EE_{ku} \geq EE_{kl}$ then
$EE_{max} \leftarrow EE_{ku}$,
Pkl $\Leftarrow$ Pkr ,
Determine B based on Equation (3.79),
$m \Leftarrow$ M
while m $\neq$ 0 do
Evaluate P_m, $\forall m \in$ M (Equation (3.61))
$m \Leftarrow m - 1$
end while
Evaluate EE_{kl} based on Equation (3.65),
else
$EE_{max} \leftarrow EE_{kl}$,
$P_{ku} \Leftarrow P_{kr}$,
Determine B based on Equation (3.79),
$m \Leftarrow$ M
while $m \neq 0$ do
Evaluate P_m, $\forall m \in$ M (Equation (3.61))
$m \Leftarrow m - 1$
end while
Evaluate EE_{ku} based on Equation (3.65),
end if
end while

3.4.3 Algorithm Convergence Analysis

The convergence of the proposed multi-stage algorithm is ensured by the properties of both the Glicksberg game (for power allocation) and the false position method (for EE optimization). The convergence of the game-theoretic power allocation is guaranteed by the Glicksberg-Fan fixed point theorem. The utility function used in the proposed algorithm satisfies the properties listed in the theorem. Besides that, the existence of a Nash equilibrium has been proven. Therefore, the PA stage of the algorithm converges to a stable PA strategy, ensuring that no user can improve their utility by unilaterally altering their strategy. The false position method for energy efficiency optimization converges based on the property that each iteration reduces the error between an upper and a lower bounds of the energy efficiency, based on linear interpolation. In terms of the termination condition: The algorithm continues to iterate until the difference between the EE in successive iterations is below a predetermined threshold, Δ. This ensures that the algorithm terminates once a sufficiently accurate solution is reached. Therefore, the combination of these two methods ensures that the proposed multi-stage algorithm converges to an optimal solution, balancing EE and data rate in the NOMA system.

3.4.4 Outage Probability Analysis

Outage probability can be used to evaluate the performance in DL NOMA systems where it is defined as the probability that the *SINR* at $UE_{m,k}$ is at a lower level than a threshold level, ζ (Arzykulov et al., 2019). The outage probability at the m-th user in imperfect CSI DL NOMA k-th cell could be given as

$$P_{out}^{m,k} = Pr\left[SINR_{m,k} \leq \zeta\right]$$

$$= Pr\left[\frac{P_{m,k}|\hat{h}_{m,k}|^2}{|\hat{h}_{m,k}|^2 \ \sum_{i=m+1}^{M} P_{i,k} + \sigma_\epsilon^2 \sum_{i=1}^{M} P_{i,k} + \sigma^2} \leq \zeta\right]$$

$$= \boldsymbol{Pr}\left[|\hat{\boldsymbol{h}}_{\boldsymbol{m,k}}|^2 \leq \boldsymbol{\xi}_{\boldsymbol{m,k}}\right], \tag{3.81}$$

where $\xi_{m,k}$ is

$$\boldsymbol{\xi}_{\boldsymbol{m,k}} = \boldsymbol{\zeta} \frac{\boldsymbol{\sigma}_\epsilon^2 \sum_{i=1}^{M} \boldsymbol{P}_{\boldsymbol{i,k}} + \boldsymbol{\sigma}^2}{\boldsymbol{P}_{\boldsymbol{m,k}} - \boldsymbol{\zeta} \sum_{j=m+1}^{M} \boldsymbol{P}_{\boldsymbol{j,k}}} \tag{3.82}$$

A conditional probability expression can be derived by first substituting Equation (3.71) in Equation (3.75):

$$B^{\frac{1}{lnB}ln\left(\frac{|\hat{h}_{m,k}|^2 \sum_{i=m+1}^{M} P_{i,k}+\sigma_\epsilon^2 \sum_{j=1}^{M} P_{j,k}+\sigma^2}{|h_{m,k}|^2 lnB}\right)} \geq \frac{M-m}{(lnB)^2} \tag{3.83}$$

From Equation (3.84), the random variable $|\hat{h}_{m,k}|^2$ is limited to

$$|\hat{h}_{m,k}|^2 \geq \frac{\sigma_\epsilon^2 \sum_{i=1}^{M} P_{i,k} + \sigma^2}{\zeta \sum_{j=m+1}^{M} P_{j,k} - \psi_{m,k}} \tag{3.84}$$

where $\psi_{m,k} = \ln\left(\frac{M-m}{(\ln B)^2}\right)$. Hence, the outage probability in Equation (3.82) could be re-written as

$$P_{out}^{m,k} = Pr\left[|\hat{h}_{m,k}|^2 \leq \xi_{m,k} \backslash |\hat{h}_{m,k}|^2 \geq \varphi_{m,k}\right], \tag{3.85}$$

where

$$\varphi_{m,k} = \frac{\sigma_\epsilon^2 \sum_{i=1}^{M} P_{i,k} + \sigma^2}{\zeta \sum_{j=m+1}^{M} P_{j,k} - \psi_{m,k}}, \tag{3.86}$$

and the channel gain $|\hat{h}_{m,k}|^2$ follows an exponential distribution with unity mean and unity variance (Arzykulov et al., 2019). Thus, the outage probability in Equation (3.86) could be expressed as

$$P_{out}^{m,k} = \frac{Pr\left[|\hat{h}_{m,k}|^2 \leq \xi_{m,k} \cap |\hat{h}_{m,k}|^2 \geq \varphi_{m,k}\right]}{Pr\left[|\hat{h}_{m,k}|^2 \geq \varphi_{m,k}\right]}$$

$$= \begin{cases} \frac{Pr\left[|\hat{h}_{m,k}|^2 \leq \xi_{m,k} \cap |\hat{h}_{m,k}|^2 \geq \varphi_{m,k}\right]}{Pr\left[|\hat{h}_{m,k}|^2 \geq \varphi_{m,k}\right]} & \varphi_{m,k} \leq \xi_{m,k} \\ 0 & \varphi_{m,k} > \xi_{m,k} \end{cases}$$

$$= \begin{cases} \frac{e^{-\varphi_{m,k}} - e^{-\xi_{m,k}}}{e^{-\varphi_{m,k}}} & \varphi_{m,k} \leq \xi_{m,k} \\ 0 & \varphi_{m,k} > \xi_{m,k} \end{cases} \tag{3.87}$$

The outage probability analysis concludes that the probability of outage in a DL NOMA system is determined by the interplay between the channel gain, power allocation, and the SINR threshold. The derived expressions show that the outage probability depends on whether the channel gain satisfies specific bounds ($\varphi_{m,k}$) and ($\xi_{m,k}$), which are functions of system parameters like power levels, noise variance, and the SINR threshold. The final outage probability formula illustrates that an outage occurs when the effective channel gain is confined within a specific range ($\varphi_{m,k} \leq \left|\hat{h}_{m,k}\right|^2 \leq \xi_{m,k}$), if $\varphi_{m,k} > \xi_{m,k}$, the outage probability is zero, indicating no overlap between the feasible and required channel conditions. Conversely, when $\varphi_{m,k} \leq \xi_{m,k}$, the outage probability depends on the exponential distribution of the channel gain and is proportional to the difference between ($\varphi_{m,k}$) and ($\xi_{m,k}$). This analysis highlights the trade-offs in power allocation and channel estimation errors under imperfect CSI. It also quantifies the conditions under which a user experiences insufficient SINR, providing insight into system reliability and performance limits.

CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents and discusses the results of four proposed power allocation techniques in optimizing the data rate and optimizing the EE for the DL NOMA system for both perfect CSI and imperfect CSI cases. The results from extensive simulation of the proposed PA techniques under various scenarios are presented. The results of the proposed methods are presented and comprehensively discussed with various performance parameter metrics such as data rate, EE, and outage probability. Furthermore, a critical analysis of the acquired results of the proposed PA algorithms is also presented in the following subsections.

4.1 Game-theoretic Power Allocation Algorithm for DL NOMA System

In this section, different scenarios are simulated by Matlab to evaluate the proposed game-theoretic power allocation algorithm and compare the results to the existing algorithms in (Lamba et al., 2019; Z. Wang et al., 2018). The accomplished sum rate in bps/Hz is measured when applying the game-theoretic power allocation algorithm on M users distributed randomly in a cell with channel gains between the BS and the users are modeled as $h_m \sim CN(0, \delta_m^2)$, $m \in M.$ First, the mechanism is performed on 2 users with channel gains of variances $\delta_1^2 = 0.5, \delta_2^2 = 1$. Secondly, the mechanism is testified on 5 users with channel gains of variance $\delta_1^2 = 0.2, \delta_2^2 = 0.4, \delta_3^2 = 0.6, \delta_4^2 = 0.8,$ and $\delta_5^2 = 1$. In both cases, the results are collected at different levels of transmission power $\frac{P_t}{\sigma^2}$ up to 30 dBm and the results are taken as an average of 1000 run trials in (Lamba et al., 2019; Z. Wang et al., 2018). The assumed *SINR* of the team leader in the game is 1.5.

The results in Figure 4.1 illustrate that the cell's sum rate will increase proportionally with the increase in the transmission power as expected. This behavior aligns with the fundamental principles of wireless communication, where a higher transmission power improves the received signal strength at the users, thereby enabling higher data rates. For the same number of users, the power price value within the GTPA algorithm will decrease with the increase of the total transmission power. According to the supply and demand principle, each user will buy more power at a cheaper price, and therefore the individual, and accordingly, the overall sum rate will increase. The results show that the proposed mechanism outperforms the existing algorithms where the achieved sum rate by this mechanism is higher at all transmission power levels than that from other methods. For M=5, as an example, there is about a 4% increase in the sum rate at a transmission power level of 20 dBm. For M=2, it is obvious that both algorithms achieved the same rate at a transmitter power of 0 dBm. At such low transmitted power, the probability that the BS can serve more than one user, at the expected QoS (the minimum level of SINR), is so low. Thus, the sum rate at low P_t is the same for both algorithms since the whole power is allocated to one user in this case. The superior performance of the proposed algorithm can be analytically attributed to its efficient utilization of the power-price relationship. By dynamically adjusting the power allocation based on user demands and the prevailing power price, the algorithm ensures that the available transmission power is optimally distributed among users to maximize the sum rate. This efficiency stems from its ability to balance supply and demand, incentivizing users to consume power strategically when prices are low. Additionally, the algorithm's adaptability to varying transmission power levels allows it to outperform existing methods consistently, as evidenced by the higher sum rates achieved across different scenarios. The mechanism's design, which prioritizes fairness and resource efficiency, highlights its robustness in handling multi-user environments and its potential for scalability in larger, more complex networks.

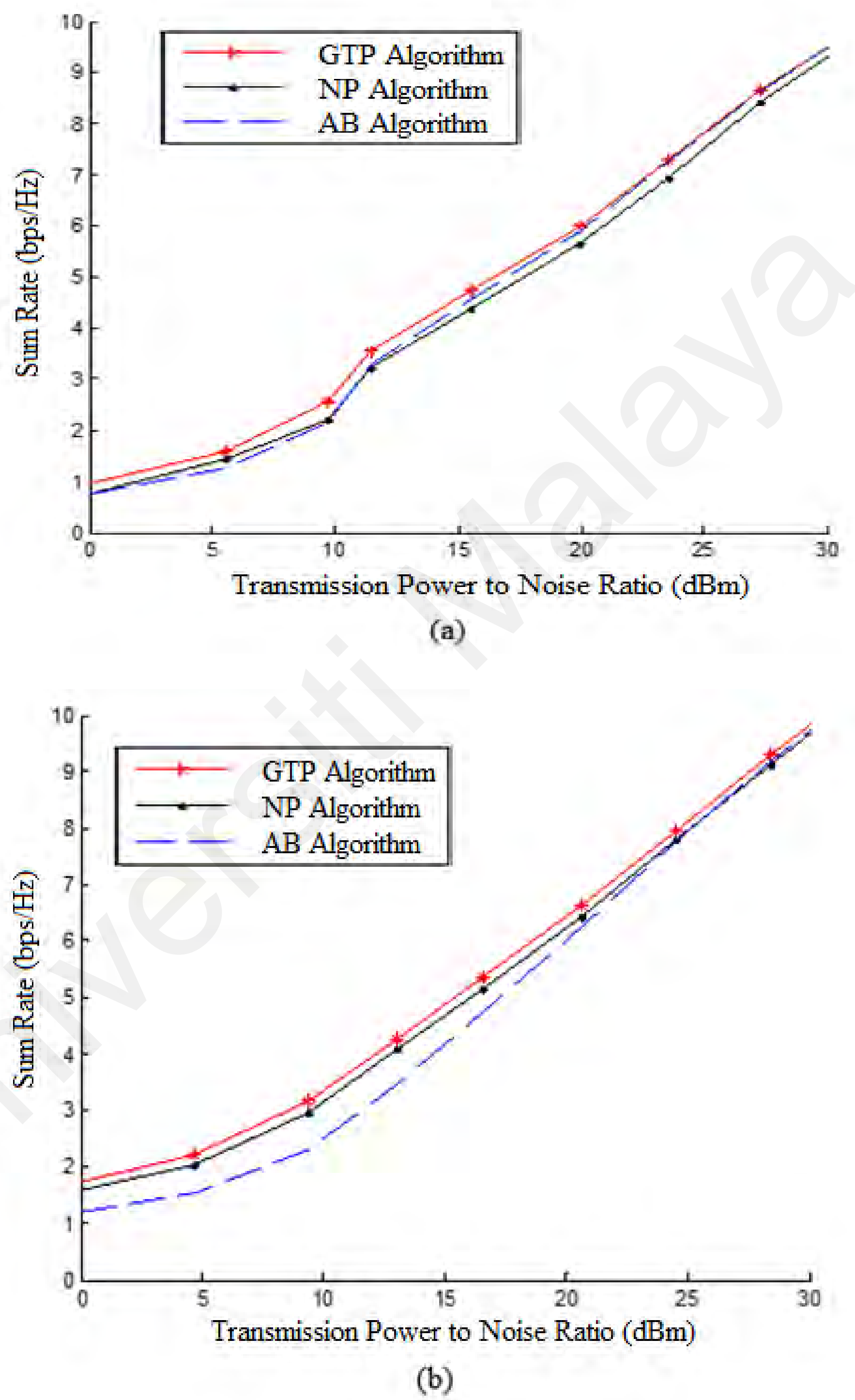


Figure 4.1: Sum rate in DL NOMA system versus P_t/σ^2, (a) For M=2, $\delta_1^2 = 0.5$ *and* $\delta_2^2 = 1$. (b) For M=5, $\delta_1^2 = 0.2$; $\delta_2^2 = 0.4$; $\delta_3^2 = 0.6$; $\delta_4^2 = 0.8$ *and* $\delta_5^2 = 1$

Another performance metric is testified, which is the average data rate of the users. The simulation is done for the same circumstances in the first experiment mentioned above. The results are illustrated in Figure 4.2. The user average data rate achieved by the GTPA proves the enhanced performance individually for each user. The results in Figure 4.2 confirm that the GTPA algorithm achieves a consistently higher average data rate for users compared to the other algorithms under the same conditions. This outperformance can be analytically explained by the algorithm's ability to dynamically allocate power resources based on real-time user requirements and the power price mechanism. By prioritizing fairness and optimizing the power distribution, the GTPA ensures that each user receives an adequate share of resources, thereby improving individual performance. However, as the number of users increases, the available power must be distributed among more users, leading to a decline in the average data rate, as evidenced by the 17% reduction at 30 dBm when the number of users increases from 5 to 10. This trend is consistent with resource-sharing limitations in multi-user environments. Nevertheless, the algorithm’s ability to maintain relatively high performance, even under increased user density, highlights its robustness and scalability. This advantage is primarily due to the efficient handling of the power-price relationship, which minimizes wastage and enhances overall system utilization. It worth to mention that the effect on EE due to the GTPA will be discussed later in the next sections.

4.2 Energy-Efficient Power Allocation for Imperfect CSI DL NOMA System

In this section, the proposed energy-efficient power allocation algorithm is evaluated in a single cellular cell with central BS which serves M users and the achieved results are compared to the conventional OMA in the case of zero-channel estimation error.

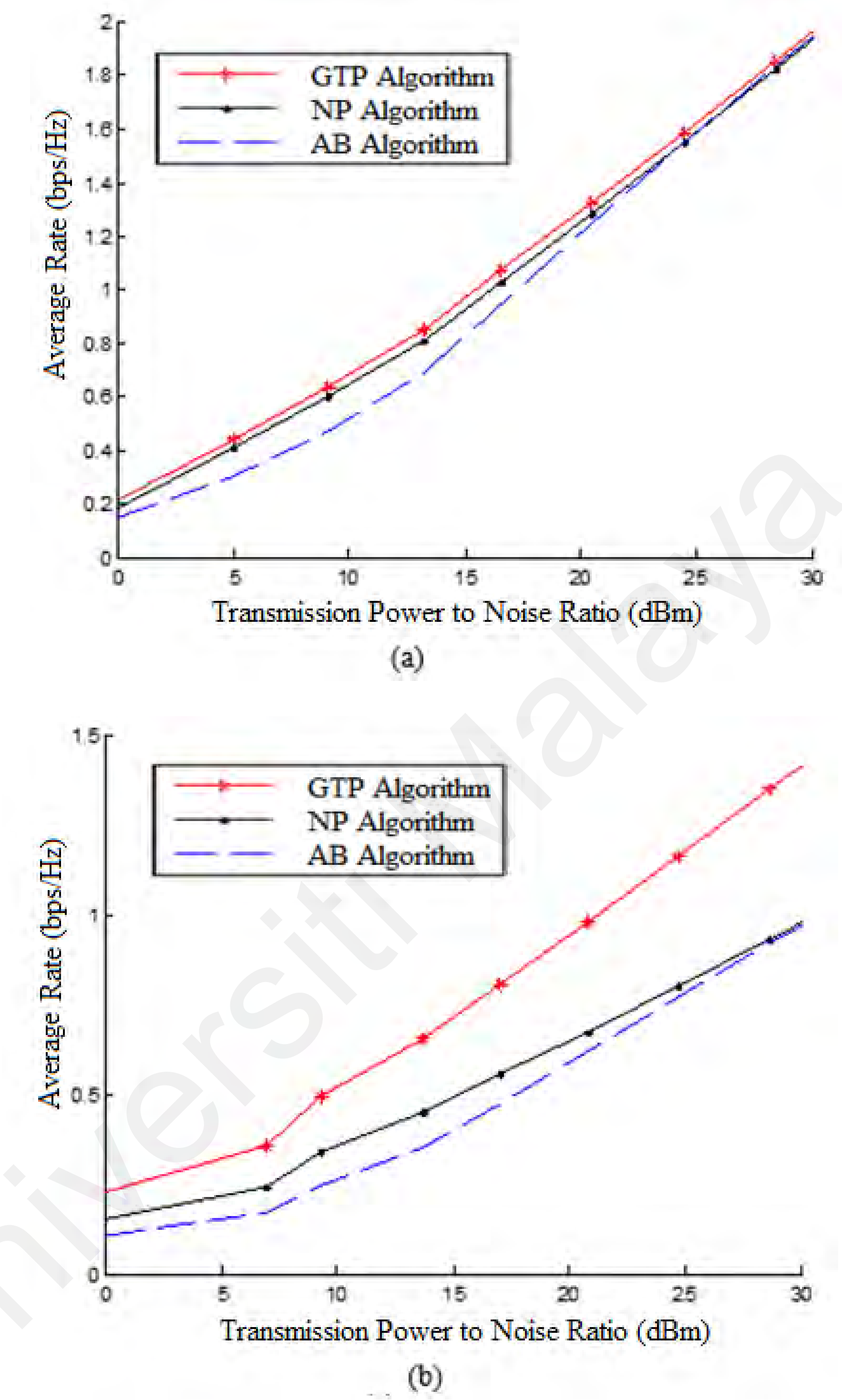


Figure 4.2: Average data rate of users versus P_t/σ^2; (a) For M=5, $\delta_1^2 = 0.2$; $\delta_2^2 = 0.4$; $\delta_3^2 = 0.6$; $\delta_4^2 = 0.8$ and $\delta_5^2 = 1$. (b) For M=10, $\delta_m^2 = m/M$

The users are distributed randomly within a single cell, where the channel from the BS to the user has been modeled as $h_m \sim CN(0, \delta_m^2)$. In this study. It is assumed that M=3 users, and the variance of the channel gains are given by $\delta_m^2 = \frac{m}{M}$. The total transmission power P_t is varied up to 1W and the assumed total BS dissipated power is P_c=1W. The system bandwidth and the AWGN spectral density are assumed to be 1MHz and -174dBm/Hz respectively (Glei & Chibani, 2019).

Results are taken as an average of 1000 run trials. The simulations in the study use varying values of M across experiments to analyze system performance under different conditions. While M=3 represents a moderate case, other experiments explored smaller and larger values to examine scalability and robustness. This approach ensures that the study comprehensively evaluates the algorithm's adaptability to different user densities.

Figure 4.3 presents the obtained energy efficiency at different transmission powers. It illustrates that the proposed algorithm causes an improvement in the system's EE compared with the conventional OMA where the total transmission power is distributed equally among all users. For example, at P_t=0.25W, the proposed algorithm achieves a more than 50% increase in energy efficiency compared to that in the OMA system. Moreover, the EE obtained by applying the proposed algorithm will increase when the transmission power increases until it reaches its maximum value at a certain P_t. Thus, any redundant power will not cause an increase in EE. The observed trend, where EE increases with transmission power up to a certain point, reflects the balance between achieving higher data rates and maintaining minimal power expenditure. Beyond this optimal transmission power level, any additional power becomes redundant, as it no longer contributes to improving data rates significantly but instead increases energy consumption. This plateau in EE underscores the importance of identifying and operating at optimal power levels to maximize system performance. The results confirm the algorithm's ability to achieve this balance, showcasing its practical value for energy-efficient communication systems.

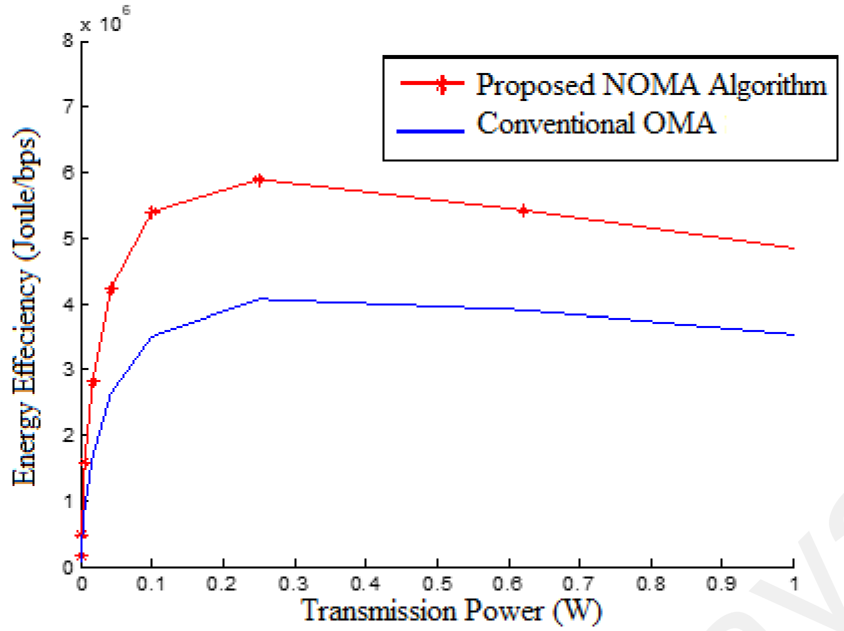


Figure 4.3: Energy efficiency versus transmission power

The results in Figure 4.4 reveal a clear advantage of the proposed algorithm in reducing the outage probability compared to the conventional OMA system. This improved performance can be attributed to the algorithm's use of NOMA, which allows multiple users to share the same resource blocks while differentiating them based on their channel conditions and power levels. By optimizing PA, the proposed algorithm ensures that even cell-edge users who typically experience weaker signal strength and higher interference achieve higher SINR levels. This results in a significant reduction in the likelihood of outage without increasing overall power consumption. The algorithm's ability to minimize outage probability while maintaining the same power budget demonstrates its efficiency in resource management and fairness in serving users across the cell. This improvement is particularly critical in scenarios with a high density of users or challenging channel conditions, where conventional OMA methods fail to sustain adequate performance for all users. Consequently, the results highlight the practical benefits of the proposed algorithm for ensuring reliable connectivity and service quality in modern wireless communication systems.

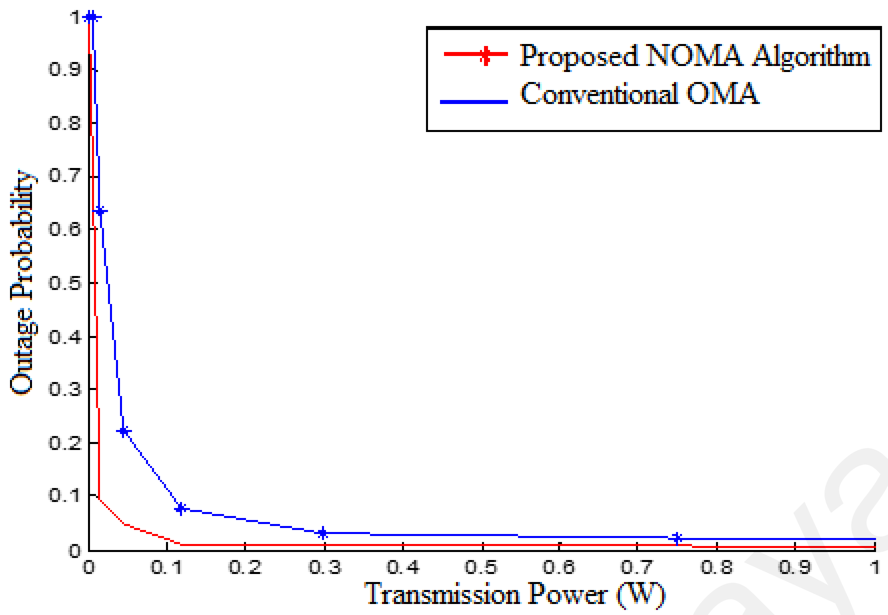


Figure 4.4: Outage probability versus transmission power

The results in Figure 4.5 illustrate the impact of imperfect CSI on the EE of the proposed algorithm compared to the conventional OMA system. The superior performance of the proposed algorithm across all levels of estimation error reaffirms its robustness and adaptability in realistic scenarios where perfect CSI is often unattainable. By leveraging the power allocation and user prioritization inherent to NOMA, the algorithm can mitigate the effects of estimation errors to some extent, maintaining higher energy efficiency than OMA even under degraded conditions. However, the results also demonstrate that both algorithms experience performance degradation as the estimation error increases. This decline is a direct result of the reduced accuracy in channel knowledge, which affects the SINR and subsequently the ability to allocate power effectively. The proposed algorithm's optimal performance at zero estimation error (perfect CSI case) highlights the critical role of accurate channel estimation in maximizing energy efficiency. This sensitivity to estimation errors suggests that enhancements, such as integrating robust estimation techniques or designing error-resilient power allocation strategies, could further improve the algorithm’s performance under imperfect CSI conditions. These findings emphasize the practicality and reliability of the proposed algorithm while highlighting areas for potential future improvement.

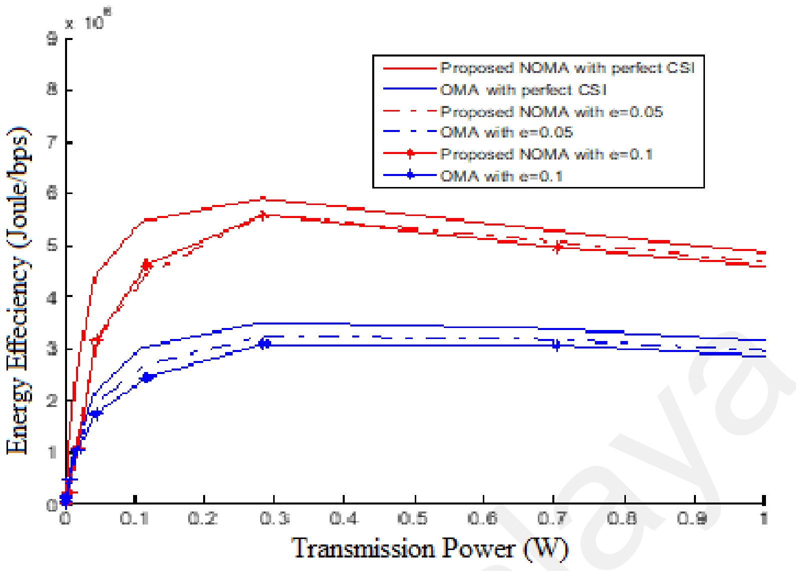


Figure 4.5: Energy efficiency versus transmission power at various estimation error values

4.3 Genetic Algorithm for Optimizing Energy Efficiency in Downlink mmWave NOMA System with Imperfect CSI

In this section, the performance of the proposed GA scheme for optimizing the EE in the DL mmWave NOMA system with user clustering is evaluated. Next, the validity of the proposed scheme is verified by evaluating the performance of the NOMA system in terms of EE and comparing it to both optimal NOMA and conventional OMA. The general scenario for the simulation is a single cell of a 500 m radius. A mmWave BS with 40 dBm power capability is located at the cell's center and equipped with multiple antennas whereas M users are distributed randomly at distances between 50m to 500m from the mmWave BS within the cell's boundary. The capacity of each cluster is only 2 users. For simplicity, the transmission beams between the mmWave and the users are assumed to have the same direction, which matches the geographical bore-sight links between them (R. Liu et al., 2020). The allocated power to each user is determined based on its required data rate. The minimum level δ_m is set randomly between 1 and 2. The parameters of the DL mmWave NOMA simulation are listed in Table 4.1 (R. Liu et al., 2020).

4.3.1 Cluster Selecting for Maximizing Energy Efficiency

The study also investigates whether increasing the data rate of the strong-channel user (UE_2) in the cluster higher than its requirements will be a benefit to the system EE. Assuming a unity channel gain, $h_2 = 1$ and the required QoS of the UE_2 is 2, the allocated power p_2 would be 2 regardless of the UE_1 requirement. On the other hand, the allocated power to the weak-channel user UE_1, p_1 would be less than p_2 when its QoS requirement is only at low levels. However, when UE_1 requests a higher data rate, its allocated power should be higher than the allocated power of UE_1. Figure 4.6 illustrates the allocated power and the EE for a cluster of 2 members with various requirements and channel states.

Table 4.1: Simulation Parameters for GPTA.

Parameter	Value
Operating frequency	24GHz
Cell radius	500m
Minimum distance between user and BS	50m
Required data rate	1-2 b/s/Hz
Total dissipated power at the Transmitter	1 Watt
Path loss component	3
BS transmission power	40 dBm
The subchannel Bandwidth	1MHz
AWGN power	-173dB/Hz
Operating beam-width of the mmWave BS	5°
Operating beam-width of the user	10
Side lobe gain	0.1
Simulation trials	1000
Maximum generations	100
Elite ratio	5% of the population size
Population Initial range	[0; 1]
Tolerance of objective function	10-12

As can be seen from Figure 4.6, the weaker channel user requires higher allocated power to achieve the data rate. Although previous studies prove that increasing the allocated power to the strong-channel user significantly increases the total throughput of the system, this rise of the allocated power decreases the system EE based on Equation (3.45). In Figure 4.6(b), the allocated power to the strong-channel member in the cluster is increased so that its new SINR is 3. This leads to a noticeable increment in the allocated power to the weaker-channel user to attain its requirement and eventually, the system EE degrades. Thus, the best scenario to achieve the highest EE to support the cluster members with the same requirements of data rate is to set the subject C5 in the optimization problem as $SINR_m = \delta_m$.

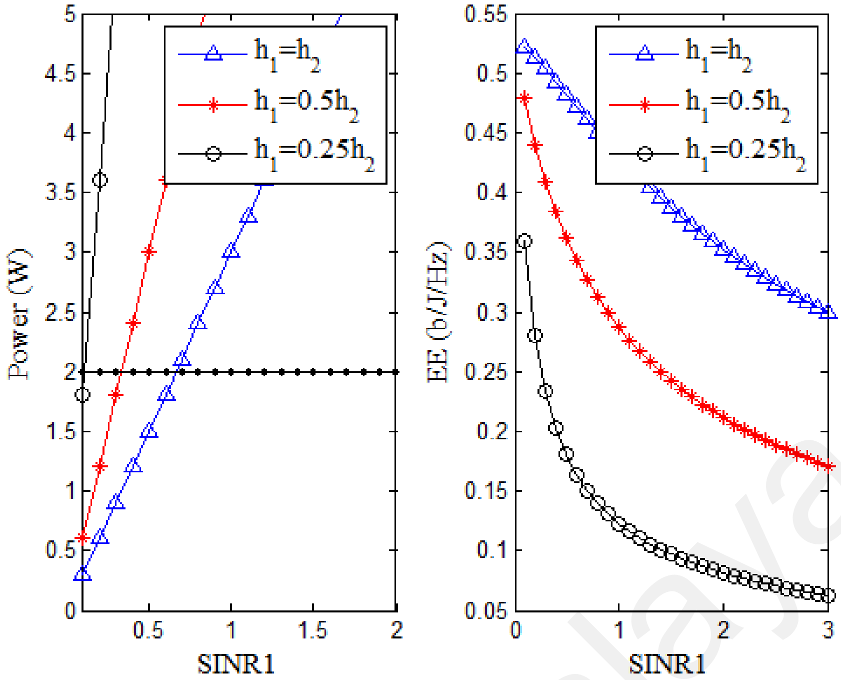
The analysis highlights the unique challenge of balancing power allocation in NOMA systems, particularly for users with diverse channel conditions. The weaker channel user UE_1, despite its higher power requirements, has a more significant impact on achieving system-level fairness and meeting individual QoS needs. As seen in the results, the power allocation mechanism ensures that UE_1's QoS is fulfilled, even if it requires disproportionately higher power. This prioritization underscores the proposed algorithm's adaptability and fairness, ensuring that the system caters to all users regardless of channel disparities. However, the observed reduction in EE with increasing power to UE_2 suggests that future work could explore optimized algorithms to balance throughput and EE, particularly in scenarios where one user has considerably stronger channel conditions. This balance is crucial for maintaining high-performance energy-efficient communication systems.

In this thesis, it is assumed that the allocated power to every user will satisfy the user's QoS (δ_m). Then, the possibility of improving the system EE by selecting different members in the cluster is studied. It is assumed there are two weak-channel users in the cell. Assuming a unity channel gain, $h_2 = 1$ and the required QoS of the UE_2 is 2, the allocated power p_2 would be 2 regardless of the UE_1 requirement. On the other hand, the allocated power to the weak-channel user UE_1, p_1 would be less than p_2 when its QoS requirement is only at low levels. However, when UE_1 requests a higher data rate, its allocated power should be higher than the allocated power of UE_1. User with $h_1 = 0.5h_2$ is referred to UE_x while user with $h_1 = 0.25h_2$ is denoted UE_y. The general assumption of selecting either one of them as a second member in the cluster depends on its channel state increases the system EE will not be an accurate conclusion where, as seen in Figure 4.6 (a). This is because the required QoS of every user plays an important role in this issue. For example, choosing UE_x leads to higher EE when the required SINR of UE_x is $\delta_x = 0.5$, and the required SINR of UE_y is $\delta_y = 0.5$ while choosing UE_y leads to higher EE when $\delta_x = 2$ and $\delta_y = 0.25$.

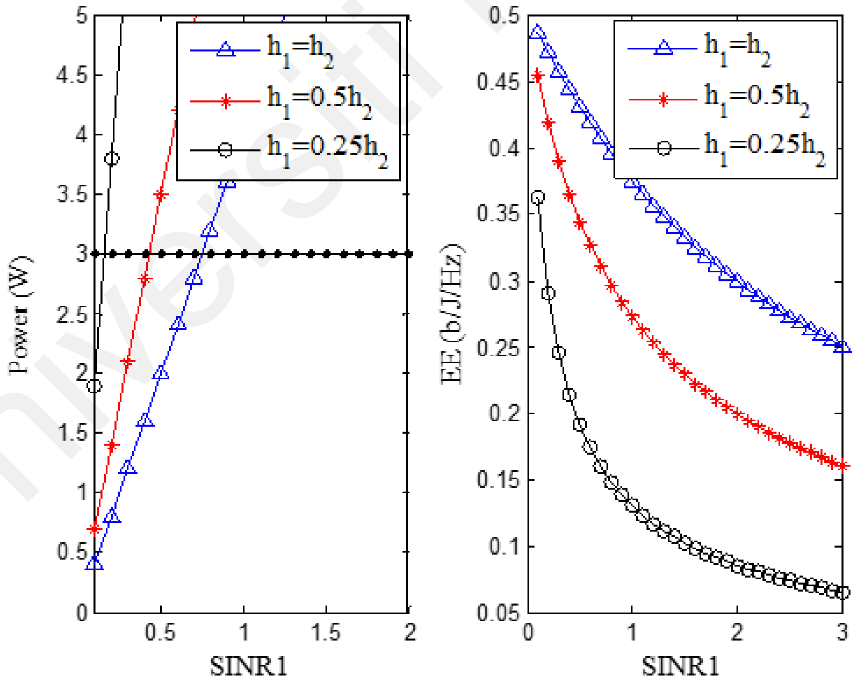
Although selecting the cluster members with various QoS requirements can be decided easily in this example, the massive number of users in real wireless communication networks makes the problem more complicated where there are $\frac{M!}{2!(M-2)!}$ different combinations of 2 members in a cell of M users (J. Zhao, Yue, Kang, & Tang, 2021), and therefore GA scheme is adopted in this study to determine the optimal cluster combinations $x_{m,b}$ to maximize the EE of the DL mmWave NOMA system.

4.3.2 Genetic Algorithm Performance

In this section, the performance of GA in solving the EE optimization problem in the DL mmWave NOMA system is evaluated. First, diverse population sizes are tested to determine the most appropriate population for different numbers of users. Starting from 2 clusters (4 users) up to 8 clusters (16 users), the population size was increased until all constraints were satisfied to determine the required population size related to the number of users. The elite ratio is 5% of the overall population and the crossover fraction is set to be 50% of the chromosome.



(a) $SINR_2$=2



(b) $SINR_2$=3

Figure 4.6: The allocated power to the two members of the cluster and the EE vs. the obtained SINR at the weaker-channel user (h_1) when the required SINR of the stronger-channel user (h_2) is 2 in (a) and 3 in (b).

Figure 4.7 illustrates the required GA population size for various traffic cases. The results show that the required size of the population in GA is relatively low at light traffic in the cell. As the number of users increases, the minimum population size that guarantees to find feasible solution and satisfy the constraints also increases. The significant increase in the population size indicates a much longer time required to solve the GA. Thus, for the DL mmWave-NOMA with clusters that consist of a massive number of users, GA could be utilized to determine the optimal clusters' pairs that maximize the EE highlighting the computational burden and extended processing time necessary to ensure constraint satisfaction and solution feasibility. This limitation poses a challenge for real-time applications in dense networks, particularly for DL mmWave-NOMA systems with large clusters. To address this issue, the integration of GA with deep learning presents a promising solution. While GA excels at exploring the solution space and determining near-to-optimal cluster configurations, its longer execution time under heavy traffic conditions makes it less practical for time-sensitive scenarios. Deep learning, on the other hand, can leverage the training data generated by GA to learn efficient patterns and provide real-time decisions that meet the timeliness requirement. This hybrid approach combines the exploratory strength of GA with the speed of deep learning, offering a scalable and efficient solution for optimizing energy efficiency in dense user environments. By leveraging such a combination, the system can achieve near-optimal performance without compromising timeliness, making it well-suited for future wireless communication systems (Pan et al., 2021).

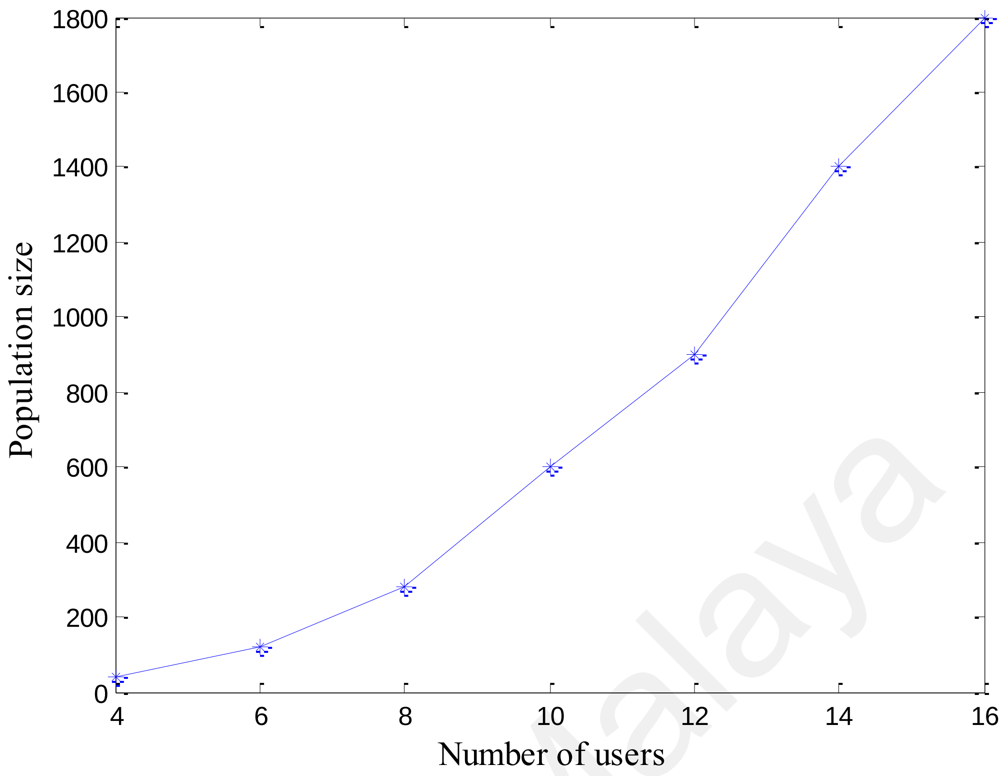
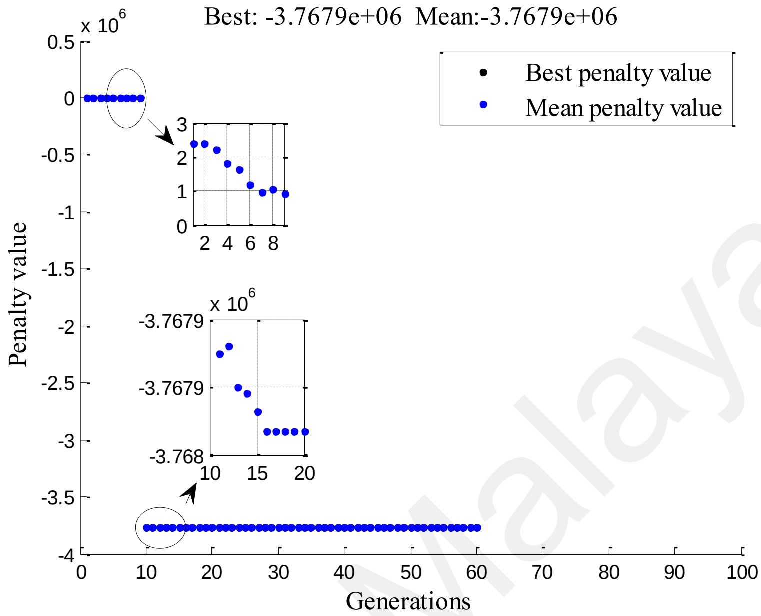
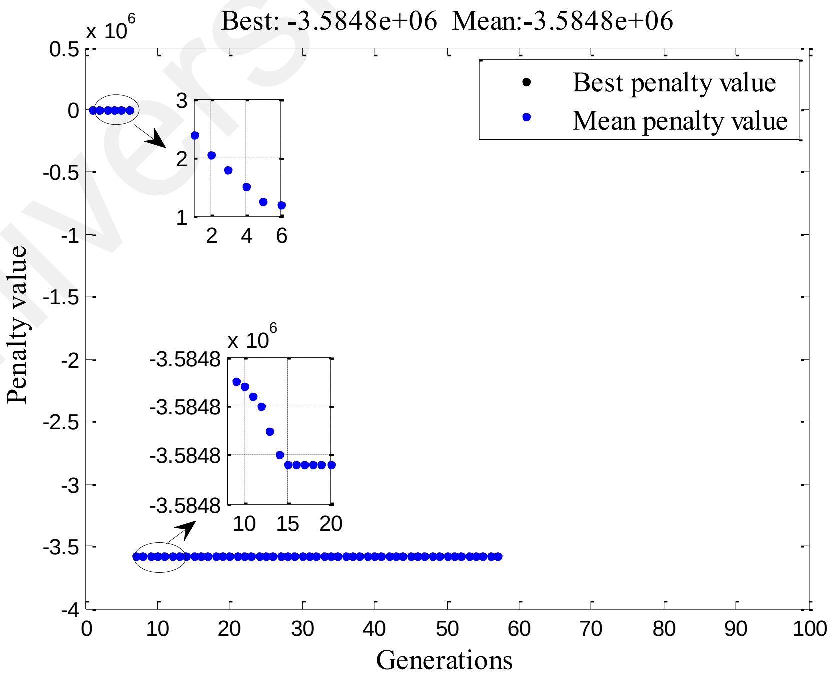


Figure 4.7:The appropriate population size of GA with respect to the number of users.

The performance of the GA convergence is evaluated in terms of the relation between the population size and the number of required iterations (generations) to find the solution. For this purpose, two cases are selected; the first case considers relatively low traffic (6 users) while the second case considers relatively heavy traffic (16 users). The results are illustrated in Figure 4.8 and Figure 4.9, respectively, which show that generally fewer iterations (generations) are required for convergence when the population size is larger for M=6 users and M=16 users, respectively. As seen in Figure 4.8(a) and Figure 4.8(b), the convergence to the solution becomes sharper after 9 generations and 6 generations where the population size increased from 120 to 160. Similar trends can be seen in Figure 4.9(a) and Figure 4.9(b) when the population size increases from 1500 to 1800. Moreover, by comparing the results in (a) and (b) for both cases shown in Figure 4.8 and Figure 4.9, it is obvious that the number of repetitions (generations) to find the solution reduces when the population size increases. The number of generations executed to solve within the tolerance increased significantly in the case of 16 users as compared to 6 users, and thus this leads to the long execution time of the GA as has been shown in Figure 4.7.

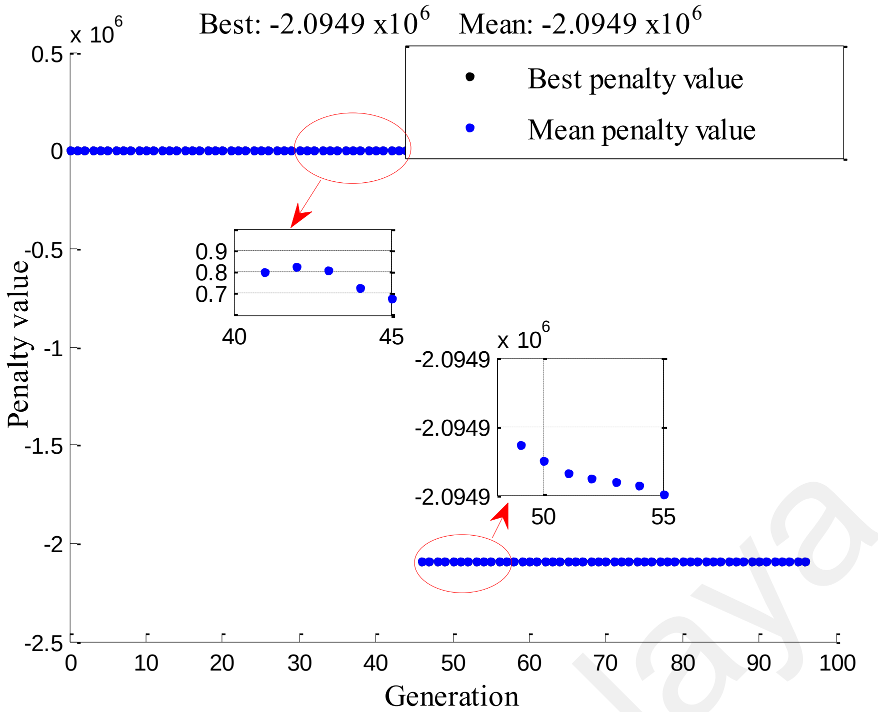


(a) Population size=120

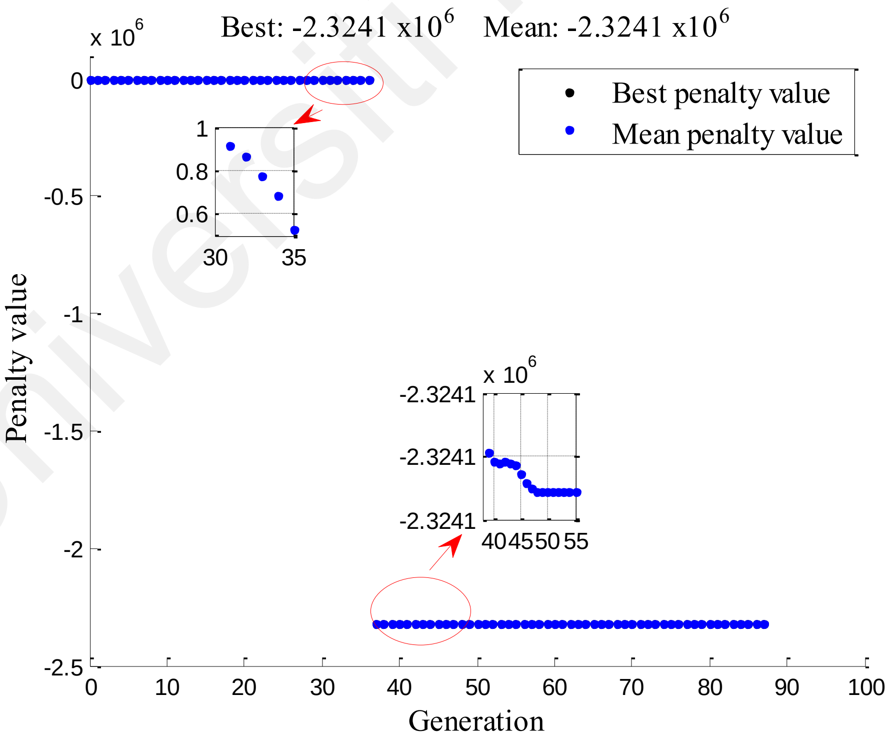


(b) Population size=160

Figure 4.8: The GA convergence to the best penalty value for light traffic case (M=6).



(a) Population size = 1500



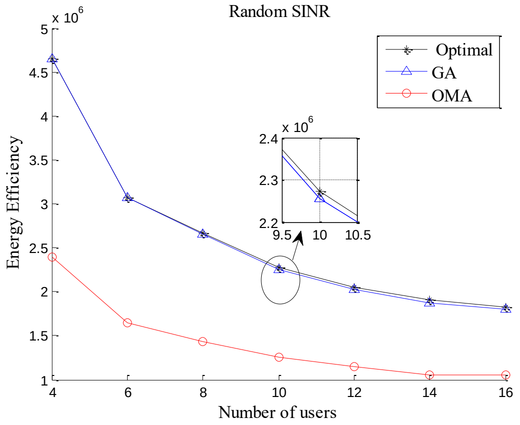
(b) Population size = 1800

Figure 4.9: The GA convergence to the best penalty value for relatively heavy traffic case (M=16).

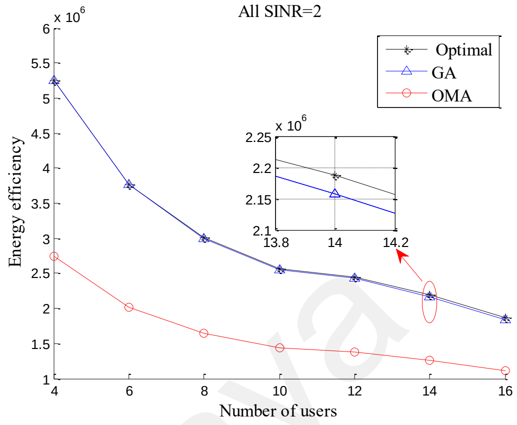
4.3.3 Impact of the Required SINR

The effect of the asymmetric users' required SINR on the EE of the proposed system is being investigated. The simulation settings remain as in the previous section while the total transmission power is sufficient to provide all users with the required QoS. In the first scenario, it is assumed that random requirement of users' data for different types of applications since some of the applications such as email require a much lower data rate than online gaming or video conference.

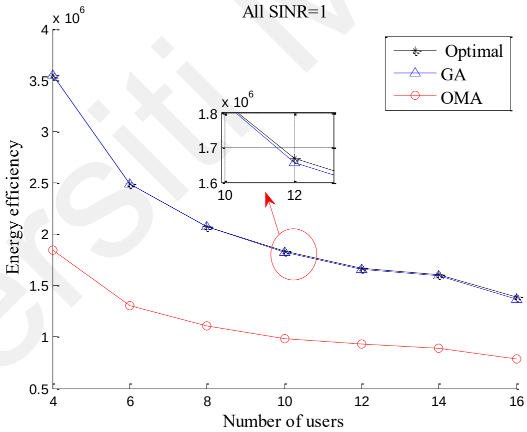
Figure 4.10(a) shows the system's EE based on random required SINR ranging between 1b/s/Hz and 2b/s/Hz for a different number of users. Then, all users are assumed to hypothetically have the same requirements either low SINR (1b/s/Hz) or high SINR (2b/s/Hz). The results are shown in Figure 4.10(b) and Figure 4.10(c), respectively. It can be seen from the figures that the GA approach achieves almost the optimal solution in all cases which proves its effectiveness for solving complex EE optimization problems. It is obvious that for all cases, the EE degrades as the number of users increases. However, as the number of users increases, the EE of the system approaches the same value for the random SINR requirements and the high SINR cases. Finally, results show the outperformance of the combination of NOMA with mmWave to improve the system EE compared to OMA-mmWave where a 75% increase in EE can be obtained. For example, the EE rises from about 1b/Joule in mmWave-OMA for 16 users to 2b/Joule in mmWave-OMA under the same circumstances. This outperformance can be attributed to NOMA's ability to increase user fairness by allocating power based on individual SINR requirements, ensuring that both strong and weak users can be served efficiently. In contrast, OMA-based systems, which typically allocate separate resources to each user, are less efficient in terms of resource utilization, leading to lower EE, especially as the user count increases. Thus, combining NOMA with mmWave not only enhances the system's ability to support more users simultaneously but also maximizes energy efficiency, making it a promising solution for future wireless networks, especially in dense urban environments where both high user density and high data rates are common.



(a) Random SINR between 1 and 2



(b) All SINR = 2



(c) All SINR = 1

Figure 4.10: The EE of mmWave-NOMA system versus the number of users at different SINR conditions.

4.3.4 Imperfect CSI

Here, GA is utilized to determine the EE of the mmWave-NOMA system in an imperfect CSI DL mmWave-NOMA system. The effect of the channel estimation error variance on EE for various numbers of user equipment is shown in Figure 4.11. The number of users is varied from 4 users to 16 users, and channel estimation error σ^2 is set to 0.01. It is evident that the maximum EE is obtained at zero error (perfect CSI), and the channel estimation error causes a decrease in EE because of the decrease in the SINR level. A degradation in the system's performance occurs in the case of imperfect CSI due to the impact of additional noise related to the channel estimation error variance.

As can be seen from Figure 4.11, the performance of the mmWave-NOMA system is better than the conventional OMA system in the imperfect CSI case when GA is employed. The use of GA in this context further enhances the system's performance by optimizing the power allocation and user scheduling, even under imperfect CSI conditions. GA helps in identifying near-optimal solutions for resource allocation, ensuring that the system can maintain relatively high EE even as channel estimation errors degrade the performance. The fact that the mmWave-NOMA system with GA still outperforms the OMA system in this imperfect CSI scenario highlights the robustness of NOMA, especially when combined with optimization techniques like GA. In summary, the outperformance of the mmWave-NOMA system over OMA, despite the presence of channel estimation errors, can be attributed to NOMA's efficient use of available spectrum and power through simultaneous transmission to multiple users. The introduction of GA to optimize resource allocation further strengthens the system's resilience to imperfect CSI, ensuring that it continues to deliver superior performance compared to traditional OMA methods.

4.4 Multi-Stage Mechanism for Optimizing EE in Imperfect CSI DL NOMA System

Here, the performance of the proposed multi-stage algorithm is evaluated where a multiple-cell DL NOMA system is considered for both perfect CSI and imperfect CSI case. The number of cells is set to 3 where user devices in every cell are set to M=4 and every device is equipped with one antenna (M. S. Ali, Hossain, & Kim, 2018). Each cell has a centered BS and serves randomly distributed user devices at a distance d_m=80m from the BS. The path loss component of the user devices channel is δ=3 (Zamani et al., 2019). The proposed algorithm has been applied at a range of BS transmission power up to 35 dBm and the channel estimation error on the system performance σ_{ε}^{2} is set to 0.01. The essential adopted parameters in this simulation are summarized in Table 4.2.

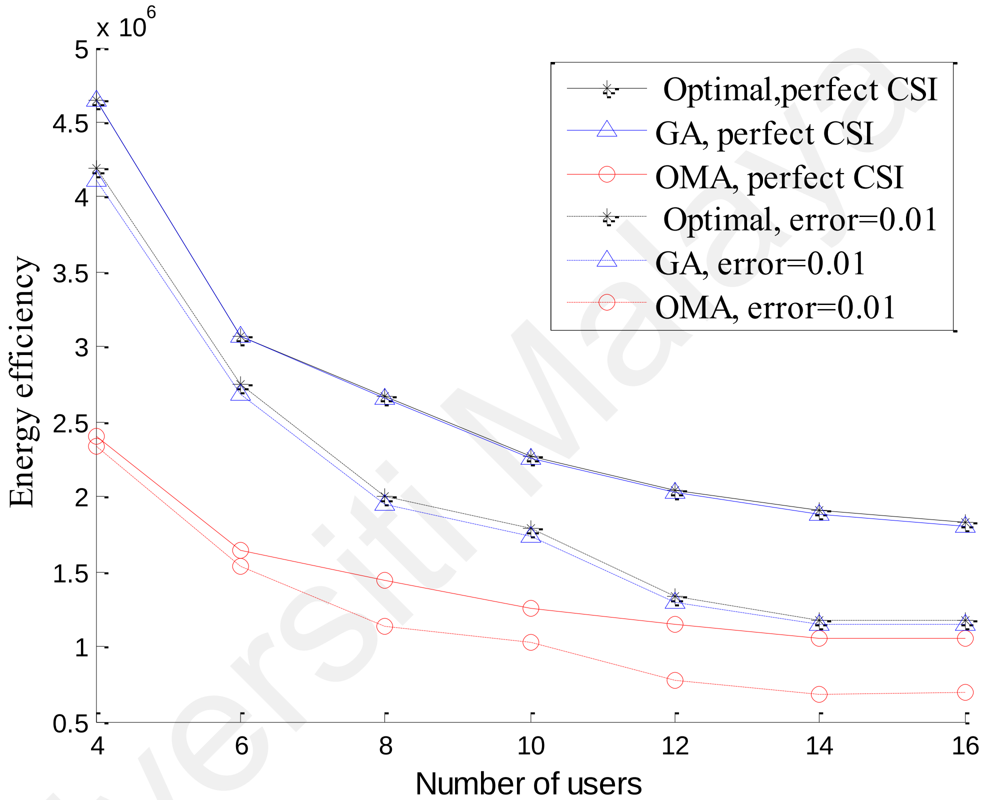


Figure 4.11: The impact of channel estimation error on the mmWave-NOMA system EE and mmWave-OMA system.

The performance of the proposed algorithm is compared with existing algorithms such as the optimum sum rate power allocation (OSRPA) algorithm (Zamani et al., 2019), GTPA algorithm (Aldebes, Dimyati, & Hanafi, 2019), and the conventional OMA (Cui, Ding, & Fan, 2016).

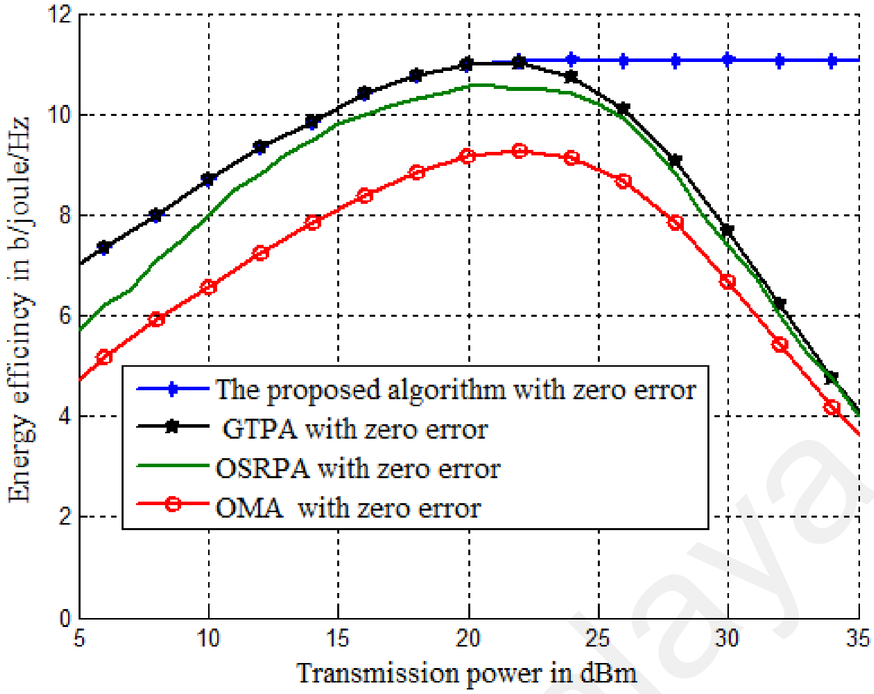
Table 4.2: Simulation parameters for multi-stage algorithm

Parameters	Value
Minimum data rate	1 b/s/Hz
Noise level at BS	-70 dBm
Total dissipated power at BS (P_c)	1 Watt
Path loss component	3
BS transmission power	0-35dB
The system Bandwidth	1MHz
The cell radius	80 m
AWGN power	-173dB
Number of device antenna	1
Tolerance (Δ)	0.1
Simulation trials	1000

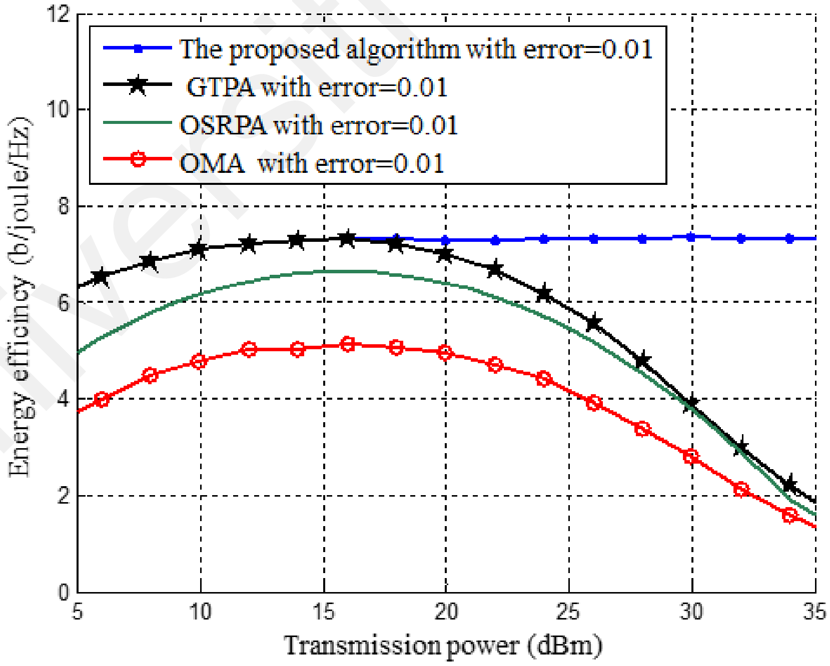
Figure 4.12 highlights the performance of the proposed algorithm in terms of EE compared to three other algorithms: OSRPA, GTPA, and OMA, under both perfect and imperfect CSI conditions. The results demonstrate that the proposed algorithm significantly outperforms the OSRPA and conventional OMA, achieving higher EE at the same transmission power. For example, at a transmission power of 25 dBm, the proposed algorithm provides an enhancement of about 5%, 7%, and 11% in EE over OSRPA, GTPA, and OMA, respectively. This improvement is a direct result of the proposed algorithm's ability to efficiently allocate resources and use the minimum transmission power required to meet the QoS requirements of each user device. One key feature that contributes to the outperformance is the proposed algorithm's efficient use of system resources. By allocating power in such a way that the minimum necessary transmission power is used to satisfy the users' QoS demands, the algorithm minimizes wasteful power expenditure and optimizes the overall energy usage. This is particularly beneficial in reducing the total power consumption while maintaining the necessary data rates for users, leading to improved energy efficiency in the system. However, the results also reveal the impact of imperfect CSI on system performance. In the case of imperfect CSI, the estimation error at the BS leads to a reduction in the SINR of the users, which in turn degrades the system's EE. As shown in Figure 4.12(b), the EE decreases by about 30%,

from 11 b/joule/Hz in the perfect CSI case to 7.5 b/joule/Hz in the imperfect CSI case. This performance degradation is expected since inaccurate CSI leads to suboptimal power allocation and increases interference, thereby reducing the system's ability to maximize EE. Despite this, the proposed algorithm still performs better than the other algorithms even in the presence of imperfect CSI. The robustness of the proposed algorithm to imperfect CSI can be attributed to its adaptive power allocation strategy, which continues to operate efficiently even when the channel conditions are not perfectly known. In comparison, algorithms like OSRPA and GTPA may not be as adaptable to CSI errors, leading to more significant performance degradation under imperfect conditions. In conclusion, the proposed algorithm outperforms OSRPA, GTPA, and OMA in terms of energy efficiency, particularly by utilizing the minimum transmission power required to meet QoS demands. While imperfect CSI does degrade performance, the proposed algorithm remains superior to other methods due to its efficient resource allocation strategy. The significant performance gap between perfect and imperfect CSI scenarios underscores the importance of accurate channel estimation, but the proposed algorithm’s design ensures that it maintains a high level of energy efficiency even when CSI is imperfect.

Figure 4.13 presents a detailed comparison of the average data rate achieved by the proposed multi-stage algorithm versus GTPA, OSRPA, and OMA for each 1Hz of the system bandwidth, under both perfect and imperfect CSI conditions. The results, shown in Figure 4.13(a) and Figure 4.13(b), reveal several important insights regarding the performance of the proposed algorithm. As expected, increasing the transmitted power leads to a higher average data rate for all cases, owing to the higher allocated power for each user.



(a)



(b)

Figure 4.12: Energy efficiency vs. transmission power at a minimum required data rate of every user, R_{mk}(min)=1 b/s/Hz in a) perfect CSI case in (a), and in b) imperfect CSI case with (σ_{ε}^{2}=0.01).

However, the proposed multi-stage algorithm consistently outperforms OSRPA and OMA in both perfect and imperfect CSI cases, with the data rate exceeding that of the other methods up to 22 dBm for perfect CSI (Figure 4.13(a)) and 15 dBm for imperfect CSI (Figure 4.13(b)). This improvement can be attributed to the ability of the proposed algorithm to effectively utilize power resources while ensuring that the minimum required data rate for each user is met, all while maintaining the system's EE (as seen in Figure 4.12).

The key advantage of the proposed multi-stage algorithm lies in its efficient use of transmitted power. Unlike other algorithms, it conserves power by allocating only the minimum necessary power to each user to meet their required QoS, without over-allocating unnecessary power. This strategy results in a significant improvement in the average data rate, which, in some cases, reaches more than 300% of the minimum required data rate. This ensures that users experience very satisfactory QoS while minimizing power consumption, making the system more energy-efficient.

Furthermore, it is noticeable from Figure 4.13 that the average data rate is lower in the imperfect CSI case compared to the perfect CSI case. This is because imperfect CSI leads to an increase in interference, which degrades the SINR, thereby reducing the achievable data rate.

The increased interference reduces the accuracy of power allocation and scheduling, causing a slight decrease in the system's overall performance. This degradation highlights the importance of accurate CSI for achieving optimal performance, but even with imperfect CSI, the proposed algorithm still provides better data rates than the other methods. In conclusion, the proposed multi-stage algorithm outperforms the GTPA, OSRPA, and OMA in terms of average data rate by utilizing power more efficiently and conserving resources while still ensuring high QoS for users. This allows it to achieve data rates well above the minimum required, providing significant benefits in terms of both throughput and EE. The lower performance observed in the imperfect CSI case further emphasizes the challenges posed by channel estimation errors but also underscores the robustness of the proposed algorithm in handling such imperfections while still delivering superior results.

The relation between the minimum required data rate and the system EE in both perfect and imperfect CSI cases is shown in Figure 4.14 for the proposed multi-stage algorithm as well as the GTPA algorithm and the conventional OMA. The distance and path loss component parameters are unchanged while the number of the user devices in every cell is assigned as M=4 and the transmission power is set to be P_k=26 dBm. All users in the cell are assumed to have the same minimum QoS, represented by the minimum accepted data rate R_{min}. From Figure 4.14, it can be seen that EE is higher in the proposed algorithm compared to the conventional OMA at all different required QoS. The allocated power to the stronger user in the proposed algorithm is relatively low compared to the OMA system to attain the minimum data rate. Therefore, the allowable transmission power is capable to serve more users even at high R_{min}.

It appears that the GTPA algorithm is better suited for achieving an optimal data rate, whereas the proposed multi-stage algorithm is designed to optimize EE. The key insight from the results is that in the proposed multi-stage algorithm, the allocated power to the stronger user is kept relatively low compared to the OMA system. This is crucial because it allows the system serving more users at higher required data rates. By conserving power while still meeting the minimum QoS requirements for each user, the proposed algorithm optimizes EE, which is particularly beneficial in power-constrained environments.

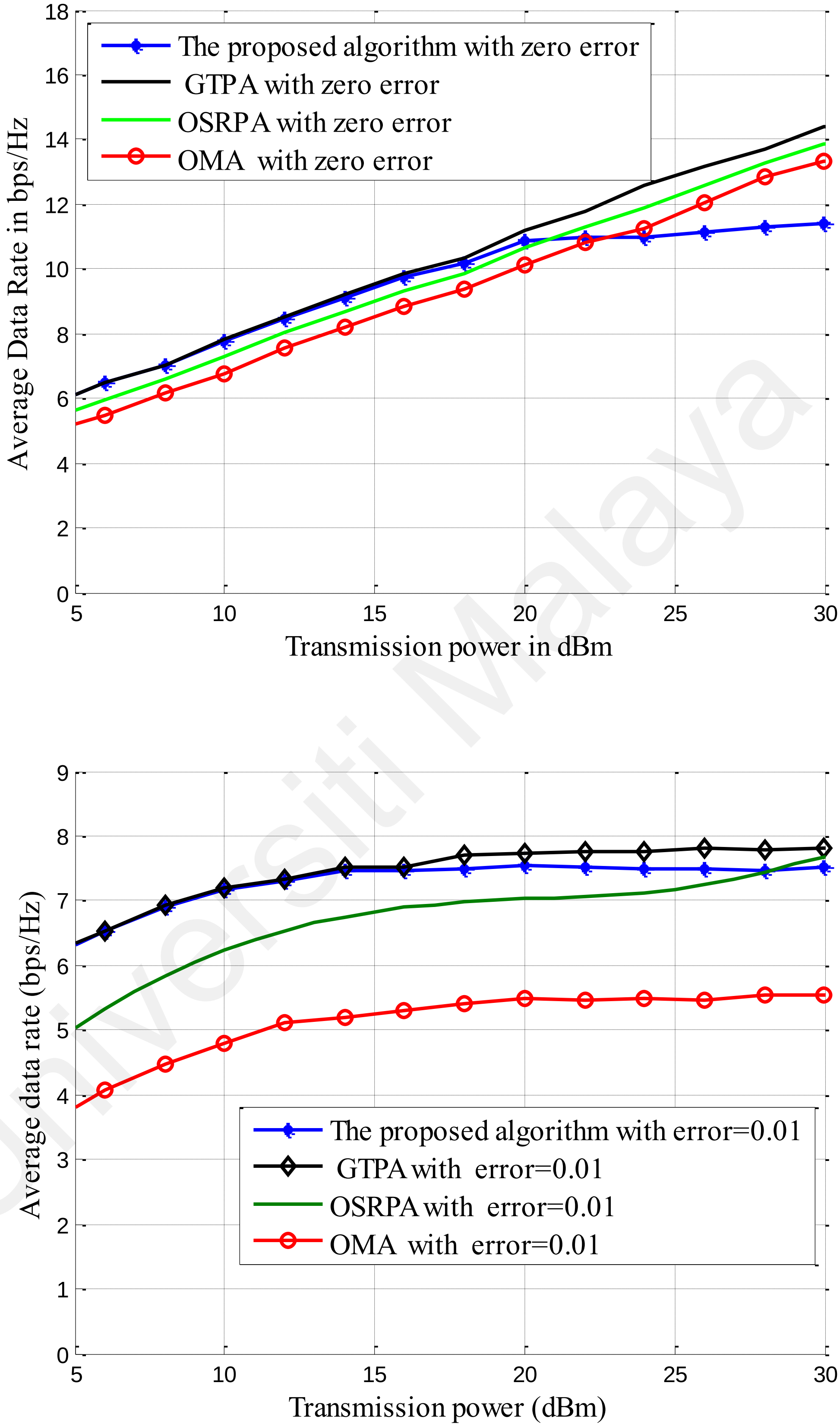


Figure 4.13: Average data rate vs. total transmission power for M=4, in a) perfect CSI case, and in b) imperfect CSI case with (σ_{ε}^{2}=0.01).

This contrasts with OMA, where higher transmission power is typically required to ensure that all users can meet their data rate requirements, leading to increased energy consumption and reduced efficiency. When comparing the proposed multi-stage algorithm with the GTPA algorithm, it becomes evident that while the GTPA algorithm is more effective at achieving higher data rates, the proposed multi-stage algorithm is specifically designed to optimize EE.

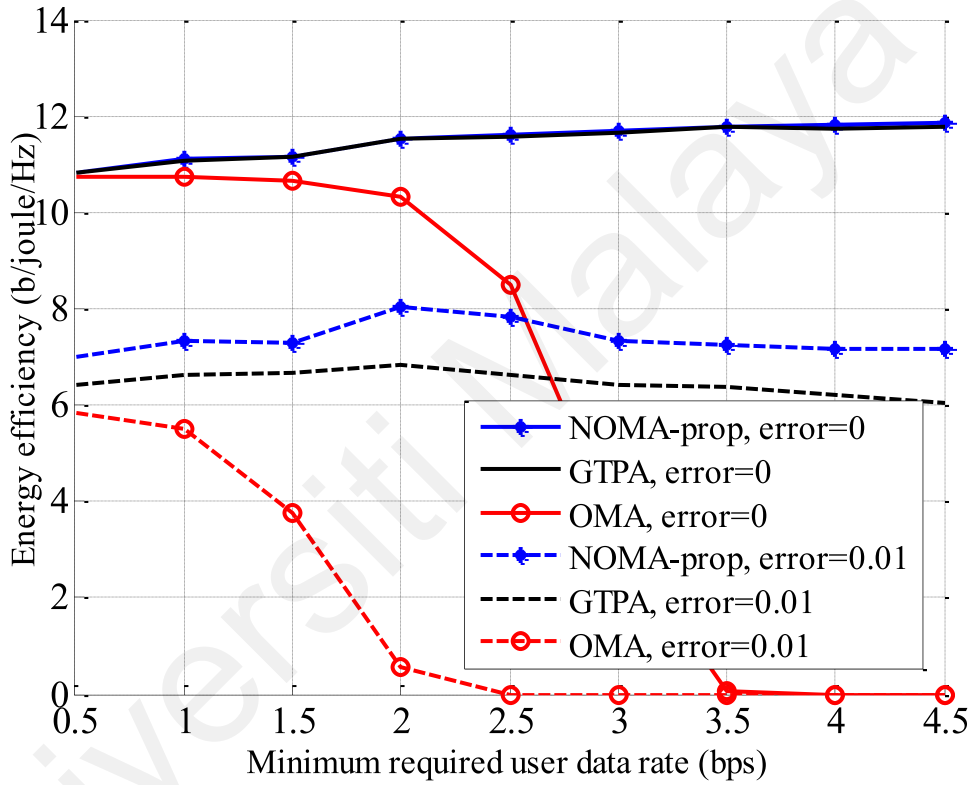


Figure 4.14: Energy efficiency vs. minimum required data rate, in perfect CSI case and imperfect CSI case (σ_{ε}^{2} =0.01).

This trade-off between maximizing data rate and optimizing energy efficiency is a key consideration in communication system design. In scenarios where energy efficiency is a critical concern (such as in battery-powered or power-limited systems), the proposed algorithm would likely be the better choice. However, in systems where maximizing data rate is the primary goal, the GTPA algorithm might be more suitable, as it can achieve higher throughput, albeit at the cost of increased power consumption. The data rate in the

OMA system is zero for any device if the transmission power is not sufficiently high to achieve the minimum QoS of that device (R_{min} is 3.5 b/s/Hz and 2.5 b/s/Hz in perfect and imperfect CSI OMA systems, respectively). This limitation further emphasizes the importance of efficient power allocation and the advantages of using algorithms like the proposed multi-stage method that optimize both energy efficiency and data rate without over-relying on high transmission power. In conclusion, the proposed multi-stage algorithm provides a clear benefit in terms of energy efficiency, particularly when dealing with high user density and stringent power constraints. While it may not achieve the maximum data rate compared to GTPA, its ability to maintain acceptable QoS at lower power consumption makes it an attractive choice for energy-efficient communication systems. The results highlight the importance of considering both data rate and energy efficiency when selecting an algorithm, as these factors are often in tension and must be balanced based on the specific goals of the system.

Figure 4.15 presents the effect of the channel estimation error on EE for a variety number of user devices. Here, R_{min}=1 b/s/Hz, number of users in each cell is set to M = {2 and 5}, and σ^2 is varied from 0 to 0.4. The transmission power is set to 20 dBm where the EE is maximized in the perfect CSI case. It is evident from Figure 4.15 that the maximum EE is obtained at zero error (perfect CSI), and an increase in the channel estimation error causes a decrease in EE due to the reduction in the SINR level. Moreover, a rise in the number of user devices number will decrease the EE. This trend is consistent with the general expectation that channel estimation errors cause additional interference, reducing the signal quality for each user and thus lowering the overall system performance. The observed degradation in EE is a direct consequence of the imperfect CSI, where the lack of accurate channel knowledge at the base station results in suboptimal power allocation. When channel estimation is inaccurate, PA decisions are less effective, leading to inefficient utilization of the available power resources.

Another important observation is the effect of user density on the EE. As the number of users in the cell increases (from M = 2 to M = 5), the EE decreases. This can be attributed to the increased complexity of managing power allocation across more users. With more users, the system has to allocate power in a way that meets the minimum QoS for each user while maintaining overall system efficiency. However, as the number of users increases, the available transmission power has to be shared, leading to reduced power per user and a corresponding decrease in the EE. Furthermore, the results show that NOMA outperforms the conventional OMA system in terms of EE in the presence of imperfect CSI.

This highlights one of the key advantages of NOMA: its ability to serve multiple users with the same time-frequency resources by optimizing power allocation. In the case of imperfect CSI, the NOMA system can still provide higher EE than OMA by utilizing power allocation strategies that are more adaptable to the available but imperfect channel information. Additionally, the results show that for M = 2, the system achieves better EE than for higher values of M (i.e., when more signals are combined). This is because, with two signals, the PA process is simpler and more efficient, as there are fewer users competing for the available power. The PA can be optimized more effectively, even with imperfect CSI. However, when M > 2, the system becomes more complex, and the allocation of power to multiple users becomes less effective, particularly under imperfect CSI conditions. The increased number of users introduces more interference and reduces the ability of the system to make optimal power allocation decisions, thus leading to a lower EE.

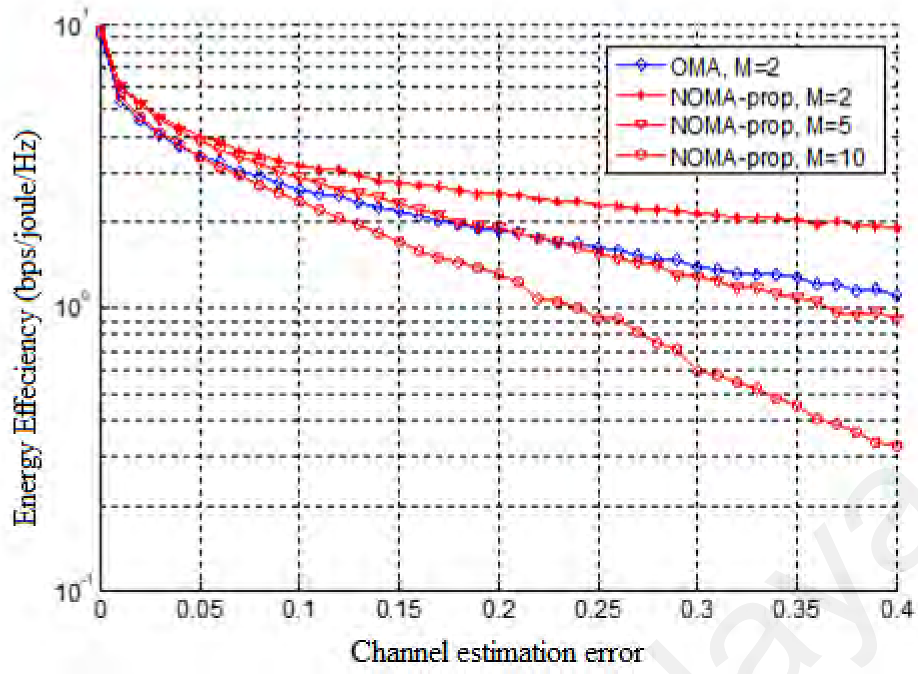


Figure 4.15: Energy efficiency vs. channel estimation error values for various number of user devices.

The analysis of outage probability, presented in Figure 4.16, provides valuable insights into the performance of the proposed multi-stage game theoretic algorithm, GTPA, and the conventional OMA under varying transmission power and channel estimation errors. The results illustrate a key finding: the outage probability decreases with increasing transmission power, which is consistent with the derived outage probability formula in Equation (3.85). As transmission power is increased, the signal strength improves, which leads to a lower probability of outage and better chances of successful communication for the users. The proposed multi-stage game theoretic algorithm outperforms both the GTPA and OMA across all scenarios (perfect and imperfect CSI). This is particularly noticeable in the cell edge user's SINR improvement, which directly contributes to the lower outage probability. For example, in the imperfect CSI case at 20 dBm, the multi-stage algorithm reduces the outage probability by approximately 10% compared to GTPA and 25% compared to OMA. This outperformance can be attributed to the algorithm's ability to optimize resource allocation more effectively, even in the presence of imperfect channel information. However, the impact of channel estimation errors on system performance is also evident. As the channel estimation error increases, the outage probability rises significantly. For instance, at 20 dBm, the outage probability increases from 0.05 to around 0.6 when the channel estimation error rises from zero to $\sigma^2 = 0.01$. This highlights the critical role of accurate CSI in achieving optimal system performance.

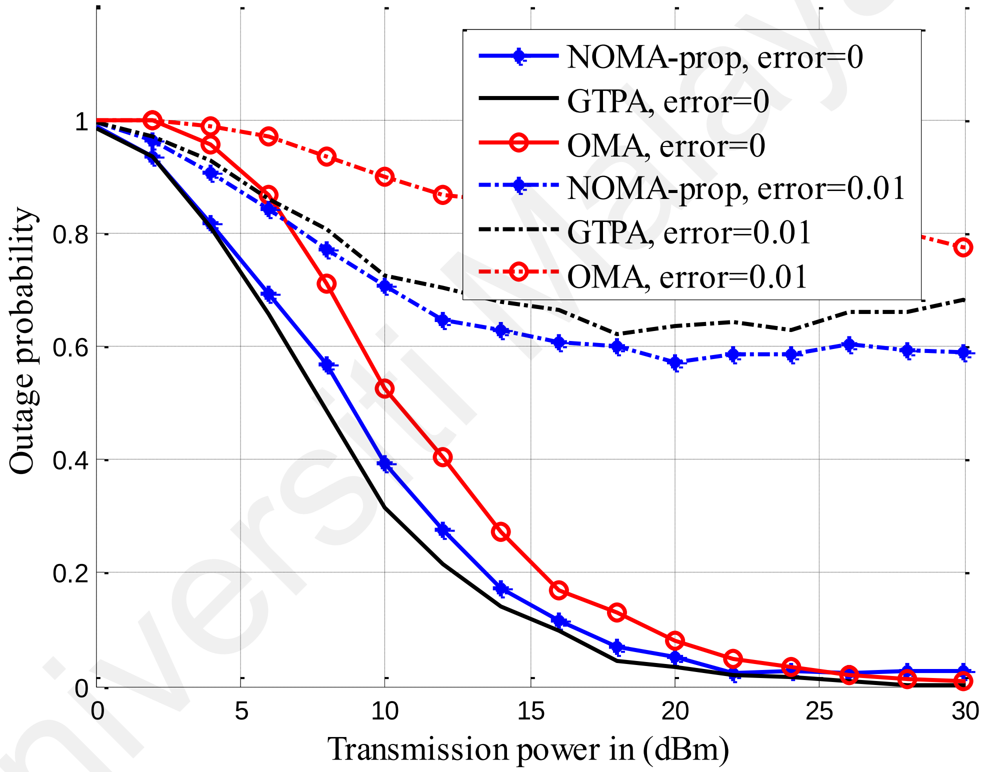


Figure 4.16: The outage probability vs. total transmission power for both perfect and imperfect CSI case.

When CSI is imperfect, the base station lacks precise information about the channel conditions, leading to suboptimal resource allocation. This can result in over-allocating resources to some users while others may experience inadequate resource allocation, causing higher interference and an increased likelihood of transmission failures. The increased outage probability in systems with imperfect CSI is largely due to the inability of the system to adapt effectively to changing channel conditions. Since resource allocation decisions are based on erroneous channel state information, the system may allocate insufficient power to users in poor channel conditions or allocate excessive power to users with better conditions, both of which can lead to inefficiencies and higher outage probabilities. In summary, while the multi-stage algorithm demonstrates significant improvements in outage probability over the other algorithms, the results underscore the importance of accurate CSI for optimal resource allocation. In the presence of imperfect CSI, the system struggles with suboptimal power allocation, leading to higher outage probabilities and reduced system performance. This analysis emphasizes the need for more robust channel estimation techniques to minimize the adverse effects of channel estimation errors and improve the overall reliability of the system.

The findings of this research effectively address the key objectives outlined for optimizing resource allocation in DL NOMA systems. First, the proposed power allocation mechanisms, grounded in game theory and GAs, demonstrate efficient resource distribution despite limited system resources, while accounting for user terminal threshold levels to maintain practical power allocation. Second, the use of game theory and GAs to solve non-concave optimization problems for data rate and energy efficiency showcases their ability to navigate complex solution spaces, offering significant improvements over traditional methods. Finally, performance evaluations under both perfect and imperfect CSI conditions confirm that the developed mechanisms enhance sum data rate and energy efficiency, ensuring robust system performance with minimal outage probability across various network configurations. The following points highlight how the research findings address each objective, demonstrating the effectiveness of the proposed power allocation mechanisms in optimizing performance in DL NOMA systems.

1. Objective 1: Power Allocation Mechanisms:

The findings demonstrate that the power allocation mechanisms based on game theory and GAs effectively manage resource distribution in NOMA systems, optimizing power use despite limited resources. The inclusion of user terminal threshold levels was critical to ensuring that the power allocation remains within practical limits while optimizing system performance.

2. Objective 2: Non-Concave Optimization:

The research findings highlight how the combination of game theory and GAs helps navigate the non-concave nature of data rate and energy efficiency optimization. By modeling user interactions strategically and leveraging GAs to explore the solution space, your results show that these methods provide effective solutions, leading to better overall system performance compared to traditional methods.

3. Objective 3: Performance Evaluation:

The results indicate that the proposed power allocation mechanisms significantly enhance the sum data rate and energy efficiency in both single-cell and multi-cell NOMA networks. In both perfect and imperfect CSI cases, the system performance remains robust, with low outage probability, proving the effectiveness of the proposed mechanisms across different conditions.

CHAPTER 5: CONCLUSION AND RECOMMENDATION FOR FUTURE WORKS

5.1 Conclusion

The objectives of this research have been successfully achieved through a systematic and comprehensive approach. The proposed methodologies, utilizing game theory and genetic algorithms, have addressed the challenges in power allocation for NOMA networks. Each objective and its corresponding achievements are summarized as follows:

Objective 1: Development of power allocation mechanisms

This research successfully developed power allocation mechanisms that leverage game theory and genetic algorithms to improve energy efficiency and data rate performance in DL NOMA systems. The game-theoretic approach formulated resource allocation as strategic interactions among users, achieving fairness and efficiency in power distribution. The proposed algorithms outperformed conventional methods by effectively balancing resource utilization and QoS, ensuring scalability for real-world applications.

Objective 2: Analysis of non-convex optimization problems

A detailed analysis of non-convex optimization problems related to EE and data rates was conducted. The study particularly focused on scenarios with imperfect CSI, where conventional optimization methods often fail. The innovative use of GA provided robust solutions to these challenges, demonstrating the adaptability and effectiveness of the proposed methods under varying network conditions.

Objective 3: Performance evaluation of power allocation algorithms

Extensive simulations were carried out to evaluate the performance of the proposed algorithms. Key metrics, such as energy efficiency, outage probability, and average data rate, were analyzed. The results highlighted significant improvements compared to traditional OMA systems. For instance, the genetic algorithm-based methods enhanced energy efficiency by up to 75% and reduced outage probabilities by 25% under challenging conditions. The integration of NOMA with advanced technologies, such as mmWave, further demonstrated the adaptability and scalability of the proposed strategies.

This research has provided a comprehensive framework for power allocation in NOMA networks, addressing critical challenges in energy efficiency and data rate optimization. The integration of NOMA and mmWaves has set a foundation for future advancements in next-generation wireless communication systems, supporting the evolution from 5G to 6G networks. The findings contribute to the body of knowledge in the field and offer practical solutions for implementing NOMA in real-world scenarios.

In sum, the research objectives were not only met but exceeded expectations through innovative methodologies and rigorous evaluation. The results affirm the potential of the proposed approaches to revolutionize resource management in NOMA networks, paving the way for more sustainable and efficient wireless communication technologies in the future.

5.2 Significance of the study

The novelty and significance of this research lie in its innovative approach to addressing critical challenges in resource management for NOMA-based wireless communication networks. This study makes unique contributions through the following aspects:

- Integration of game theory and GA: The research proposes game-theoretic models and genetic algorithms to develop novel power allocation mechanisms that address both fairness and efficiency. While game theory provides a strategic framework for resource allocation, genetic algorithms are employed to solve complex non-convex optimization problems, enabling robust and efficient solutions under varying network conditions.

- Addressing imperfect CSI challenges: This study pioneers the analysis of resource allocation strategies in scenarios involving imperfect CSI. By accounting for real-world conditions where perfect CSI is often unattainable, the proposed algorithms demonstrate enhanced adaptability and robustness, ensuring optimal performance in dynamic and uncertain environments.
- Focus on energy efficiency and data rate optimization: Unlike traditional methods, this research prioritizes both EE and data rate optimization as dual objectives. The proposed solutions achieve significant improvements in these metrics, with EE enhancements of up to 75% and substantial reductions in outage probabilities, making them highly relevant for sustainable 5G and beyond networks.
- Application to advanced technologies: The integration of NOMA with emerging technologies such as mmWave is a groundbreaking aspect of this research. This combination enhances the scalability and applicability of the proposed methods, paving the way for their adoption in future communication systems, including 6G networks.
- Comprehensive evaluation and validation: The research employs extensive simulations to validate the proposed algorithms across diverse scenarios, including single-cell and multi-cell networks. By comparing the performance with conventional OMA systems, the study highlights the superiority of NOMA in terms of EE, data rates, and robustness.
- Practical implications and contributions to the field: This study provides actionable insights and practical solutions for implementing NOMA in real-world scenarios. By addressing critical challenges and demonstrating the

effectiveness of the proposed methods, this research contributes to advancing the state-of-the-art in resource management for next-generation wireless communication networks.

By addressing these three objectives, this thesis contributes a comprehensive solution to the resource allocation problem in DL NOMA cellular systems. The proposed mechanisms provide equitable and efficient resource distribution while optimizing critical performance metrics like data rate and EE. The findings collectively advance the understanding of NOMA system performance, especially in realistic scenarios involving imperfect CSI, and provide practical methods for resource allocation in modern cellular networks. In summary, the novelty of this study lies in its innovative methodologies and focus on real-world challenges, while its significance is underscored by the impactful contributions to both theory and practice in the field of wireless communications.

5.3 Recommendations for future works

The introduction of 6G technology holds the potential to bring about revolutionary improvements in energy efficiency and data rates in the rapidly evolving field of wireless communications. Leading this change have been NOMA systems, which are renowned for their capacity to support numerous users on the same time-frequency resource. Looking ahead, the combination of GA, as an AI methodology, with NOMA's cooperation with other emerging technologies opens a door to previously unimaginable possibilities.

Despite their high computational cost, genetic algorithms have shown to be very useful for improving NOMA systems. They are a great option because of their capacity to search through large solution spaces and identify the best configurations. Their primary disadvantage, though, is the amount of time needed for operations. Researchers are looking into creative ways to apply GA's results to address this challenge. In the field of optimization, artificial intelligence, especially machine learning techniques, appears to be revolutionary. AI algorithms can be quickly trained to predict ideal configurations by utilizing GA-generated data. The quantity of data that GA provides can be processed by neural networks, reinforced learning, and deep learning techniques to produce effective, real-time solutions that drastically cut down on the amount of time needed for optimization. Future 6G technology research projects should concentrate on combining the outcomes of GA with AI algorithms to establish a mutually beneficial relationship between prediction and optimization. AI models can be trained on historical GA data, which enables researchers to quickly and reliably predict the best NOMA configurations. This combination of prediction and optimization provides a real-time adaptive method for allocating resources in NOMA systems. Advantages of the combined methods include:

i. Shorter Operation Time: The time needed for optimization is greatly reduced when AI models trained on GA data are used. It becomes possible to adapt in real-time to changing network conditions, guaranteeing peak performance constantly.

ii. Enhanced Energy Efficiency: Rapid optimization results in less energy being used when allocating resources. Proactive adjustments are made possible by AI-driven predictions, guaranteeing energy-efficient operations even in dynamic network environments.

iii. Increased Data Rates: The hybrid GA-AI approach's optimal resource allocation guarantees increased data rates and better spectral efficiency. Customers benefit from quicker, more dependable connections that easily handle the demands of bandwidth-intensive applications.

The combination of NOMA, and genetic algorithms is a shining example of innovation. Through the utilization of AI's predictive power and GA's optimization capabilities, researchers can achieve unprecedented levels of efficiency and performance for NOMA systems. This collaboration not only tackles present issues but also sets the stage for wireless communication to become adaptive and intelligent in the future, in addition to being quick and dependable. In addition to bringing about a paradigm change in optimization techniques, the era of 6G signals the arrival of a time when intelligence and efficiency coexist peacefully in the wireless communications industry.

There is significant potential to build on the advancements made in this study by exploring the integration of NOMA with emerging 6G technologies, such as terahertz communication and intelligent reflecting surfaces, to further enhance EE and SE. Additionally, future research could delve deeper into AI-driven optimization techniques, such as deep reinforcement learning and federated learning, to address resource allocation challenges in highly dynamic and ultra-dense networks. These methods could provide more robust and scalable solutions that adapt to the unique demands of 6G, including ultra-low latency and massive connectivity for diverse IoT applications. The exploration of hybrid approaches that combine NOMA with other multiple access schemes, such as orthogonal time-frequency-space), could also be a fruitful direction, enabling even greater performance gains in complex communication scenarios. Moreover, further refinement of power allocation mechanisms under real-world conditions, such as imperfect CSI in heterogeneous networks, would provide practical insights for deploying these strategies in large-scale 6G environments.

These potential research directions build upon the foundational work presented in this thesis, offering pathways to address the evolving challenges and opportunities in next-generation wireless communication systems

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