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Resource Allocation for Energy Harvesting D2D Communications Underlaying NOMA Cellular Networks

., Vatsala


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Resource Allocation for Energy Harvesting D2D Communications Underlaying NOMA Cellular Networks

by

Vatsala

A THESIS
SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
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Abstract

The fifth generation (5G) cellular networks promise higher data rates, lower latency, higher energy efficiency, and increased bandwidth as compared to the fourth generation (4G) networks. To fulfill requirements raised by 5G networks, notable technologies such as Simultaneous Wireless and Information Power Transfer (SWIPT), device to device (D2D) communications and non-orthogonal multiple access (NOMA) are being extensively researched by the academia and industry. This thesis attempts to fulfill the requirements raised by current users and thus studies these technologies in the form of resource allocation problems for two SWIPT receiver architectures, namely, time switching (TS) and power splitting (PS) enabled D2D communications underlaying a NOMA based network with the objective of maximizing the D2D throughput while the rate requirements of the cellular users are guaranteed. The performance is compared with orthogonal multiple access (OMA) scheme. The problems are solved using two approaches: conventional optimization and deep learning. The conventional optimization entails a large number of iterations and involves significant time to solve the problem. Thus, deep learning is used where neural networks can learn from a dataset provided and used to predict an output. The neural networks involve less computation time and are more efficient. Therefore, a feed forward neural network (FFNN) - a kind of Deep Neural Network (DNN) is used to predict the D2D throughput. It was found that the efficient integration of D2D with the conventional cellular networks depends upon several factors such as environment, density of the network, geographical position of the devices and the rate requirement of the cellular users. Also, deep learning gives almost same results as that of the conventional optimization algorithm but is much more time efficient. In all the
scenarios, the NOMA based networks give much better performance than the OMA based networks. The significance of the project lies in adopting D2D communications equipped with TS and PS SWIPT architectures in practical scenarios efficiently by studying the various factors that impact the adoption of D2D communications.
Acknowledgements

First, I would like to express my sincere gratitude towards Dr. Abraham O. Fapojuwo for the immense support he has provided throughout the duration of my Master’s. He has inspired me for every single day in these two years and the kind of dedication and commitment he displays towards each, and every work is commendable. Not only he has been an outstanding mentor, but he has always been compassionate and accommodating in times of need. I am so fortunate to meet him at this stage of my life when I am starting my career. If I can display even half of the qualities he has later in my career, I will be more than elated. He has really helped me to grow technically and as a person and I really thank him for that.

My mother has been a constant source of motivation and she is the reason behind every move I take. I thank her for every effort she has put forward for my growth and has never let me down. I also want to thank my friends and lab mates who were just a call away every time I needed them; there are a lot of names worth mentioning without whose support I wouldn’t have finished this.

I would like to extend my sincere thanks to the examination committee; Dr. Behrouz Far and Dr. Abu Sesay for their time and suggestions for improving this thesis.

Lastly, a heartfelt thank you to Mitacs and University of Calgary for providing me with the financial support.
To my mother Meenakshi Bhavi Chand Sharma
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<th>Description</th>
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<tr>
<td>D2D</td>
<td>Device-to-Device</td>
</tr>
<tr>
<td>SWIPT</td>
<td>Simultaneous Wireless and Information Power Transfer</td>
</tr>
<tr>
<td>NOMA</td>
<td>Non-Orthogonal Multiple Access</td>
</tr>
<tr>
<td>OMA</td>
<td>Orthogonal Multiple Access</td>
</tr>
<tr>
<td>DNN</td>
<td>Deep Neural Network</td>
</tr>
<tr>
<td>BS</td>
<td>Base Station</td>
</tr>
<tr>
<td>TS</td>
<td>Time Switching</td>
</tr>
<tr>
<td>PS</td>
<td>Power Splitting</td>
</tr>
<tr>
<td>EH</td>
<td>Energy Harvesting</td>
</tr>
<tr>
<td>ID</td>
<td>Information Decoding</td>
</tr>
<tr>
<td>FFNN</td>
<td>Feed Forward Neural Network</td>
</tr>
<tr>
<td>RNN</td>
<td>Recurrent Neural Network</td>
</tr>
<tr>
<td>LSTM</td>
<td>Long Short-Term Memory</td>
</tr>
<tr>
<td>SWIPT</td>
<td>Nonlinear autoregressive network with exogenous inputs</td>
</tr>
<tr>
<td>DTX</td>
<td>Device Transmitter</td>
</tr>
<tr>
<td>DRX</td>
<td>Device Receiver</td>
</tr>
<tr>
<td>UE</td>
<td>User Equipment</td>
</tr>
<tr>
<td>CU</td>
<td>Cellular User</td>
</tr>
<tr>
<td>5G</td>
<td>Fifth Generation</td>
</tr>
<tr>
<td>4G</td>
<td>Fourth Generation</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RF</td>
<td>Radio Frequency</td>
</tr>
<tr>
<td>MANET</td>
<td>Mobile Ad-Hoc Network</td>
</tr>
<tr>
<td>CSI</td>
<td>Channel State Information</td>
</tr>
<tr>
<td>FDMA</td>
<td>Frequency Division Multiple Access</td>
</tr>
<tr>
<td>TDMA</td>
<td>Time Division Multiple Access</td>
</tr>
<tr>
<td>CDMA</td>
<td>Code Division Multiple Access</td>
</tr>
<tr>
<td>eMBB</td>
<td>Enhanced Mobile Broadband</td>
</tr>
<tr>
<td>mMTC</td>
<td>Massive Machine Type Communications</td>
</tr>
<tr>
<td>URLLC</td>
<td>Ultrareliable and Low Latency Communications</td>
</tr>
<tr>
<td>MUSA</td>
<td>Multiuser Shared Access</td>
</tr>
<tr>
<td>SCMA</td>
<td>Sparse Code Multiple Access</td>
</tr>
<tr>
<td>LDS</td>
<td>Low Density Spreading</td>
</tr>
<tr>
<td>SIC</td>
<td>Successive Interference Cancellation</td>
</tr>
<tr>
<td>KKT</td>
<td>Karush-Kuhn-Tucker</td>
</tr>
<tr>
<td>FD</td>
<td>Full Duplex</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal to Interference and Noise Ratio</td>
</tr>
<tr>
<td>SISO</td>
<td>Single Input Single Output</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Squared Error</td>
</tr>
<tr>
<td>$h_i$</td>
<td>channel coefficient between the BS and the cellular user</td>
</tr>
<tr>
<td>$h_D$</td>
<td>channel coefficient between the DTX and DRX</td>
</tr>
<tr>
<td>$h_{B,D_i}$</td>
<td>channel coefficient between BS and DTX</td>
</tr>
<tr>
<td>$h_{B,D_r}$</td>
<td>channel coefficient between the BS and DRX</td>
</tr>
<tr>
<td>$h_{D,i}$</td>
<td>channel coefficient between DTX and cellular users</td>
</tr>
</tbody>
</table>
\( s_k \)  
BS transmit signal for cellular user \( k \)

\( \nu_k \)  
BS power allocation coefficient for cellular user \( k \) in first timeslot

\( N^2 \)  
Variance of the antenna noise

\( E^h_D \)  
Energy Harvested by the DTX

\( \eta \)  
Energy Conversion Efficiency at the DTX

\( P_{BS} \)  
BS Transmit Power

\( \lambda_k \)  
BS power allocation coefficient for cellular users \( k \) in second timeslot

\( x^i_B \)  
Composite BS transmit signal for \( i^{th} \) timeslot

\( P_D \)  
Transmit Power by DTX

\( p^e_D \)  
Circuit Power consumption for energy harvesting

\( p^t_D \)  
Circuit power consumption for data transmission

\( \varepsilon \)  
Power Splitting Ratio

\( R^c_i \)  
Achievable rate for \( c^{th} \) time slot for cellular user \( i \)

\( R_D \)  
Achievable rate for D2D

\( \gamma_i \)  
minimum rate requirement for cellular user \( i \)

\( U_D \)  
D2D Throughput

\( d \)  
Maximum distance between DTX and DRX

\( L \)  
Side of Cell

\( T \)  
Frame length

\( \theta \)  
Accuracy parameter

\( \tau_{Ec} \)  
Energy Harvesting time for DTX \( c \)

\( \tau_{Sc} \)  
Signal Transmission time for DTX \( c \)

\( h_{DC} \)  
channel coefficient between the DTX \( c \) and DRX \( c \)

\( h_{B,Dtc} \)  
channel coefficient between BS and DTX \( c \)

\( h_{B,Drc} \)  
channel coefficient between the BS and DRX \( c \)

\( h_{DC,i} \)  
channel coefficient between DTX \( c \) and cellular user \( i \)

\( h_{Dtc,Dr} \)  
channel coefficient between DTX \( c \) and DRX \( l \)
1.1. Background

The number of connected devices has increased exponentially in the past few years and are expected to increase even more in the coming years. From 22 billion connected devices worldwide in 2018 the number is expected to increase to 50 billion in by 2030 [1]. Because of the popularity of huge bandwidth demanding and data-intensive applications such as Netflix, Amazon Prime videos, Instagram, and Facebook, the user’s data demand is significantly increasing, thus creating pressure on the existing network. The current fourth generation (4G) technology is not able to support these ever-increasing data rates and the ever-increasing number of devices. Thus, the fifth generation (5G) networks have come into attention for dealing with the requirements for the current system. The 5G is supposed to offer up to 10Gbps data rate, 1-millisecond latency, 1000x bandwidth per unit area as compared to 4G, up to 100x number of connected devices per unit area (compared with 4G long-term evolution (LTE)), 99.99% availability, 100% coverage and 90% reduction in network energy usage, up to 10-year battery life for low power IoT devices [2].

Novel technologies are being researched on for 5G. The goal of this thesis is to study three of the main technologies for 5G, device-to-device (D2D) communications, simultaneous wireless and information power transfer (SWIPT) and non-orthogonal multiple access (NOMA) and to ensure efficient resource utilization using these technologies to ensure the required data demands are met with the technologies.
1.2. Problem Statement

The research in this thesis centers on the three major streams in a wireless information and power transfer system, addressing three main problems.

*Problem #1 and #2 (Chapter 3 and Chapter 4): How to maximize the throughput of power splitting (PS) and time switching (TS) SWIPT enabled D2D communications in a NOMA based network and what factors affect the D2D throughput?*

Though the battery technology has improved over the years, yet the pace has been slow as compared to the fast-changing technologies which demand more and more power. Therefore, energy harvesting is a viable option that is being investigated by the academia and industry. Also, to reduce the traffic going to the BS and to offload traffic from the BS, devices in proximity can communicate with each other directly without getting the BS involved. These devices have limited battery capacity and thus SWIPT enabled devices are investigated where the devices can harvest energy and transmit information concurrently.

The PS and TS enabled receiver architectures for D2D communications have been popularly studied in the literature as compared to the other receiver architectures. When the PS and TS enabled D2D communications are deployed in a NOMA based network, it becomes rational to develop resource allocation algorithms to achieve maximum D2D throughput to achieve better performances. Also, it becomes crucial to study which parameters of the network affect the D2D throughput and to ensure that the interferences caused by the devices do not affect the performance of the cellular networks operating in the network. Thus, this thesis aims at studying resource allocation problems for PS and TS enabled D2D communications such that the rate requirements of the cellular users are satisfied.
Problem #3 (Chapter 5): How to reduce the computation time and complexity of conventional optimization algorithms and predict accurate results?

Problems #1 and #2 are solved by the conventional gradient technique. Though, the conventional gradient technique is effective in obtaining the maximized throughput of the devices, yet the technique takes a lot of time and is computationally inefficient. Therefore, this research uses a feed forward neural network (FFNN), a kind of DNN (deep neural network) to predict the D2D throughput for both the TS and PS SWIPT receiver architectures, and finally the obtained results are compared with the results from the conventional optimization algorithm.

1.3. Thesis Motivation and Objectives

1.3.1. Thesis Motivation

The main motivation behind the work in this thesis is to improve the performance of the wireless network and to incorporate the demands raised by the current users such that 5G technology can be well implemented using the technologies studied in this thesis. The formulation of optimization problems and mathematically analyzing them and hence solving them becomes necessary to support this motivation. Also, it is important to study the network parameters which affect the performance of the network. Further, the thesis uses a neural network to predict the throughput using the data given by the optimization algorithm and see how it performs as compared to the optimization algorithm. The motivation behind this step is to obtain results using less time and less computational complexity.
1.3.2. Thesis Objectives

The following research objectives are defined to solve the three research problems described in this thesis:

- **Thesis Objective #1 (Chapter 3):** Formulate and solve an optimization problem with the objective of maximizing the PS SWIPT enabled D2D throughput guaranteeing the rate requirements of the cellular users.

  A resource allocation problem is formulated with the objective of maximizing the PS enabled D2D throughput in a NOMA based network. The problem is formulated considering the two SWIPT time intervals, the first interval being the energy harvesting time and the second interval being the signal transmission time. The problem is formulated taking all the constraints relevant to the NOMA scheme and the mutual interference of the D2D users and the cellular users. The main constraint to consider is the satisfaction of the rate requirement of the cellular users. The problem is simplified mathematically, and then the gradient method is applied to solve the problem and find the optimal power splitting ratio. The optimal power splitting ratio gives the optimal D2D throughput. Finally, the variation of throughput with the network parameters is studied.

- **Thesis Objective #2 (Chapter 4):** Formulate and solve an optimization problem with the objective of maximizing the sum throughput of TS enabled D2D communications guaranteeing the rate requirement of cellular users.

  A resource allocation problem is formulated with the objective of maximizing the sum throughput of TS enabled devices in a NOMA based network. The problem is formulated considering the two SWIPT time intervals, the first interval being the
energy harvesting time and the second interval being the signal transmission time. The problem is formulated taking all the constraints relevant to the NOMA scheme and the mutual interference of the D2D users and the cellular users. The main constraint to consider is the satisfaction of the rate requirement of the cellular users. The problem is simplified mathematically, and then the gradient method is applied to solve the problem and find the optimal signal transmission time. The optimal signal transmission time gives the optimal D2D throughput. Finally, the variation of throughput with the network parameters is studied.

- Thesis Objective #3 (Chapter 5): Use a deep neural network (DNN), specifically a feed forward neural network (FFNN) for predicting the D2D throughput for both the PS and TS configurations.

The chapter 4 and chapter 5 use conventional optimization algorithms to solve the problem. Though the optimization algorithms are slow, yet they give accurate predictions. Therefore, taking the data from conventional optimization algorithms, a feed forward neural network (FFNN) is trained, and results are obtained and compared with the test set.

1.4. Summary of Thesis Contributions

The thesis contributes to the study of TS and PS SWIPT enabled receiver architectures in D2D communications thus maximizing their D2D throughput in a cellular network while satisfying the rate requirement of cellular users in a NOMA based network. The further paragraphs specify the contributions of individual chapters, corresponding to the content of each chapter.
In chapter 3, a resource allocation problem is formulated considering a PS enabled D2D communication underlaying a NOMA-based cellular network with the objective of maximizing D2D throughput where both the transmit power and power splitting ratio are jointly optimized such that the minimum rate requirement of the cellular users is satisfied. The formulated optimization problem is mathematically analyzed, and closed-form solutions are derived in some scenarios and in other scenarios, a sub-optimal solution is obtained using the gradient descent method. The numerical results of the NOMA-based cellular network are compared with those of the conventional orthogonal multiple access (OMA)-based cellular network and a random resource allocation algorithm.

In chapter 4, a resource allocation problem is formulated considering a TS enabled D2D communication underlaying a NOMA-based cellular network with the objective of maximizing the sum D2D throughput of device users where both the transmit power and signal transmission times are jointly optimized such that the minimum rate requirement of the cellular users is satisfied. The formulated optimization problem is mathematically analyzed, and a sub-optimal solution is obtained using the gradient descent method. The numerical results of the NOMA-based cellular network are compared with those of the conventional OMA-based cellular network and the effect of multiple D2D pairs is observed on the sum throughput of D2D users in the network.

In chapter 5, the data obtained in chapters 3 and 4 are used to train a specific class of deep neural network (DNN), the feed forward neural network (FFNN). The data is used to train the neural network and it is shown that using neural networks is much more computationally efficient than using conventional optimization algorithm. The results
obtained after training the neural network are compared with the optimization results to show the accuracy of the results obtained at the training stage.

**Table 1.1. Summary of Main Contribution of the thesis**

<table>
<thead>
<tr>
<th>Contribution</th>
<th>Chapter/Section</th>
</tr>
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<tbody>
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<td>1. Problem Formulation of PS SWIPT enabled D2D communications in a NOMA based network with the objective of maximizing the D2D throughput</td>
<td>3.3.</td>
</tr>
<tr>
<td>2. Analysis of the PS SWIPT enabled D2D communications of the formulated problem</td>
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</tr>
<tr>
<td>3. Results and comparison with the OMA based network</td>
<td>3.6.</td>
</tr>
<tr>
<td>4. Problem Formulation of TS SWIPT enabled D2D communications in a NOMA based network with the objective of maximizing the sum device throughput</td>
<td>4.3.</td>
</tr>
<tr>
<td>5. Analysis of the TS SWIPT enabled D2D communications of the formulated problem</td>
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</tr>
<tr>
<td>6. Results and comparison with the OMA based network</td>
<td>4.6.</td>
</tr>
<tr>
<td>7. Optimization problem solution using DNN</td>
<td>5</td>
</tr>
<tr>
<td>8. Testing results and comparison with the optimization algorithm</td>
<td>5.6.</td>
</tr>
</tbody>
</table>
1.4.1 Thesis Organization

1. Chapter 2 gives a review of the technologies used in this thesis. Apart from the technologies, the chapter gives the comparison of the existing literatures with the work done in the thesis.

2. Chapter 3 of this thesis studies resource allocation of power splitting (PS) SWIPT enabled D2D communications underlaying NOMA based networks via conventional optimization techniques.

3. Chapter 4 of this thesis studies the resource allocation of time switching (TS) SWIPT enabled D2D communications underlaying NOMA based networks via conventional optimization techniques.

4. Chapter 5 of this thesis studies the resource allocation of time switching (TS) and power splitting (PS) SWIPT enabled D2D communications underlaying NOMA based networks using deep learning.

5. Chapter 6 concludes the thesis, gives the major engineering significance and recommendations of the future work.
Chapter 2: Literature Review

The goal of this chapter is to give a background of the three main technologies used for this thesis i.e., device to device (D2D) communications, simultaneous wireless and information power transfer (SWIPT) and non-orthogonal multiple access (NOMA). This chapter also presents a literature survey of the existing works related to this thesis thus comparing them with the work done in this thesis.

Section 2.1 gives an overview of the D2D communications. Section 2.2 gives the overview of the SWIPT technology. Section 2.3 gives an overview of the NOMA scheme. Section 2.4 gives an overview of the existing literature regarding power splitting (PS) architecture for heterogeneous cellular in underlay D2D communications. Section 2.5 gives an overview of the existing literature regarding TS architecture for heterogeneous cellular in underlay D2D communications. Section 2.6 gives an overview of the deep learning architectures for heterogeneous cellular with underlay D2D communications. Section 2.7 gives the comparison of the previous literatures with the work done in this thesis. Section 2.8 provides the summary of this chapter.

2.1. Device to Device Communications

D2D communications refer to devices in proximity directly communicating with each other without the information traversing through a base station (BS) [3]. The traditional cellular networks require all the communications to pass through the base station (BS) which can severely overload the system in today’s world where data hungry applications which require larger bandwidths are gaining popularity. Therefore, the D2D communications can be rewarding in today’s world and can help to offload traffic in
cellular network, thus providing higher throughput and increased spectral efficiency. Fig. 2.1. shows a cell with D2D communications occurring in the cell.

![Figure 2.1. D2D Communications, (UE = user equipment).](image)

Thus, D2D communications is a key technology in 5G cellular networks as it helps to achieve higher data rates, Quality of Service (QoS), reduced latency and increased system capacity [4]. There are many similar technologies such as Bluetooth, Wi-Fi etc. but they work in unlicensed bands which results in security issues. D2D communications can work in both licensed as well as unlicensed spectrum.

2.1.1. Configuration of D2D Communications

The configuration of D2D communications are as follows [5]:

1. Network controlled D2D communication: In this scenario, the base station (BS) controls the D2D communications and cellular users. Though interference management and
resource allocation become efficient under centralized control, but it involves a lot of signalling overhead.

2. Autonomous D2D communication: In this scenario, the D2D communications operate on their own without the involvement of the base station (BS). Since the D2D users operate autonomously, they access the unoccupied spectrum and find information about the cellular users in the network and the channel state information. Though this avoids the signalling overhead, but it raises the security concerns in autonomous D2D communications.

3. Network assisted D2D communication: This scenario has semi-involvement of BS in D2D communications as the BS aids in D2D communication by controlling the D2D signal or helping the devices to discover and establish connection with other devices. The D2D users then communicate within themselves, which helps in reducing the signalling overhead.

2.1.2. Categorization of D2D Communications

The D2D communications are categorized as inband and outband based on the spectrum usage [6]. Fig. 2.2. shows a general breakdown of the categorization of D2D communications.

The inband D2D communications use the licensed spectrum meaning that the cellular users and the D2D users share the same radio resources. The inband D2D communications can further be divided as underlay and overlay. For the underlay inband D2D communications, the D2D users opportunistically access the same resources as used by the cellular users. Though the underlay inband D2D communications utilize the spectral resources efficiently, yet the problem with inband underlay D2D communications lies in controlling the interference among the D2D users and the cellular users. The overlay
inband D2D communications have dedicated resource block for D2D communications. Though this solves the problem of interference between the D2D tier and the cellular tier, but it results in poor utilization of resources.

Figure 2.2. Categorization of D2D communications based on spectrum usage

The interference challenge of the underlay inband D2D communications can be dealt with using proper resource allocation strategies and hence, since the aim of this work is to improve the throughput which can be done considerably with underlay inband D2D communications, the work uses inband D2D communications in formulating the resource allocation problems.

For the overlay inband D2D communications, a part of the cellular spectrum is fully dedicated for D2D communication. Since, both the cellular and D2D communications are taking place in cellular spectrum, the interference problem gets solved as there is no mutual interference between the devices and the cellular users. Though the D2D power control and scheduling is improved for overlay inband D2D communications, yet, since a portion
of the cellular spectrum is dedicated for D2D communication it leads to poor resource
utilization and system throughput.

For the outband communications, the cellular users use the licensed cellular spectrum
whereas the D2D communications take place in the unlicensed spectrum, usually ISM
bands. Since the cellular and D2D communications occur in licensed and unlicensed
spectrum, there is no mutual interference between cellular and D2D communications.
There are two types of outband D2D communications: Controlled and Autonomous

In controlled D2D communications, the coordination between the radio interfaces such
as Bluetooth or ZigBee is controlled by the cellular network. In autonomous outband D2D
communications, the cellular users are controlled by the base station (BS) while the devices
communicating in D2D mode are controlled by the D2D communication.

2.1.3. Resource Management for D2D Communications

For resource management in D2D communications, the following factors have been
widely considered in the literature [7].

1) Mode Selection: The D2D communications underlaying cellular networks switch
in between two modes depending upon the real time conditions. These two modes
are the D2D mode and the cellular mode. When the D2D users operate in the D2D
mode, the D2D users use the same resource as that of the cellular users (CUs) thus,
there is considerable mutual interference between D2D users and the cellular users
resulting in difficulty to ensure QoS requirements of cellular users. When D2D
users operate in cellular mode, the signal of the D2D users is sent to the base station
thus the D2D direct link is deactivated. There are pros and cons associated with
both the modes thus selection of these modes is crucial in the interference management of D2D communications.

2) Power Allocation: A lot of literatures available in the field focus on power allocation of the D2D users and the cellular users for when D2D users are operating in the network. Allocating power to devices and cellular users is of great importance as it is a direct way to control interference in the network. When dealing with D2D communications underlaying cellular network, the cellular users are often treated as the primary users, and it becomes important to fulfill the QoS requirements of the cellular users. The power of the D2D users must be kept in such a way that the performance of the cellular users doesn’t degrade. Not only the power of D2D users can be controlled but the power of the BS can be lowered to improve the performance of the network as a whole and not affecting the performance of the CUs.

3) Resource Block Allocation: Since underlay D2D communication utilizes the shared spectrum with the cellular users, efficient allocation of sub-carrier resources plays an important role in D2D communication. Poor resource utilization might complicate the interference issues and reduce the system throughput or the energy efficiency of the system.

4) Rate Control/ QoS Satisfaction: Since in D2D communications, there exist a complicated interference scenario because not only there is interference from the devices but also the other users operating in the network, therefore rate adaptation or rate control becomes necessary especially in the case of D2D assisted video
transmission where we need rate adaptation to encode the video at different target
transmission rates for both the D2D link and the cellular user link.

These are the main resource allocation elements studied by the literatures present. There are other resource allocation elements as well such as relay selection, antenna selection etc. but since they haven’t been studied extensively in the literature, we would not go into the details.

2.1.4. Use Cases of D2D Communications

Not only the performance of D2D users is crucial in their adoption but also the introduction of D2D communications to interesting applications [8] is crucial to the adoption of D2D communications. Some of the applications are described here:

1. Emergency Services: During a natural catastrophe, for example, an earthquake, the cellular infrastructure usually gets damaged. In such a situation, the D2D communications come in use. The devices can establish an autonomous connection and communicate with each other even in the absence of a centralized control. This approach is similar to Mobile Ad-hoc NETworks (MANETs) but the difference is that the MANET communication occurs in the unlicensed spectrum whereas the D2D communication occurs in the reserved licensed spectrum.

2. Cellular coverage extension: When the cellular users are located out of the cell coverage area or on the edge of the cell, they experience poor signal strength and intensive channel fading. The cellular users can establish a connection with a nearby device and relay the information to the base station (BS). This can enhance the network throughput of the users which is affected by the edge users.
3. Offloading traffic: If the devices are in the communication range of the BS and use the licensed spectrum for communication, the D2D communications can help to reduce the load of the BS.

4. Health Monitoring: For health monitoring applications, D2D communications can be put to good use. If devices are attached to a patient’s body, they can effectively and securely communicate with the sink nodes. Also, since they are connected to the internet, doctors can access the real time conditions of a particular patient.

5. Data Dissemination: Geographical proximity can be very well utilized for advertising purposes. For example, restaurants can offer promotions and deals to people who walk around the restaurant. Also, information can be sent to a particular social group for promoting a particular product and revenue can be generated.

2.2. Simultaneous Wireless and Information Power Transfer (SWIPT)

The problem with D2D communications is the limited battery capacity of the devices which results in shorter operation times of the devices. SWIPT is a recently developed technique based on the concepts of energy harvesting (EH) and wireless power transfer (WPT). SWIPT enables energy harvesting and information transfer wirelessly.

Since the EH and information decoding (ID) cannot be performed simultaneously on the same received signal, to enable SWIPT on wireless systems, fundamental changes need to be made to the conventional wireless networks. Therefore, to achieve SWIPT, either the received signal must be divided into two parts or there should be two antennas to use SWIPT.

This concept was first proposed in [9] where trade-off to transmit a commodity between two points and simultaneously transmitting information is studied. Wireless networks with
RF energy harvesting are studied in [10]. The work discusses the circuit configurations for RF energy harvesting. The works [11], [12], [13], [14] have made significant contributions in exploring this field. SWIPT can be deployed along with many technologies and a comprehensive survey has been done as in [15]. D2D communications utilizing SWIPT is a relatively unexplored field. Some works such as [16], [17], [18] deploy energy harvesting with D2D communications. For an efficient SWIPT, there are some changes required in the wireless system. Generally, single receiver cannot be used to harvest energy and decode information simultaneously as it would lead to the destruction of the information in the signal. There are several receiver architectures that can be deployed with energy harvesting D2D communications:

- Separate receiver: In this architecture, separate receivers are used for EH (Energy Harvesting) and ID (Information Decoding). Hence, energy harvesting and information decoding can be performed independently and simultaneously. The separate receiver scheme can be easily implemented. Channel state information (CSI) and receiver feedback can be used to achieve the trade-off between energy harvested and achievable information.
rate. Separate receiver scheme is discussed in works such as [19], [20]. Fig. 2.3. shows the separate receiver architecture.

Figure 2.4. Time switching SWIPT architecture.

- Time switching scheme: In the time switching (TS) receiver scheme, a single antenna is deployed for energy harvesting and information decoding. The TS receiver has an energy harvester, an information decoder, and a switch to change between the energy harvester and the information decoder according to the time switching sequence as shown by Fig. 2.4. In general, for a device, if $\alpha T$ is time required for energy harvesting then $(1 - \alpha)T$ is time for information decoding where $\alpha$ is the time switching ratio and $T$ is the duration of time frame where both the operations have to be applied.

During the energy harvesting (EH) mode, the harvested energy by $j^{th}$ receiver is given as:

$$E_{i,j} = \alpha \eta |h_{ij}|^2 P_i T,$$

where $\eta$ is the energy conversion efficiency of the receiver, $h_{ij}$ is the channel coefficient between the $j^{th}$ receiver and the $i^{th}$ source, $P_i$ is the transmit power of the $i^{th}$ source. During the ID operation, [21] calculates the ID rate as:
\[ R_{i,j} = B \log \left( 1 + \frac{P_i |h_{ij}|^2}{N^2} \right), \]

where \( B \) is the transmission bandwidth and \( N^2 \) is the noise power.

Time switching scheme is discussed in [22], [23], [24].

- Power splitting scheme: For the PS scheme, the received signal is divided into two components of different power levels according to the power splitting (PS) ratio before it is processed at the PS receiver. The power streams are then sent to the information decoder and energy harvester such that simultaneous EH and ID can be performed as shown in Fig. 2.5.

During the EH operation, the harvested energy can be given as:
\[ E_{i,j} = \eta \varepsilon |h_{ij}|^2 P_i, \]
where \( \eta \) is the energy conversion efficiency, \( \varepsilon \) is the PS ratio of the PS device, \( h_{ij} \) is the channel coefficient between the \( j \)th receiver and the \( i \)th source, \( N^2 \) is the noise power and \( P_i \) is the transmit power of the \( i \)th source.

During the ID operation, [10] calculates the rate as:
\[ R_{j,i} = B \log \left( 1 + \frac{(1 - \varepsilon)P_i |h_{ij}|^2}{N^2} \right), \]
where \( N^2 \) is the noise power. The PS ratio can be optimized at each receiver. The information rate and the harvested energy can be balanced according to the system requirements by varying the PS ratio. PS scheme is discussed in [23], [24].
• Antenna Switching: As the name suggests, antenna switching refers to the phenomenon where in a set of antennas, a subset of antennas at the receiver work on energy harvesting (EH) and the other subset works on information decoding (ID). It is an easy and practical to implement scheme for SWIPT architectures. Fig 2.6. shows the antenna switching architecture. [26] and [27] discuss antenna switching scheme.

Several works have integrated D2D communications with SWIPT. [28] investigates the problem of interference mitigation through power allocation in D2D communications with
SWIPT PS architecture using a novel game theoretic approach. Transmit power and PS ratio are simultaneously allocated for D2D communications. Also, pricing strategies are proposed for the proposed mechanism. Simulations results show that the proposed mechanism provide a 50% more energy efficiency than the conventional Stackelberg game approach. [29] was one of the first works where D2D communications with SWIPT was presented. Decode and forward nodes were considered in the network which could harvest energy. The system model incorporates Rayleigh fading channel with path loss. Simulation results analyzed the performance of the proposed technique by varying the network parameters. [30] presents D2D communication underlaying a cellular network utilizing SWIPT where the devices harvest energy during downlink and then utilize the harvested energy during the uplink communication while ensuring the quality of service for cellular users as well as D2D users. Non-convex optimization problems are constructed for both phases and solved by using inner convex optimization techniques.

2.3. Non-Orthogonal Multiple Access (NOMA)

In the conventional orthogonal multiple access (OMA) scheme, each user uses orthogonal resources (specific time slots, frequency, or code) for communication to avoid multiple access interferences. The FDMA (frequency division multiple access), TDMA (time division multiple access), CDMA (code division multiple access) and OFDMA (orthogonal frequency division multiple access) are the OMA schemes that were deployed in 1G, 2G, 3G and 4G networks respectively. Due to no mutual interference among users, the OMA scheme can achieve good performance with the simple receivers but fail to address the requirements of the 5G networks. The 5G networks are supposed to support enhanced mobile broadband (eMBB), massive machine type communications (mMTC),
and ultrareliable and low-latency communication (URLLC). The eMBB scenario require 100Mbps user perceived data rate and substantially higher spectral efficiency to provide services such as virtual reality and high-definition video experience. The mMTC requires the connection density of 1 million devices per km$^2$. The URLLC require end to end latency of 0.5 ms and 99.99% reliability [31], [32].

The NOMA scheme is the best proven scheme among all the other multiple access scheme to fulfill these requirements. The NOMA scheme enables multiple users to use non orthogonal resources concurrently by allowing multiple access interference at the receivers.

The NOMA schemes can be classified into two types i.e., power domain multiplexing and code domain multiplexing [33]. The power domain multiplexing technique for NOMA allocates different power coefficients to the users according to their channel conditions to improve the system performance. At the transmitter side, the composite signal is the superimposition of multiple users’ information signals. Successive interference cancellation (SIC) is an important feature of the NOMA scheme which is applied at the receiver side for decoding the signals one by one until the desired user’s signal is obtained.

In code domain multiplexing, each user is allocated a unique code and multiplexed over the same frequency-time resources such as multiuser shared access (MUSA), sparse code multiple access (SCMA) and low density spreading (LDS).

The code-domain multiplexing increases the spectral efficiency more than the power-domain multiplexing, but it is difficult to implement it to the existing systems as it requires high transmission bandwidth. One the other hand, the power-domain multiplexing can easily be implemented on the existing networks and does not require additional bandwidth to increase the spectral efficiency. Therefore, owing to the better practical feasibility of the
power-domain multiplexing NOMA, this work aims to study power-domain multiplexing NOMA.

The NOMA scheme offers the following advantages over the OMA scheme:

1) Enhanced spectral efficiency and throughput: A specific frequency resource is assigned to each user irrespective of the channel condition it is experiencing, thus, achieving lower throughput and lower spectral efficiency. In NOMA based systems, a single resource is shared by multiple users irrespective of the channel conditions as shown in Fig. 2.7. The top sub-figure in Fig. 2.7. shows that the power allocated to different users operating in the network is different while they use the same frequency band for transmission for the NOMA scheme. The bottom sub-figure in Fig. 2.7. shows that the powers used by the users operating in the OMA based network is same, but they operate at different frequencies. Each user is depicted with a different colour. Therefore, the weak and the strong user share the same resource and the interference is mitigated by successive interference cancellation (SIC) at the receiver of the users.

2) User fairness, low latency, and massive connectivity [34]: In OFDMA networks with scheduling, the users with strong channel conditions are served first leading to user unfairness, increase in latency and cannot support massive connectivity. NOMA networks can serve multiple users simultaneously irrespective of their channel conditions, hence provides improved user fairness, lower latency and increase connectivity.
Though the NOMA scheme provides greater benefits over the other OMA schemes, yet there are a certain number of limitations that need to be addressed when deploying the NOMA scheme. Due to the feature of successive interference cancellation (SIC), the receiver side of the user must decode the signals of other users before decoding its own signal. This leads to higher computational complexity as compared to the OMA scheme, thus resulting in longer delays. In a NOMA based network, it is required to feed the channel gain information to the base station (BS), leading to channel state information (CSI) feedback overhead. It’s very difficult to obtain perfect CSI and the errors in estimating the

**Figure 2.7. Comparison of NOMA and OMA schemes [33].**
channel state information (CSI) will lead to increase in error probability of successive decoding. To avoid this, number of users should be reduced [34].

2.4. Power Splitting Architecture for Heterogeneous Cellular with Underlay D2D Communications

Time switching SWIPT architectures and the power splitting SWIPT architectures are the most popular architectures integrated with D2D communications. This section gives a literature survey of the power splitting enabled D2D communications underlaying heterogeneous cellular networks.

[35] investigates the power allocation in power splitting architecture enabled D2D communications to enhance the energy efficiency of the D2D communications. The paper proposes two power allocation mechanisms to simultaneous find optimal power allocation and power splitting ratio by establishing a novel game theoretic method. Finally, simulation results are obtained to evaluate the effectiveness of the proposed scheme. [36] studies energy efficient mode selection by using ergodic capacity values for three D2D modes (D2D, dedicated and reuse) for power splitting D2D communications. The simulation results show that using the mode selection techniques proposed by the authors improve the energy efficiency especially in the reuse mode.

[37] proposes to maximize the sum energy efficiency of D2D pairs by optimizing resource and power allocation. This work considers a non-linear energy harvesting model for RF energy harvesters. A two-layer iterative algorithm is proposed to jointly optimize the D2D transmission power and the power splitting ratio. The simulation results show that the proposed algorithms achieve a significant increase in sum energy efficiency as compared to the existing energy-efficient resource allocation scheme for the system. [38]
aims to maximize the energy efficiency of NOMA based D2D network with power splitting scheme and the imperfect channel state information (CSI). A non-convex problem is formulated considering the maximum tolerable outage probability of each D2D user, successive interference cancellation decoding order, maximum transmit power of the base station and the D2D users. The transmit power, power splitting ratio and resource block assignment factor are jointly optimized for the problem. The problem is turned into a convex problem and an iterative algorithm is used to solve the problem.

2.5. Time Switching Architecture for Heterogeneous Cellular with Underlay D2D Communications

This section presents the existing literatures on the time switching SWIPT enabled D2D communications underlaying cellular networks.

[39] studies TS SWIPT enabled D2D communications with a focus on disaster like situations. During a disaster, it is important to select a reliable peer to transfer information to maximize the energy efficiency of the D2D link. Therefore, the paper studies a joint problem considering peer association and selecting optimal time switching ratio considering a device in a destructed disaster hit environment. The proposed algorithm presents a much better energy efficiency as compared to the uniform allocation scheme.

[40] investigates energy harvesting and information decoding cellular users and devices. The problem aims at D2D rate maximization without letting the performance of the cellular users degrade. Two schemes aimed at changing time duration of the D2D pairs are analyzed and based on the analysis, a closed form solution of the problem is obtained. [41] investigates time switching enabled D2D communications underlaying a non-orthogonal multiple access or a NOMA based network. The devices harvest energy in the downlink
and transmitting information in the uplink. The objective of the work is to maximize the energy efficiency of the D2D pair ensuring the rate requirement of the cellular users. Though the problem is non-convex, yet a global optimal solution is obtained using the Karush Kuhn Tucker (KKT) conditions. Authors in [42] study D2D communications underlaying a NOMA based cellular network with the aim of maximizing the D2D throughput while guaranteeing the rate requirement of cellular users. The problem is formulated as a non-convex problem and transformed into a convex problem for some of the scenarios whereas for other scenarios the solution is obtained with the gradient method.

[43] studies full duplex (FD) relaying and time switching SWIPT enabled D2D communications. Also, the NOMA scheme is used at the base station to reduce latency. Both the cellular users and the devices harvest energy from the base station (BS) and further decode the signal through SIC technique and send the signal to the desired user equipment. The ergodic capacities at the devices are obtained and considering the imperfect CSI closed form expressions for the outage probabilities are also obtained. The results are compared with the OMA scheme, and it is found that the NOMA scheme performs much better as compared to the OMA scheme.

2.6. Deep Learning Architecture for Heterogeneous Cellular with Underlay D2D Communications

The existing literatures studying energy harvesting D2D communications underlaying cellular networks formulate optimization problems where the objective functions are subject to certain constraints crucial to the functioning of the network. These problems are generally solved by conventional optimization methods. Though these optimization
methods give accurate results, yet the computational complexity and the running times of most of the algorithms used in the literatures are significantly high.

Artificial neural networks have the capability to learn from a particular provided dataset and provide optimal solutions for new inputs coming in. The artificial neural networks have proved to consume lesser time and provide equally good solutions as compared to the conventional optimization techniques [44]. Hence, the neural networks are being increasingly integrated with the field of wireless communications to solve the resource allocation problems [45], [46].

2.6.1 Neural Networks Used for Deep Learning Research for D2D Communications

There exist different neural networks whose applications depend on the input and the output data. This section gives a note of the significant literatures which use deep learning to predict the output of the neural networks.

[47] studies the joint optimization of energy harvesting and spectrum efficiency in a wireless network where power splitting SWIPT enabled D2D communications are present. The objective function is obtained using the weighted sum method and it is required to find the optimal transmit power and the power splitting ratio. The optimal transmit power and the power splitting ratios are obtained using the conventional iterative algorithms such as the exhaustive search method to find the global optimum and the gradient search method to find the sub optimal solution. Finally, a DNN based algorithm is deployed and it is proved that the DNN based algorithm gets a near optimal solution with much lower computational complexity. [48] also uses a feed forward neural network to predict the system capacity of the energy harvesting D2D communications based on non-orthogonal multiple access (NOMA). The problem is first solved using an offline algorithm and the
data obtained from the offline optimization algorithm is further fed to the neural network as the training dataset. The neural network is used to obtain the optimal model of the transmission power thus making the process computationally efficient.

[49] uses multi-user single input single output (SISO) D2D communications using the power splitting scheme. The objective of the problem is to minimize the sum transmit power of the transmitters by optimizing the power splitting ratios and the transmit power under the constraints of fulfillment of the required SINR and the harvested energy. The problem is constructed as a non-convex problem and further solved by conventional optimization algorithms. The data obtained from the optimization algorithms i.e., the input and the output are fed into neural networks, FFNN, and three varieties of RNN: the LRN, NARX, and LSTM to train the neural networks. The output data is generated providing the inputs during the testing stage and the results are compared with that from the traditional optimization algorithm. It is proved that the neural networks provide near to the optimal values in most cases and take much lesser time as compared to the optimization algorithm. [50] aims at autonomous optimal D2D power allocation using distributed deep learning algorithm to achieve higher cell throughput.

2.7. Similarities and Differences between Previous Works and Thesis

Chapters 3, 4 and 5 deal with resource allocation for power splitting SWIPT enabled D2D communications underlaying a NOMA based cellular network, resource allocation for time switching SWIPT enabled D2D communications underlaying a NOMA based cellular network and resource allocation for power splitting and time switching SWIPT enabled D2D communications underlaying a NOMA based cellular network using a kind of DNN (deep neural network): the feed forward neural network (FFNN).
To begin with, as said, chapter 3 focuses on power splitting SWIPT enabled D2D communications underlaying NOMA based cellular networks. Though the power splitting scheme is investigated in the literatures, yet, it is not fully exploited, and there exist certain gaps which need to be addressed in the literature. Though [35], [36], [37] and [38] study power splitting SWIPT enabled D2D communications, yet the papers aim to maximize the energy efficiency. Also, NOMA scheme is not considered in these papers. Furthermore, different variables are optimized to maximize the objective function. The work present in this thesis is one of the first works to consider optimizing the power splitting ratio and transmit powers with the aim of maximizing the D2D throughput.

Though the time switching scheme has been investigated well in the literature, yet the work done in this thesis is different from the work currently present in the literatures. [39] is specifically for disaster like situations where the authors aim to select the best possible nearest device whereas the work in this thesis deals with normal situations and selecting the best possible device isn’t the scope of this work. Also, [39], [41] and [43] have different objectives rather than maximizing the throughput while this work aims to maximize the sum throughput.

[40] aims at D2D sum rate maximization where D2Ds operate without letting the performance of the cellular users degrade. Though, we aim at the sum throughput maximization for D2Ds along with guaranteeing the rate requirement of cellular users, but we consider a NOMA based network which isn’t considered in [40]. The work done in [42] is similar to the work done in this thesis but only one D2D pair is considered which doesn’t really apply to practical scenarios. This work considers multiple D2D pairs thus considering the practical scenarios. For the neural network scenario, as the other works
aimed to include deep learning in their problems to make the work computationally more efficient, this thesis also uses the deep learning part to make the problem more computationally efficient and less time consuming.

2.8 Summary

This chapter gives the details of the technologies used in this thesis namely, D2D communications, SWIPT and NOMA. First, a brief introduction of D2D communications is provided. Further, the system architecture of D2D communications and the categorization of D2D communications based on spectrum usage; inband and outband D2D communications are discussed. We then discussed the underlay and overlay inband communications in detail. Most popular resource allocation elements were also discussed. Further, a brief introduction of the SWIPT was given along with the receiver architectures that enable SWIPT support by the systems. Further, the NOMA scheme is discussed where the different types of NOMA schemes such as the power domain multiplexing or the code domain multiplexing are discussed. The benefits of NOMA over the OMA schemes are discussed and then the drawbacks of using the NOMA scheme are also discussed.

The chapter also discusses the most relevant works in the fields of TS and PS SWIPT enabled D2D communications along with the most relevant works in the field of deep learning applied to resource allocation problems and compares them with the work in the thesis.
Chapter 3: Resource Allocation for Power Splitting SWIPT enabled D2D Communications Underlaying a NOMA Based Cellular Network

3.1. Introduction

From the previous chapter, it is pristinely clear that most of the present literatures focus on TS SWIPT enabled D2D communications and, limited literatures have studied PS SWIPT enabled D2D communications underlaying non-orthogonal multiple access (NOMA) cellular networks so far. Therefore, to advance the work on PS SWIPT enabled D2D communications underlaying NOMA networks, this chapter considers solving a resource allocation problem with the objective of maximizing the throughput of PS SWIPT enabled D2D communications under the constraint of satisfying the minimum rate requirements of the cellular users. This chapter presents one of the first works to consider jointly optimizing the power splitting ratio and transmit power to maximize the D2D throughput. The main objectives of the chapter are as follows:

1. A resource allocation problem is formulated considering a PS enabled D2D communication underlaying a NOMA-based cellular network with the objective of maximizing D2D throughput where both the transmit power and power splitting ratio are jointly optimized such that the minimum rate requirement of the cellular users is satisfied.

2. The formulated optimization problem is mathematically analyzed, and closed-form solutions are derived in some scenarios and in other scenarios, a sub-optimal solution is obtained using the gradient descent method.
3. The numerical results of the NOMA-based cellular network are compared with those of the conventional OMA-based cellular network and a random resource allocation scheme.

The chapter is divided into the following sections. Section 3.2 presents the system model. Section 3.3 presents the problem formulation. Section 3.4 presents the problem reformulation and analysis. Section 3.5 presents problem analysis for the OMA scheme. Section 3.6 presents the results and discussion. Finally, section 3.7 presents the summary of the work presented in the chapter.

3.2. System Model

3.2.1. Network Topology

A NOMA-based cellular network is considered, and the total number of cellular users is taken as $K$ which are uniformly distributed in a square shaped cell, where $L$ is the length of side of the cell. The square shaped cell is assumed since it can easily be modelled during the simulation process. Let Q be the set which contains the total number of cellular users. To avoid additional complexity in the problem formulation, a single cell covered by one base station (BS) is considered which is located at the center of cell area. The locations of the device transmitter and device receiver (abbreviated by DTX and DRX, respectively) are also uniformly distributed inside the cell such that the distance between them does not exceed a certain distance $d$, the communication range.

The network considered is a 2-tier network comprising a cellular network tier with device to device (D2D) tier as an underlay. The D2D tier comprises one D2D pair, for simplicity. The network diagram of the 2-tier heterogeneous network is shown in Fig. 3.1. Downlink transmission is considered, where the cellular users receive signals from the base
station at different powers since we are considering the power domain NOMA. All the users in the system (cellular or D2D) are equipped with one antenna. That is, a SISO (single input single output) system is considered, for simplicity.

![Network Diagram showing the signal flow.](image)

**Figure 3.1. Network Diagram showing the signal flow.**

### 3.2.2. Time Frame Organization

The system time is organized into frames each of length $T$ seconds. DTX operates in half duplex mode, spending equal amount of time to receive signal from the BS and to transmit to the DRX during each time frame [51]. This implies that the time frame comprises two time slots each of length $T$ seconds. That is, in each frame, the DTX receives from the BS during the first timeslot and transmits to DRX in the second timeslot. DTX harvests energy from the signal received from the BS during the first timeslot and uses the energy harvested to transmit to DRX in the second timeslot.
3.2.3. Power Splitting SWIPT architecture and its deployment

A power splitting (PS) structure is adopted by DTX for energy harvesting (Fig. 3.2.), to achieve better tradeoff between the data rate and the harvested energy. Further, the PS device is assumed to be passive and ideal. This implies the PS device neither consumes any power nor introduces any power loss or signal processing noise to the system.

The PS device splits the received power from the BS with a PS ratio $\epsilon$, $0 \leq \epsilon \leq 1$ where $\epsilon$ of the received signal power is used for energy harvesting and the balance $(1 - \epsilon)$ is used for information processing. Due to the non-ideality of the energy harvesting circuit components, an energy conversion efficiency denoted by $\eta$, $(0 \leq \eta \leq 1)$ is assumed for the $\epsilon$ of the harvested energy.

Figure 3.2. Power splitting architecture at DTX and DRX

3.2.4. Channel Model

The wireless channel between the BS and the cellular users, between the BS and the D2D users, between DTX and the cellular users, and between DTX and DRX is modeled by average path loss and small-scale fading. The average path loss is distance dependent
with path loss exponent $\alpha$. Small-scale fading is modeled by Rayleigh fading. The small-scale fading coefficient is constant within a time frame but changes from frame to frame (i.e., block fading). This implies that in each time frame, the channel power gain (i.e., absolute channel coefficient squared) is a product of the average path loss and the fading channel power gain for that frame. Denote the channel coefficients as follows:

$h_i$ is the channel coefficient between the BS and the $CU_i$ ($i=1,2,\ldots,K$), $h_D$ is the channel coefficient between the DTX and DRX, $h_{B,D_t}$ is the channel coefficient between BS and DTX, $h_{B,D_r}$ is channel coefficient between the BS and DRX, and $h_{D,i}$ is the channel coefficient between DTX and $CU_i$.

### 3.3. Problem Formulation

Now, since NOMA utilizes successive interference cancellation, hence for $K$ cellular users it can be deduced that

$$|h_1| \geq |h_2| \geq |h_3| \geq \cdots \geq |h_K|.$$  

(3.1)

a. Signal model in the first time slot of interval $\left(0 \leq t \leq \frac{T}{2}\right)$

The composite transmit signal by the base station to the cellular users during the first timeslot $x_B^1$ can be written as

$$x_B^1 = \sum_{k=1}^{K} \sqrt{\nu_k P_{BS}} s_k,$$  

(3.2)

where $s_k$ is the BS transmit signal for cellular user $CU_k$, $\nu_k$ is the BS power allocation coefficient for $CU_k$. Since all the cellular users are active in the first timeslot, therefore,

$$\sum_{k=1}^{K} \nu_k = 1,$$  

(3.3)
where \( \nu_k > 0 \), for all \( k = 1, 2, 3, \ldots, K \). Now, since the NOMA technique is utilized with successive interference cancellation invoked, hence, for any \( j > i \), the received SINR for any cellular user \( CU_i \) for decoding the signal can be calculated as

\[
SINR_{i,j}^1 = \frac{\nu_j |h_i|^2 P_{BS}}{\sum_{k=1}^{j-1} \nu_k |h_i|^2 P_{BS} + N^2},
\]  

(3.4)

where \( N^2 \) is the variance of the antenna noise.

The numerator of eq. (3.4) gives the signal power of the particular cellular user \( CU_i \). The denominator gives the interference power caused by other cellular users plus the noise power.

The energy harvested by the DTX is given as

\[
E^h_D = \frac{T}{2} \eta P_{BS} |h_{B,D} t|^2.
\]  

(3.5)

b. Signal Model in the second time slot of interval \( \left( \frac{T}{2} \leq t \leq T \right) \)

The composite transmit signal by the BS \( x^2_B \) in the second timeslot.

\[
x^2_B = \sum_{k=1}^{K} \sqrt{\lambda_k P_{BS}} s_k.
\]  

(3.6)

where \( \lambda_k \) is the BS power allocation coefficient for \( CU_k \).

\[
\sum_{k=1}^{K} \lambda_k \leq 1,
\]  

(3.7a)

and,

\[
\lambda_k \geq 0,
\]  

(3.7b)

for all \( k \in Q \). Also, the following energy balance equation given below holds:

\[
\frac{T}{2} P_D + \rho^e_D + \rho^f_D \leq E^h_D,
\]  

(3.8)

where \( P_D \) is the transmit power by DTX (\( P_D \) is unknown, to be determined). The DTX circuit energy consumption \( \rho^e_D = \frac{T}{2} p^e_D \), and \( \rho^f_D = \frac{T}{2} p^f_D \), where \( p^e_D \) and \( p^f_D \) are the DTX
circuit power consumption for energy harvesting and data transmission, respectively (are assumed to be constant and known).

The received SINR at the D2D receiver can be calculated as

$$SINR_D^2 = \frac{|h_D|^2(1-\varepsilon)P_D}{\sum_{k=1}^{K} \lambda_k|h_{B,D_R}|^2P_{BS}+N^2}. \quad (3.9)$$

Now, in the second timeslot, each cellular user gets interference from the fellow cellular users as well as from the D2D transmitter due to DTX sharing the downlink spectrum of the cellular users. The received SINR at each $CU_i$ decoding a signal $s_j$ such that $j > i$ is given by:

$$SINR_{i,j}^2 = \frac{|h_i|^2\lambda_jP_{BS}}{\sum_{k=1}^{i-1} \lambda_k|h_i|^2P_{BS}+|h_D,i|^2P_D+N^2}. \quad (3.10)$$

Now, to decode a signal $s_j$, the received SINR at $CU_i$ should be no less than that received at $CU_j$ itself, i.e. $SINR_{i,j}^2 \geq SINR_{j,j}^1 (j > i)$. Therefore:

$$\frac{|h_D,i|^2P_{D+N}^2}{|h_i|^2} \leq \frac{|h_D,j|^2P_{D+N}^2}{|h_j|^2}. \quad (3.11)$$

$$K \geq j \geq i \geq 1$$

Equation (3.11) can be recast as

$$\frac{|h_D,i|^2P_{D+N}^2}{|h_i|^2} \leq \frac{|h_D,i+1|^2P_{D+N}^2}{|h_{i+1}|^2}. \quad (3.12)$$

$$K - 1 \geq i \geq 1$$

The achievable rates by the $CU$’s in the first and second time slots, and by the D2D link in the second time slot are calculated by the Shannon formula (with the bandwidth normalized)

$$R_i^1 = \log_2(1 + SINR_{i,i}^1), \quad (3.13a)$$
\[ R_i^2 = \log_2 (1 + SINR_i^2), \quad (3.13b) \]
\[ R_D^2 = \log_2 (1 + SINR_D^2), \quad (3.13c) \]

The minimum rate requirement of the cellular users should be met for both time slots. Hence,

\[ R_i^1 \geq \gamma_i, \quad (3.14a) \]
\[ R_i^2 \geq \gamma_i, \quad (3.14b) \]

where \( \gamma_i \) is the minimum rate requirement for \( CU_i \).

The power splitting ratio satisfies the constraint:

\[ 0 \leq \varepsilon \leq 1. \quad (3.15) \]

Therefore, the objective is to maximize the throughput of D2D communication under the constraint of the QoS of the cellular users. The resource allocation problem can then be formulated as:

\[
\max_{\varepsilon, \lambda, \rho_D, \nu} U_D = \frac{T}{2} R_D^2, \quad (3.16a)
\]
\[
\text{s.t. } (3.3), (3.7), (3.8), (3.12), (3.14), (3.15). \quad (3.16b)
\]

The problem (3.16) is non-convex because both the objective function (3.16a) and the constraints (3.16b) are non-convex with respect to the optimization variables.

### 3.4 Problem Reformulation and Analysis

Therefore, to find the solution of problem (3.16) which is non-convex, an approach similar to [42] is followed, the problem (3.16) is reformulated with variables \( \varepsilon \) and \( \rho_D \) in this section.

It can be seen from equations (3.4) and (3.10) that \( R_i^1 > R_i^2 \) for \( \lambda = \nu \). Therefore, if \( \lambda^* \) satisfies \( R_i^2 \geq \gamma_i \) for all \( i \in Q \), we can set from (3.3) that \( \nu_1^* = 1 - \sum_{k=2}^{K} \nu_k^* \) and \( \nu_2^* = \)
\( \lambda_2^*, \ldots, \nu_K^* = \lambda_K^* \) which means that \( \nu^* \) satisfies \( R_i^1 \geq \gamma_i \) for all \( i \in Q \). Hence, constraint (3.14) can be written just as

\[
R_i^1 \geq \gamma_i,
\]

(3.17)

for \( i \in Q \). Therefore, having solved for \( \nu^* \), the problem (3.16) can be re-formulated as

\[
\max_{\varepsilon, \lambda, \rho_D} U_D = \frac{T}{2} R_D^2,
\]

(3.18a)

\[
\text{s.t. } (3.7), (3.8), (3.12), (3.15), (3.17).
\]

(3.18b)

The problem (3.18) is still non-convex because both the objective function (3.18a) and the constraints (3.18b) are non-convex with respect to the optimization variables.

**Theorem 3.1:** The optimal solution of the problem (3.18) can be derived when the equality of the constraint (3.17) holds such that

\[
R_i^2^* = \gamma_i.
\]

(3.19)

**Proof:** See Appendix A.

**Theorem 3.2:** The optimal power allocation coefficient \( \lambda^* \) can be derived from eq. (3.19) such that

\[
\lambda_i = \frac{\sum_{j=1}^{l-1} \left( |h_{i,j}^{l-1}(1+\psi_u)\psi_i|/|h_i|^{2}\right)+\psi_i|/|h_i|^{2}\right)}{\rho_{BS}}.
\]

(3.20a)

where,

\[
\psi_i = 2^{\gamma_i} - 1,
\]

(3.20b)

\[
\sigma_i = \frac{|n_D|^{2}}{|h_i|^{2}},
\]

(3.20c)

\[
\zeta_i = \frac{1}{|h_i|^{2}},
\]

(3.20d)

where \( \rho_D = \frac{P_D}{N^2} \) and \( \rho_{BS} = \frac{P_{BS}}{N^2} \), for all \( i \in Q \).

**Proof:** See Appendix B.
Theorem 3.2 depicts the relationship between $\lambda_i^*$ and $\rho_D^*$. Now, from eq. (3.7a), $\sum_{i=1}^{K} \lambda_i \leq 1$. Hence, the next step is evaluating $\sum_{i=1}^{K} \lambda_i$ to analyze the feasible region of the decision variable $\rho_D$.

Now substituting (3.20a):

$$\sum_{i=1}^{K} \lambda_i = \frac{\sum_{j=1}^{K} \left[ \prod_{u=j+1}^{K} (1+\psi_u) \right] \psi_j (\sigma_j \rho_D + \zeta_i) }{\rho_{BS}},$$

(3.21)

$$\sum_{i=1}^{K} \lambda_i = \bar{P} \rho_D + \bar{Q} \leq 1.$$  

(3.22)

where the inequality in (3.22) follows from (3.7a),

$$\bar{P} = \frac{\sum_{j=1}^{K} \left[ \prod_{u=j+1}^{K} (1+\psi_u) \right] \psi_j }{\rho_{BS}},$$

and

$$\bar{Q} = \frac{\sum_{i=1}^{K} \left[ \prod_{u=j+1}^{K} (1+\psi_u) \right] \psi_j }{\rho_{BS}}.$$

It can be easily seen from (3.20a), (3.20b), (3.20c), (3.20d) that $\psi_i > 0, \sigma_i > 0$ and $\zeta_i > 0$ for all $i \in Q$.

Now, combining (3.22), (3.20c), (3.20d), and (3.12) gives:

$$0 \leq \rho_D \leq \rho_{\text{max}},$$

(3.23a)

$$\rho_{\text{max}} = \left\{ \frac{1-\bar{Q}}{\bar{P}}, \min_{i \in I} \frac{\zeta_{i+1} - \zeta_i}{\sigma_i - \sigma_{i+1}} \right\},$$

(3.23b)

where $I = \{ i | \sigma_i > \sigma_{i+1}, 1 \leq i \leq K - 1 \}$.

Next, we describe the relationship between $\epsilon^*$ and $\rho_D^*$. Substituting (3.5) in (3.8) and solving for $\rho_D$.

$$0 \leq \rho_D \leq \bar{c} \epsilon - \bar{D},$$

(3.24)

where $\bar{c} = \rho_{BS}^2 \max_{h_{B,D}} |h_{B,D}|^2$ and $\bar{D} = \rho_B^e + \rho_D^e$.

Clearly, $\bar{c} \geq 0, \bar{D} \geq 0$.

Now, since $\lambda^*$ is solved for from Theorem 2, the Problem (3.18) reduces to
\[ \max_{\varepsilon, \rho_D} U_D = \frac{T}{2} \log_2 \left( 1 + \frac{|h_D|^2(1-\varepsilon)\rho_D}{j\rho_D + \bar{s}} \right), \]  

(3.25a)

\[ \text{s.t. (3.23a), (3.24),} \]  

(3.25b)

where \( \bar{f} = \bar{p}|h_{B,D_r}|^2 \rho_{BS} \) and \( \bar{s} = \bar{q}|h_{B,D_r}|^2 \rho_{BS} + 1. \)

Problem (3.25) is feasible when the following conditions are met:

**Condition 1:** From (22), \( \frac{1-\bar{q}}{\bar{p}} \geq 0 \Rightarrow \bar{q} \leq 1. \)

**Condition 2:** The DTX circuit power consumption for energy harvesting should be less than the power harvested by the DTX

\[ \rho_D^{e} \leq \eta|h_{B,D_t}|^2 \rho_{BS}. \]

From (3.15), (3.23), (3.24), \( \varepsilon \) can be divided into two intervals to simplify the constraint (3.25b).

**Interval I** \( \left( \frac{\bar{D}}{\bar{C}} \leq \varepsilon \leq \frac{\bar{D} + \rho_{D_{\text{max}}}}{\bar{C}} \right) : \)

The problem (3.25) becomes

\[ \max_{\varepsilon} U_D = \frac{T}{2} \log_2 \left( 1 + \frac{|h_D|^2(1-\varepsilon_1)\rho_{D_1}}{j\rho_{D_1} + \bar{s}} \right), \]  

(3.26a)

\[ \text{s.t.} \frac{\bar{D}}{\bar{C}} \leq \varepsilon \leq \frac{\bar{D} + \rho_{D_{\text{max}}}}{\bar{C}}. \]  

(3.26b)

The problem given by (3.26) is convex.

*Proof: Appendix C*

If only one saddle point for \( U_D(\varepsilon) \) in interval I is present, then the solution to the problem (3.26) obtained using Algorithm 1 is indeed the optimal. An accuracy control parameter \( \theta \) is taken and the step size \( \Delta \) is evaluated by the backtracking line search method. The gradient is obtained as
\[ H = \frac{T}{2 \ln 2} \left[ \frac{m_1 n_1 \varepsilon^2 + 2 m_1 n_2 \varepsilon + m_2 n_2 - m_3 n_1}{(n_1 \varepsilon + n_2)(m_1 \varepsilon^2 + m_2 \varepsilon + m_3)} \right]. \]  

(3.27)

where, \( m_1 = -|h_D|^2 \bar{C} \), \( m_2 = \bar{J} \bar{C} + |h_D|^2 (\bar{C} + \bar{D}) \), \( m_3 = \bar{S} - |h_D|^2 \bar{D} \), \( n_1 = \bar{J} \bar{C} \), \( n_2 = \bar{S} - \bar{J} \bar{D} \).

The optimal solution can then be derived as \( \rho_{D,1}^* = \bar{C} \varepsilon_1^* - \bar{D} \) and \( U_{D,1}^* = \frac{T}{2} \log_2 \left( 1 + \frac{|h_D|^2 (1 - \varepsilon_1^*) \rho_{D,1}^*}{\bar{J} \rho_{D,1}^* + \bar{S}} \right) \).

**Interval II** \( \left( \frac{\bar{D} + \rho_{D,1}^*}{\bar{C}} \leq \varepsilon \leq 1 \right) \):

Referring to our objective function given by (3.25a), \( U_D \) decreases with \( \varepsilon \) and increases with \( \rho_D \). So, the optimal solution becomes \( \rho_{D,2}^* = \rho_{D,1}^* \) and \( \varepsilon_2^* = \frac{\rho_{D,1}^* + \bar{D}}{\bar{C}} \). The corresponding throughput of the D2D communication is \( U_{D,2}^* = \frac{T}{2} \log_2 \left( 1 + \frac{|h_D|^2 (1 - \varepsilon_2^*) \rho_{D,2}^*}{\bar{J} \rho_{D,2}^* + \bar{S}} \right) \).

In summary, depending on the throughput obtained in both the intervals I and II, the greater throughput of the two is the throughput for the particular system time frame, and the corresponding solution for the greater throughput is the optimal solution to the problem (3.25). The algorithm to find the optimal power splitting ratio \( \varepsilon_1^* \) during interval I is given in Algorithm 3.1.

The explanation for Algorithm 3.1 is as follows. For Interval I, the value of \( \varepsilon \) varies between \( \frac{\bar{D}}{\bar{C}} \) and \( \frac{\bar{D} + \rho_{D,1}^*}{\bar{C}} \). The inputs and output from the Algorithm 3.1 are as mentioned.

The output of the algorithm is to find \( \varepsilon^* \). Line 1 provides the values for initialization to the algorithm; \( \varepsilon_p = \frac{\bar{D}}{\bar{C}} + \theta \), \( \varepsilon = \frac{\bar{D}}{\bar{C}} \). Line 2 calculates the values of \( m_1, m_2, m_3, n_1, n_2 \) from eq.
(3.27). Line 3 marks the starting of the algorithm. The gradient ascent method finds the maximum value of objective function by finding the optimal PS ratio.

In the algorithm, $\epsilon_p$ refers to the old value of the PS ratio and $\epsilon$ refers to the new value of PS ratio after the gradient update. Line 6 updates the value of $\epsilon$ using the gradient ascent method which involves utilizing the derivative of the objective function. The step size with which the gradient method updates the optimization variable ($\epsilon$) is calculated by the backtracking line search as in line 5. If the PS ratio goes beyond the range as specified in Interval I, lines 7 to 12 bring it in the specified range. Once the optimization variable gets updated, line 4 sets the old value as the value obtained from line 6. This process continues until the error between the new and old values is within $\theta$, the accuracy control parameter and the optimal value is obtained.
The complexity for Algorithm 3.1 can be given as \( O\left(\frac{1}{\theta}\right) \), where \( \theta (\ll 1) \) is the accuracy control parameter.

In summary, depending on the throughput obtained in both the intervals I and II, the greater throughput of the two is the throughput for a particular system time frame, and the corresponding solution for the greater throughput is the optimal solution to the problem (3.25).
3.5. The OMA Scheme

In this section, the resource allocation problem for the conventional orthogonal multiple access (OMA) - based scheme is formulated. The OMA scheme is set as a benchmark for comparison against the NOMA-based scheme.

The process for the first time slot is the same as that in NOMA-based scheme, while for the second time slot, the total bandwidth is equally divided into \( M \) -bandwidth units and each cellular user is allocated a distinct single bandwidth unit.

Hence, after formulating and simplifying in the same way as done for NOMA scheme, the problem becomes

\[
\max_{\epsilon^o, \rho_D^o} U_D = \frac{T}{2} \log_2 \left( 1 + \frac{|h_D|^2(1-\epsilon^o)\rho_D^o}{f\rho_D^o+S} \right),
\]

s.t.

\[
0 \leq \rho_D^o \leq \bar{C} \epsilon^o - \bar{D},
\]

\[
0 \leq \rho_D^o \leq \frac{1-\bar{Q}^o}{\bar{\rho}^o},
\]

where \( \psi_i^o = 2^{\psi_i} - 1 \), \( \sigma_i = \frac{|h_{D,i}|^2}{|h_i|^2} \), \( \zeta_i = \frac{1}{|h_i|^2} \), \( \bar{P}^o = \frac{\Sigma_{i=1}^K \psi_i^o \sigma_i}{\rho_{BS}} \), \( \bar{Q}^o = \frac{\Sigma_{i=1}^K \psi_i^o \zeta_i}{\rho_{BS}} \), \( \bar{J}^o = \frac{\rho_{BS}}{\rho_{BS}} \), \( \bar{P}^o \frac{|h_{B,D,r}|^2}{\rho_{BS}}, \bar{S}^o = \bar{Q}^o \frac{|h_{B,D,r}|^2}{\rho_{BS}} + 1 \).

The problem (3.28) is similar to problem (3.25) and the optimal solution can be found using the similar procedure as in the NOMA scheme.

3.6. Results and Discussion

This section presents the numerical results of the NOMA cellular network compared with the conventional OMA cellular network.

The detailed network settings are listed in Table 3.1.
Table 3.1 Simulation settings

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$ (frame length)</td>
<td>10 seconds [42]</td>
</tr>
<tr>
<td>$P_{BS}$ (BS transmit power)</td>
<td>3W</td>
</tr>
<tr>
<td>$p^e_D$ (DTX circuit power consumption for energy harvesting)</td>
<td>5 mW [42]</td>
</tr>
<tr>
<td>$p^t_D$ (DTX circuit power consumption for signal transmission)</td>
<td>10 mW [42]</td>
</tr>
<tr>
<td>$N^2$ (noise power)</td>
<td>$3 \times 10^{-6}$W</td>
</tr>
<tr>
<td>$\gamma_i$ (minimum rate requirement)</td>
<td>0.1 bps/Hz [42]</td>
</tr>
<tr>
<td>$\eta$ (energy conversion efficiency)</td>
<td>0.9</td>
</tr>
<tr>
<td>$\theta$ (accuracy parameter)</td>
<td>0.001</td>
</tr>
<tr>
<td>$d$ (maximum distance between DTX and DRX)</td>
<td>10 m [42]</td>
</tr>
<tr>
<td>$L$ (side of cell)</td>
<td>100 m</td>
</tr>
</tbody>
</table>

The simulation is performed in MATLAB 2020b. The values in table 3.1 are the inputs. The $(x,y)$ coordinates of the devices and cellular users are uniformly generated and the distance between them is calculated using the generated coordinates. The distance is used to calculate the path loss with path loss exponent ($\alpha$). The channel coefficient is the product of the path loss and the Rayleigh fading channel coefficient. Finally, all values needed to calculate $\rho_{D_{\text{max}}}$, $m_1$, $m_2$, $m_3$, $n_1$, $n_2$ are calculated and fed to the Algorithm 3.1. Finally, the outputs as predicted by the Algorithm 3.1 are fed to calculate the D2D throughput and it is
checked in which interval the D2D throughput is greater. The greater throughput is the final throughput for that particular frame.

Each simulation run is of length 50000 frames, and the results presented are averaged over the 50000 frames. Two scenarios are considered in terms of number of cellular users. The first scenario considers 4 cellular users, and the second scenario considers 2 cellular users present in the cell.

![Graph 1](image1.png)

**Figure 3.3. D2D Throughput versus rate threshold of the Cellular Users**

Figure 3.3 depicts the relationship between the D2D throughput and the rate requirement threshold of the cellular users. First, for either $K=2$ or $K=4$ cellular users, it is observed that the D2D throughput decreases as the minimum rate requirement of the cellular users increases. Since $R_i^{2*} = \gamma_i$ and the minimum rate requirement increases, the
DTX transmit power must be decreased to lower the interference caused by D2D communication. This lowered DTX transmit power results in lower received $\text{SINR}$ at DRX, hence lower achievable D2D rate and eventually lower D2D throughput in the NOMA cellular network. Second, at a given minimum rate requirement of the cellular users, the D2D throughput with 4 cellular users per cell is less than that achieved with 2 cellular users. The four cellular users create a larger interference than that of the two cellular users thus limiting the D2D throughput. Next, comparing the result of the NOMA cellular network with that of the OMA network, the division of total bandwidth in the OMA network demands further decrement of the DTX power in comparison to NOMA based network to achieve the specified rate requirement, thus lowering the D2D throughput in OMA based network. The random allocation gives a lower result that the NOMA scheme because the optimization variables are selected randomly rather than being optimized.
Figure 3.4. D2D Throughput versus path loss exponent

Figure 3.4. shows the impact of path loss exponent on the D2D throughput. As we can see, the D2D throughput decreases with the path loss exponent. As the path loss exponent increases, the path loss becomes severe which naturally results in lower received power at DRX, and, consequently, lower throughput. It can also be observed that the NOMA cellular network offers a much better result than the conventional OMA cellular which leads to lower D2D throughput than that of NOMA cellular network because of the decrement in device transmit power. More cellular users contribute to more interference leading to a lower D2D throughput.
Figure 3.5. D2D Throughput versus conversion efficiency of DTX

Figure 3.5. shows the relationship between the D2D throughput and the energy conversion efficiency at the DTX. It is seen that the D2D throughput increases as the energy conversion efficiency increases because the DTX can harvest more energy and hence it can transmit with higher power. The reason why the NOMA cellular network offers a greater throughput than that of the OMA cellular network is as explained previously. As the number of cellular users increases, the interference for the DTX to transmit the signal also increases resulting in a lower D2D communication rate, thus, leading to a lower D2D throughput.
Figure 3.6. D2D Throughput versus maximum distance between DTX and DRX

Figure 3.6. depicts the relationship between D2D throughput and maximum distance between DTX and DRX. The increasing distance between DTX and DRX leads to greater path loss between the devices, hence lower value of D2D throughput is observed as the maximum distance increases. When 2 cellular users are present in the cell, the D2D throughput is considerably higher than when there are 4 cellular users in the cell due to reduced interference for the DTX to transmit the signal.

3.7. Summary

This chapter solves a resource allocation problem considering SWIPT PS enabled D2D communications underlaying a NOMA based cellular network. The objective of the resource allocation problem is to maximize the device throughput such that the minimum
rate requirements of the cellular users is guaranteed. The problem is formulated as a non-convex problem which is further simplified using rigorous mathematical calculations and the problem is solved using the gradient descent method to find the sub-optimal solution. The results obtained are varied with different network parameters.
4.1. Introduction

In the previous chapter, PS-SWIPT enabled D2D communications were studied. This chapter focuses on TS-SWIPT enabled D2D communications. Though TS scheme is widely studied in the literature, yet, as it is shown in Chapter 2 of this thesis, there are still gaps in the literature regarding the TS scheme. To address these gaps, we consider a system with multiple D2D pairs and attempt to study the effect of D2D interferences as well as the interference from the cellular users on the D2D throughput. The main objectives of the chapter are as follows:

1. A resource allocation problem is formulated considering the TS-SWIPT enabled D2D communications underlaying a non-orthogonal multiple access (NOMA)-based cellular network with the objective of maximizing the sum D2D throughput where both the transmit power and times (energy harvesting and signal transmission) are jointly optimized such that the minimum rate requirement of the cellular users is satisfied.

2. The formulated optimization problem is mathematically analyzed, and, owing to the non-convexity of the resource allocation problem, a sub-optimal solution is obtained using the gradient method.

3. The numerical results of the NOMA-based cellular network are compared with those of the conventional orthogonal multiple access (OMA)-based cellular network.

The chapter is divided into the following sections. Section 4.2 presents the system model. Section 4.3 presents the problem formulation. Section 4.4 presents the problem
reformulation and analysis. Section 4.5 presents problem analysis for the OMA scheme. Section 4.6 presents the results and discussion. Finally, Section 4.7 presents the summary of the work presented in the chapter.

4.2 System Model

4.2.1. Network Topology

A NOMA-based cellular network is considered and the total number of cellular users is taken as $N$. To avoid additional complexity in the problem formulation, a single cell covered by one base station (BS) is considered. The reason of selecting a NOMA based cellular network are the benefits it provides in terms of spectral efficiency, throughput, and user fairness [34]. The cellular users ($CUs$) are uniformly distributed in a square shaped cell of dimensions $L \times L$, where $L$ is the length of side of the cell, and, because we assume uniformity throughout the system, we assume that the BS is located at the center of the cell. The transmit power of the base station is $P_{BS}$. The device transmitters and device receivers (abbreviated by DTX and DRX, respectively) are also uniformly distributed inside the cell such that the distance between them does not exceed a certain distance $d$, the communication range.

A 2-tier network is considered comprising a cellular network tier with device-to-device (D2D) tier as an underlay. The network is as shown in figure. 4.1. Downlink transmission is considered, where the cellular users receive signals from the base station at different powers since the power domain NOMA is being considered. Also, due to the utilization of power domain NOMA, $N$ $CUs$ are multiplexed in a single channel. Let $\mathbb{N} = \{1, 2, \ldots, N\}$ be the set of $CUs$ multiplexed in a channel. Let $\mathbb{C} = \{1, 2, \ldots, C\}$ be the set
of underlaid D2D pairs. All the users in the system (cellular or D2D) are equipped with one antenna. That is, a SISO (single input single output) system is considered, for simplicity. Due to the non-ideality of the energy harvesting circuit components, an energy conversion efficiency denoted by $\eta$ ($0 \leq \eta \leq 1$) is assumed for the harvested energy.

![Figure 4.1. Network diagram showing the signal flow.](image)

4.2.2. Time frame organization

The system time is organized into frames each of length $T$ seconds. The time frame is divided into two parts such that each DTX harvests energy during the first phase during energy harvesting time ($\tau_{Ec}$) and transmits signal to the respective DRX during the second phase during the signal transmission time ($\tau_{Sc}$), $c \in \mathbb{C}$. The DTXs use the harvested energy
to transmit signal to the DRXs in the second phase. The time frame is divided for each DTX as shown in figure 4.2.

![Diagram](image)

**Figure 4.2. Time frame division for each DTX**

### 4.2.3. Channel Model

The wireless channel between the BS and the cellular users, between the BS and the D2D users, between DTX and the cellular users, and between DTXs and DRXs, etc., is modeled by average path loss and small-scale fading. The average path loss is distance dependent with path loss exponent $\beta$. Small-scale fading is modeled by Rayleigh fading. The small-scale fading coefficient is constant within a time frame but changes from frame to frame (i.e., block fading). This implies that in each time frame, the channel power gain (i.e., absolute channel coefficient squared) is a product of the average path loss and the fading channel power gain for that frame. Denote the channel coefficients as follows:
$h_i$ is the channel coefficient between the BS and the $CU_i$ ($i=1,2,...,N$), $h_{Dc}$ is the channel coefficient between the DTX $c$ and DRX $c$ such that $c \in \mathbb{C}$, $h_{B,Dtc}$ is the channel coefficient between BS and DTX $c$ such that $c \in \mathbb{C}$, $h_{B,Dr,c}$ is channel coefficient between the BS and DRX $c$ such that $c \in \mathbb{C}$, and $h_{Dc,l}$ is the channel coefficient between DTX $c$ and $CU_i$ such that $c \in \mathbb{C}$, and $h_{Dtc,Dr,l}$ is the channel coefficient between DTX $c$ and DRX $l$ such that $c \neq l$ and $c, l \in \mathbb{C}$.

4.3. Problem Formulation

Since NOMA utilizes successive interference cancellation, hence we can deduce the fact that for $N$ cellular users

$$|h_1| \geq |h_2| \geq |h_3| \ldots \geq |h_N|.$$  \hspace{1cm} (4.1)

Now, since the frame is of the duration $T$ seconds, therefore, the time durations $\tau_{Ec}$ and $\tau_{Sc}$ should satisfy

$$\tau_{Sc} + \tau_{Ec} \leq T.$$  \hspace{1cm} (4.2)

a) Signal model in the energy harvesting time slot of a time frame of interval $(0 \leq t \leq \tau_{Ec})$

The composite transmit signal $x_B^1$ by the BS during the first-time phase

$$x_B^1 = \sum_{n=1}^{N} \sqrt{\nu_n P_{BS}} s_n,$$  \hspace{1cm} (4.3)

where $s_n$ is the transmit signal for $CU_i$ and $\nu_n$ is the power allocation coefficient for $CU_i$

Since all the cellular users are active in the first time slot, therefore,

$$\sum_{n=1}^{N} \nu_n = 1,$$  \hspace{1cm} (4.4)

where $\nu_n > 0$, for all $n \in \mathbb{N}$. Since the NOMA technique with successive interference cancellation invoked is utilized, hence, for any $j > i$, the received SINR for any cellular user $CU_i$ for decoding the signal can be calculated as
\[ SINR_{i,j}^1 = \frac{v_j|h_i|^2\rho_{BS}}{\sum_{k=1}^{j-1}|v_k|h_i|^2\rho_{BS} + 1} \] (4.5)

where \( \rho_{BS} = \frac{P_{BS}}{\sigma^2} \) is the transmit SNR at the BS and \( \sigma^2 \) is the variance of the antenna noise.

The received power from the BS is used for energy harvesting by the DTX \( c \) in the first phase. The energy harvested by the DTX \( c \) such that \( c \in \mathbb{C} \) is given as

\[ E_{\text{harv,Dtc}} = \tau Ec \eta P_{BS} |h_{B,Dtc}|^2, \] (4.6)

The power harvested by the DTX \( c \) becomes

\[ P_{\text{harv,Dtc}} = \frac{E_{\text{harv,Dtc}}}{\tau Ec} = \eta P_{BS} |h_{B,Dtc}|^2, \] (4.7)

b) Signal Model in the second time slot of a time frame of interval \((\tau_{Ec} \leq t \leq T)\)

The composite transmit signal by the BS \( x_B^2 \) in the second time slot

\[ x_B^2 = \sum_{i=1}^{N} \sqrt{\lambda_i} P_{BS} s_i \] (4.8)

where \( \lambda_i \) is the BS power allocation coefficient for \( CU_i \).

\[ \sum_{i=1}^{N} \lambda_i \leq 1, \] (4.9a)

and,

\[ \lambda_i \geq 0, \] (4.9b)

for all \( i \in \mathbb{N} \).

Now, the sum of power allocation coefficients is less than or equal to 1 as all the cellular users might not be active during the second slot since the DTX now transmits to the DRX using the downlink cellular spectrum thereby interfering with cellular user’s signal reception. Now, the sum of the energy expended by DTX for signal transmission, the energy consumed by DTX energy harvesting circuit electronics in the first time slot.
and the energy consumed by DTX transmit circuit electronics in the second time slot should not exceed the energy harvested by the DTX. Hence, the following energy balance equation given below holds:

\[ \tau E_c p_{Dc}^e + \tau Sc P_{Dc} + \tau Sc p_{Dc}^t \leq E_{harv.Dtc}, \]  

(4.10)

where \( P_{Dc} \) is the transmit power by DTX \( c \) (\( P_{Dc} \) is unknown, to be determined), \( p_{Dc}^e \) is the power consumed by the energy harvesting circuit electronics and \( p_{Dc}^t \) is the power consumed by the transmit circuit electronics in the first and second time slots respectively.

The received SINR at the \( c^{th} \) D2D receiver can be calculated as

\[ SINR_{Dtc}^2 = \frac{|h_{Dc}|^2 \rho_{DC}}{\Sigma_{i=1}^N \lambda_i |h_{B,src}|^2 \rho_{BS} + \Sigma_{t=1, t\neq c}^C |h_{Dtt,src}|^2 \rho_{DC} + 1}, \]  

(4.11)

where \( \rho_{DC} = \frac{P_{DC}}{\sigma^2} \) for \( c \in \mathbb{C} \). Now, each cellular user gets interference from the fellow cellular users as well as from the D2D transmitters due to DTXs sharing the downlink spectrum of the cellular users. The received SINR at each \( CU_i \) decoding a signal \( s_j \) such that \( j > i \), is given as

\[ SINR_{i,j}^2 = \frac{|h_i|^2 \lambda_j \rho_{BS}}{\Sigma_{k=1}^{i-1} \lambda_k |h_i|^2 \rho_{BS} + \Sigma_{c=1}^C |h_{DC,|c|^2} \rho_{DC} + 1}, \]  

(4.12)

such that \( c \in \mathbb{C} \). Now, to decode a signal \( s_j \), the received SINR at \( CU_i \) should be no less than received SINR at \( CU_j \) itself, i.e. \( SINR_{i,j}^2 \geq SINR_{j,j}^1 \) \((j > i)\). Therefore,

\[ \frac{\Sigma_{c=1}^C |h_{DC,|c|^2} \rho_{DC} + 1}{|h_i|^2} \leq \frac{\Sigma_{c=1}^C |h_{DC,|c|^2} \rho_{DC} + 1}{|h_j|^2}, \]  

(4.13)

\[ N \geq j > i \geq 1 \]

Equation (4.13) can be recast as
The achievable rates by the \textit{CU’s} in the first and second time slots, and by the \(c^{th}\) D2D link in the second time slot are calculated by the Shannon formula (with the bandwidth normalized)

\[
R^1_i = \log_2(1 + SINR^1_{i,1}), \quad (4.15a)
\]

\[
R^2_i = \log_2(1 + SINR^2_{i,1}), \quad (4.15b)
\]

\[
R^2_{Dtc} = \log_2(1 + SINR^2_{Dtc}). \quad (4.15c)
\]

The minimum rate requirement of the cellular users should be met for both the time slots. Hence,

\[
R^1_i \geq \gamma_i, \quad (4.16a)
\]

\[
R^2_i \geq \gamma_i, \quad (4.16b)
\]

where \(\gamma_i\) is the minimum rate requirement for \textit{CU}_i.

The objective is to maximize the sum throughput of D2D communication under the constraint of the QoS of the cellular users.

The resource allocation problem can then be formulated as:

\[
\max_{\theta, \lambda, \nu, \rho_{DC}, \tau_{Sc}, \tau_{Ec}} \sum_{c=1}^C U_{DC} = \sum_{c=1}^C \tau_{Sc} R^2_{Dtc}, \quad (4.17a)
\]

s.t. (4.2), (4.4), (4.9), (4.10), (4.14), (4.16). \quad (4.17b)

The problem (4.17) is non-convex because both the objective function (4.17a) and the constraints (4.17b) are non-convex with respect to the optimization variables.
4.4. Problem Reformulation and Analysis for NOMA Scheme

As the problem formulated in (4.17) is non-convex, hence it is not easy to find the solution of the problem. Therefore, to find the solution the problem (4.17) is reformulated similar to [42] with variables \( \tau_{sc} \) and \( \rho_{dc} \) in this section.

From (4.5) and (4.11), it can be clearly seen that \( R_i^1 > R_i^2 \) for \( \lambda = \nu \). Therefore, if \( \lambda^* \) satisfies \( R_i^2 \geq \gamma_i \) for all \( i \in \mathbb{N} \), we know from (4.4) that, \( \nu_1^* + \nu_2^* + \cdots + \nu_N^* = 1 \). Hence, we can set \( \nu_1^* = 1 - \sum_{k=2}^{N} \nu_k \) and \( \nu_1^* = \lambda_1^*, \ldots, \nu_N^* = \lambda_N^* \) which says that \( \nu^* \) satisfies \( R_i^1 \geq \gamma_i \) for all \( i \in \mathbb{N} \). Hence, constraint (4.16) can be written just as

\[
R_i^2 \geq \gamma_i, \tag{4.18}
\]

for all \( i \in \mathbb{N} \).

Therefore, having \( \nu^* \) solved for our problem (4.17) can be re-formulated as

\[
\begin{align*}
\max_{\tau_{Ec}, \tau_{Sc}, \lambda, \rho_{dc}} & \quad \sum_{c=1}^{C} U_{dc} = \sum_{c=1}^{C} \tau_{sc} R_{dtc}^2, \\
\text{s.t} & \quad (4.2), (4.9), (4.10), (4.14), (4.18). \tag{4.19b}
\end{align*}
\]

The problem (4.19) is non-convex because both the objective function (4.19a) and the constraints (4.19b) are non-convex with respect to the optimization variables.

**Theorem 4.1:** The optimal solution of the problem (4.19) can be obtained when the equalities of the constraint (4.2), (4.18) hold such that

\[
\begin{align*}
\tau_{sc} + \tau_{Ec} &= T, \tag{4.20a} \\
R_i^2 &= \gamma_i. \tag{4.20b}
\end{align*}
\]

for all \( i \in \mathbb{N} \).

*Proof: See Appendix D.*

**Theorem 4.2:** The optimal power allocation \( \lambda^* \) can be derived from eq. (4.15b) such that \( \lambda_i \) can be calculated as
\[
\lambda_i = \frac{\sum_{j=1}^{i-1}\left[\prod_{l=j+1}^{i-1}(1 + \zeta_l)\right] \zeta_i \zeta_j (\sum_{c=1}^{C} \psi_{DC,c} \rho_{DC_c} + \delta_j)}{\rho_{BS}}, \tag{4.21a}
\]

where,
\[
\zeta_i = 2^{\gamma_i} - 1, \tag{4.21b}
\]
\[
\psi_{DC,i} = \frac{|h_{DC,i}|^2}{|h_i|^2}, \tag{4.21c}
\]
\[
\delta_i = \frac{1}{|h_i|^2}, \tag{4.21d}
\]

for all \(i \in \mathbb{N}\).

Note that in (4.21a), \(\sum_{j=1}^{i-1}\left[\prod_{l=j+1}^{i-1}(1 + \zeta_l)\right] \zeta_i \zeta_j (\sum_{c=1}^{C} \psi_{DC,c} \rho_{DC_c} + \delta_j) = 0\) for \(i = 1\), and
\[
\prod_{u=j+1}^{i-1}(1 + \zeta_u) = 1 \text{ for } j + 1 > i - 1.
\]

**Proof:** See Appendix E.

**Theorem 4.2** depicts the relationship between \(\lambda_i^*\) and \(\rho_{DC}^*\). Now, from eq. (4.9a), \(\sum_{i=1}^{N} \lambda_i \leq 1\) hence let’s evaluate \(\sum_{i=1}^{N} \lambda_i\) to analyze the feasible region of variable \(\rho_{DC}\).

Now substituting (21a):
\[
\sum_{i=1}^{N} \lambda_i = \frac{\sum_{j=1}^{N}\left[\prod_{l=j+1}^{N}(1 + \zeta_l)\right] \zeta_i \zeta_j (\sum_{c=1}^{C} \psi_{DC,c} \rho_{DC_c} + \delta_j)}{\rho_{BS}}, \tag{4.22}
\]
\[
\sum_{i=1}^{N} \lambda_i = \sum_{c=1}^{C} \bar{A}_c \rho_{DC} + \bar{B}, \tag{4.23}
\]
\[
\sum_{c=1}^{C} \bar{A}_c \rho_{DC} + \bar{B} \leq 1, \tag{4.24}
\]

where the inequality in (4.24) follows from (4.9a),
\[
\bar{A}_c = \frac{\sum_{j=1}^{N}\left[\prod_{l=j+1}^{N}(1 + \zeta_l)\right] \zeta_j \psi_{DC,j}}{\rho_{BS}},
\]
and,
\[
\bar{B} = \frac{\sum_{j=1}^{N}\left[\prod_{l=j+1}^{N}(1 + \zeta_l)\right] \zeta_j \delta_j}{\rho_{BS}}.
\]
The maximum values of $\rho_{DC}$ can be calculated from (4.24),

$$\rho^\text{max}_{DC1} = \frac{1 - B}{A_c}. \tag{4.25}$$

The range of values of $\rho_{DC}$ can be calculated as

$$0 \leq \rho_{DC} \leq \frac{1 - B}{A_c}. \tag{4.26}$$

Also, eq (4.14) can be written as

$$\left\{ \sum_{c=1}^{C} \psi_{DC,i} \left( \sum_{c=1}^{C} \psi_{DC,i+1} \right) \right\} \rho_{DC} \leq 1,$$  \tag{4.27}

$$0 \leq \sum_{c=1}^{C} \bar{p}_{c,i} \rho_{DC} - \sum_{c=1}^{C} \bar{Q}_{c,i+1} \rho_{DC} \leq 1,$$ \tag{4.28}

where, $\bar{p}_{c,i} = \frac{\psi_{c,i}}{\delta_i - \delta_{i+1}}$ and $\bar{Q}_{c,i+1} = \frac{\psi_{c,i+1}}{\delta_i - \delta_{i+1}}$.

The maximum values of $\rho_{DC}$ can be calculated from (4.27)

$$\rho^\text{max}_{DC2} = \frac{\delta_i - \delta_{i+1}}{\psi_{c,i} - \psi_{c,i+1}}. \tag{4.29}$$

From (4.25) and (4.29), the maximum value of $\rho_{DC}$ can be calculated as

$$\rho^\text{max}_{DC} = \min\left( \rho^\text{max}_{DC1}, \rho^\text{max}_{DC2} \right). \tag{4.30}$$

The range of device power ($\rho_{DC}$) is between 0 to the value of $\rho^\text{max}_{DC}$

$$0 \leq \rho_{DC} \leq \rho^\text{max}_{DC}. \tag{4.31}$$

We can easily see from (4.21b), (4.21c), (4.21d) that $\psi_{c,i} > 0$, $\delta_i > 0$ and $\zeta_i > 0$ for all $i \in \mathbb{N}$. Hence, $\bar{A}_c > 0$ and $\bar{B} > 0$. Also, from (4.22), $\sum_{i=1}^{N} \lambda_i$ has a linear relationship with $\rho_{DC}$.

Next, we describe the relationship between $\tau_{Sc}$ and $\rho_{DC}$. Substituting (4.31) in (4.10) and solving for $\rho_{DC}$,

$$0 \leq \tau_{Sc} \rho_{DC} \leq D_c - \tau_{Sc} E_c, \tag{4.32}$$

where $D_c = T \eta |P_{BS}| h_{B, Dtc} |^2 - T \rho^6_{DC}$ and $E_c = \eta |P_{BS}| h_{B, Dtc} |^2 - \rho^6_{DC} + \rho^5_{DC}$
Clearly, $\bar{D}_c > 0$ and $\bar{E}_c > 0$.

Now, the problem can be simplified as
\[ \max_{\tau_{Sc}, \rho_{Dx}} \sum_{c=1}^{C} U_{Dc} = \sum_{c=1}^{C} \tau_{Sc} \log_2 \left( 1 + \frac{|h_{Dc}|^2 \rho_{Dc}}{\sum_{c=1}^{C} F_c \rho_{Dc} + \sum_{l=1}^{L} \bar{G}_l \rho_{Dl} + \bar{H}_c} \right), \] (4.33a)

s.t.
\[ 0 \leq \tau_{Sc} \rho_{Dc} \leq \bar{D}_c - \tau_{Sc} \bar{E}_c, \] (4.33b)
\[ 0 \leq \sum_{c=1}^{C} \bar{P}_{c,l} \rho_{Dc} - \sum_{c=1}^{C} \bar{Q}_{c,l+1} \rho_{Dc} \leq 1, \] (4.33c)
\[ 0 \leq \sum_{l=1}^{L} \bar{A}_{l} \rho_{Dl} + \bar{B} \leq 1, \] (4.33d)

where $\bar{P}_c = \bar{A}_c |h_{B,Drc}|^2 \rho_{BS}, \bar{G}_l = |h_{Dtl,Drc}|^2$ and $\bar{H}_c = \bar{B} |h_{B,Drc}|^2 \rho_{BS} + 1$.

The problem (4.33) can be re-written as
\[ \max_{\tau_{Sc}, \rho_{Dx}} \sum_{c=1}^{C} U_{Dc} = \sum_{c=1}^{C} \tau_{Sc} \log_2 \left( 1 + \frac{|h_{Dc}|^2 \rho_{Dc}}{\sum_{c=1}^{C} F_c \rho_{Dc} + \sum_{l=1}^{L} \bar{G}_l \rho_{Dl} + \bar{H}_c} \right), \] (4.34a)

s.t.
\[ 0 \leq \rho_{Dc} \leq \frac{\bar{D}_c - \tau_{Sc} \bar{E}_c}{\tau_{Sc}}, \] (4.34b)
\[ 0 \leq \rho_{Dc} \leq \rho_{Dc,max}. \] (4.34c)

The constraint (4.34b) can be obtained from simplifying constraint (4.33b).

The range of each device’s power can help to determine the range of signal transmission time ($\tau_{Sc}$) of each device. The signal transmission time of each device can be divided into two intervals, the first one being $0 \leq \tau_{Sc} \leq \frac{\bar{D}_c}{\rho_{Dc,max} + \bar{E}_c}$ and the other one $\frac{\bar{D}_c}{\rho_{Dc,max} + \bar{E}_c} \leq \tau_{Sc} \leq \frac{\bar{D}_c}{\bar{E}_c}$. For interval one, since the objective function increases with the increase in $\tau_{Sc}$, the optimum value of $\tau_{Sc}$ is $\frac{\bar{D}_c}{\rho_{Dc,max} + \bar{E}_c}$ and therefore the optimal power of $\rho_{Dc}$ is $\rho_{Dc,max}$. 

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The case scenario of interval one has been considered in Algorithm 4.1. where the initial point is taken as \( \frac{D_c}{\rho_{\text{DC}} + E_c} \). In case the optimal signal transmission time is \( \frac{D_c}{\rho_{\text{DC}} + E_c} \), the value will remain the same during the next iterations. If this isn’t the case, the value will lie in the second interval \( \left( \frac{D_c}{\rho_{\text{DC}} + E_c} \leq \tau_{sc} \leq \frac{D_c}{E_c} \right) \) for a device which can still be obtained utilizing the Algorithm 4.1.

Algorithm 4.1. Finding the optimal device times \( \tau_{sc}^* (c \in \mathbb{C}) \)

Input:
\( \{h_i, h_{DC,i}, \gamma_i, \ i = 1,2, \ldots, K\} \),
\( h_{D,c}, h_{B,DCc}, h_{B,DCc}, T, P_{BS}, \sigma^2, \eta, p_B^e, p_B^t, \theta \);

Output:
\( \tau_{sc}^* \);

1: Initialization: \( \tau_{scp} = \frac{D_c}{\rho_{\text{DC}} + E_c} + \theta, \tau_{sc} = \frac{D_c}{\rho_{\text{DC}} + E_c}; \)
2: while \( |\tau_{s1} - \tau_{s1p}| \geq \theta \) or \( |\tau_{s2} - \tau_{s1p}| \geq \theta \) --- or \( |\tau_{sc} - \tau_{scp}| \geq \theta \) do
3: \( \text{Set } \tau_{scp} = \tau_{sc}; \) [for all \( c \in \mathbb{C} \)]
4: \( \text{Calculate the step size } \Delta \text{ by backtracking line search} \)
5: \( \text{Calculate } \tau_{sc} = \tau_{scp} + \Delta * H; \) [for all \( c \in \mathbb{C} \)]

\((H \text{ is calculated using eq. (4.35)})\)
6: \( \text{if } \tau_{sc} < \frac{D_c}{\rho_{\text{DC}} + E_c} \text{ then} \)
\( (\rho_{\text{DC}} \text{ is calculated in eq. (4.30)})\)
7: \( \text{Set } \tau_{sc} = \frac{D_c}{\rho_{\text{DC}} + E_c}; \)
8: \( \text{end if} \)
9: \( \text{if } \tau_{sc} > \frac{D_c}{E_c} \text{ then} \)
10: \( \text{Set } \tau_{sc} > \frac{D_c}{E_c}; \)
11: \( \text{end if} \)
12: \( \text{for } \tau_{s1}, \tau_{s2}, \cdots, \tau_{sc} \text{ do check} \)
13: \( \text{if } |\tau_{sc} - \tau_{scp}| \leq \theta \text{ then} \)
14: \( \text{Set } \tau_{sc} = \tau_{scp}; \)
15: \( \text{end if} \)
16: \( \text{end for} \)
17: \( \text{end while} \)
18: return \( \tau_{sc}^* = \tau_{sc} \)
The explanation for Algorithm 4.1 is as follows. For Interval I, the value of $\tau_{sc}$ varies between $\frac{\bar{D}_c}{\rho_{Dc}^{max}+E_c}$ and $\frac{\bar{D}_c}{E_c}$. The inputs and output from the Algorithm 4.1 are as mentioned.

The output of the algorithm is to find $\tau_{sc}^*$. Line 1 provides the values for initialization to the algorithm; $\tau_{scp} = \frac{\bar{D}_c}{\rho_{Dc}^{max}+E_c} + \theta$, $\tau_{sc} = \frac{\bar{D}_c}{\rho_{Dc}^{max}+E_c}$. Line 2 marks the starting of the algorithm. The gradient ascent method finds the maximum value of the objective function by finding the optimal signal transmission time.

In the algorithm, $\tau_{scp}$ refers to the old value of the signal transmission time and $\tau_{sc}$ refers to the new value of signal transmission time for each DTX after the gradient update. Line 5 updates the value of $\tau_{sc}$ using the gradient ascent method which involves utilizing the derivative of the objective function. The step size with which the gradient method updates the optimization variable ($\tau_{sc}$) is calculated by the backtracking line search as in line 4. If the signal transmission time goes beyond the range as specified in Interval I, lines 6 to 11 bring it in the specified range. Once the optimization variable gets updated, line 3 sets the old value as the value obtained from line 5. This process continues until the error between the new and old values is within $\theta$, the accuracy parameter and the optimal value is obtained. Line 12 to line 16 fix the value of each signal transmission time once it does not fluctuate and has reached the optimal value. The complexity of algorithm 4.1 is $O\left(\frac{C}{\theta}\right)$, where $\theta(\ll 1)$ is the accuracy control parameter.

The problem (4.34) is a non-convex problem, and it can be solved by using the gradient ascent method. To deploy the gradient ascent method, the objective function should be differentiable, and in this scenario the objective function is differentiable everywhere with respect to the variable $\tau_{sc}$.
\[ H = \frac{\partial \sum_{c=1}^{C} u_{DC}}{\partial \tau_{sc}} \]  

(4.35)

4.5. Problem Formulation for OMA Scheme

In this section, the resource allocation problem for the conventional orthogonal multiple access (OMA) - based scheme is formulated. The OMA scheme is set as a standard for comparison against the NOMA-based scheme.

The process for the first time slot is same as the NOMA-based scheme, while for the second time slot, the total bandwidth is equally divided into \( M \) bandwidth units and each cellular user is allocated a distinct single bandwidth unit, to prevent mutual interference among the cellular users. However, it is assumed that the BS allocates a fraction \( \lambda_i^o \) of its total power to \( CU_i \) even with the OMA scheme.

Now, the energy consumption constraint of the \( c^{th} \) DTX is

\[ \tau_{sc} P_{DC}^o + \tau_{Ec} P_{DC}^e + \tau_{sc} P_{Dc}^t \leq E_{harv,dtc}, \]  

(4.36)

where \( P_{DC}^o \) is the transmit power by DTX (\( P_{DC}^o \) is unknown, to be determined) under the OMA-based scheme, designated by the superscript \( o \), \( P_{DC}^e \) and \( P_{DC}^t \) are the DTX circuit power consumption for energy harvesting and data transmission, respectively (assumed to be constant and known).

The SINR at the cellular user \( i \in \mathbb{N} \) and \( c^{th} \) DRX during the second time slot can be respectively calculated as

\[ SINR_i^2 = \frac{\lambda_i^o |h_i|^2 \rho_{BS}}{\sum_{c=1}^{C} |h_{Dc}|^2 \rho_{Dc}^o + 1}, \]  

(4.37)

\[ SINR_{dtc, i}^2 = \frac{|h_i|^2 \rho_{Dc}^o}{\sum_{i=1}^{N} \lambda_i^o |h_{B, Dc}|^2 \rho_{BS} + \sum_{i=1, i \neq c}^{C} |h_{Dc,drc}|^2 \rho_{Dc}^{o+1}}. \]  

(4.38)
where \( \lambda_i^o \) should satisfy

\[
\sum_{i=1}^{N} \lambda_i^o \leq 1,
\]

(4.39a)

and,

\[
\lambda_i^o \geq 0.
\]

(4.39b)

for all \( i \in \mathbb{N} \).

The transmission rate of cellular user \( i \) during the second time slot is given as

\[
R_i^2 = \frac{1}{M} \log_2 (1 + SINR_i^2).
\]

(4.40)

The transmission rate of cellular user \( i \) should be at least equal to minimum rate requirement

\[
R_i^2 \geq \gamma_i.
\]

(4.41)

To maximize the achievable throughput of the DTX, the resource allocation problem can be formulated as

\[
\max_{\tau_{Sc}, \rho_{Dc}^o} \sum_{c=1}^{C} U_{Dc} = \sum_{c=1}^{C} \tau_{Sc} R_{Dtc,i}^2,
\]

(4.42a)

s.t. (4.36), (4.39), (4.41).

(4.42b)

Similarly, we can prove that the equality for constraint (4.41) holds and, hence, problem (4.42) can be written as

\[
\max_{\tau_{Sc}, \rho_{Dc}^o} \sum_{c=1}^{C} U_{Dc} = \sum_{c=1}^{C} \tau_{Sc} R_{Dtc,i}^2,
\]

(4.43a)

s.t

\[
0 \leq \tau_{Sc} \rho_{Dc}^o \leq \bar{D}_c^o - \tau_{Sc} E_c^o,
\]

(4.43b)

\[
0 \leq \sum_{c=1}^{C} \bar{\lambda}_c^o \rho_{Dc}^o + \bar{B}^o \leq 1,
\]

(4.43c)

where,
\[ \psi_i = 2^{M_i} - 1, \quad \bar{A}_c^o = \frac{\sum_{i=1}^{N} \psi_i \zeta_i}{\rho_{BS}}, \quad \bar{B}^o = \frac{\sum_{i=1}^{N} \delta_i \zeta_i}{\rho_{BS}}, \quad \bar{D}_c^o = \eta P_{BS} |h_{B,Dtc}|^2 - \rho_{dc}^e \quad \text{and} \quad \bar{E}_c^o = \eta P_{BS} |h_{B,Dtc}|^2 - \rho_{dc}^e + \rho_{dc}^r \]

The problem (4.43) is similar to problem (4.34) and the optimal solution can be found using the similar procedure as in NOMA scheme.

### 4.6. Results and Discussion

This section presents the effect of specific network parameters over the sum throughput of time switching enabled D2D communications. Two scenarios are considered for obtaining the results; in the first scenario 2 D2D pairs are considered in a single cell and in the second scenario 4 D2D pairs are considered in the cell.

The simulation parameters are as shown in Table 4.1.

#### Table 4.1. Simulation settings

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N ) (Number of cellular users)</td>
<td>2</td>
</tr>
<tr>
<td>( C ) (Number of devices)</td>
<td>4</td>
</tr>
<tr>
<td>( \gamma_i ) (Minimum rate requirement of cellular users)</td>
<td>0.1 bps/Hz [42]</td>
</tr>
<tr>
<td>( \eta ) (Energy conversion efficiency)</td>
<td>0.9[42]</td>
</tr>
<tr>
<td>( P_{BS} ) (BS transmit power)</td>
<td>2W [42]</td>
</tr>
<tr>
<td>( p_{dc}^e ) (Device circuit power for energy harvesting)</td>
<td>5 mW[42]</td>
</tr>
<tr>
<td>( p_{dc}^t ) (Device circuit power for signal transmission)</td>
<td>10 mW [42]</td>
</tr>
<tr>
<td>$\sigma^2$ (Noise Power)</td>
<td>$2 \times 10^{-6}$ W [42]</td>
</tr>
<tr>
<td>-------------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>$T$ (Time frame)</td>
<td>10 seconds [42]</td>
</tr>
</tbody>
</table>

The simulations are done in MATLAB and results are presented averaging 10,000 simulations. The values in table 4.1. are the inputs. The (x,y) coordinates of the devices and cellular users are uniformly generated and the distance between them is calculated using the generated coordinates. The distance is used to calculate the path loss with path loss exponent ($\beta$). The channel coefficient is the product of the path loss and the Rayleigh fading channel coefficient. Finally, all values needed to calculate $\rho_{D_{max}}$ and the value of objective function are calculated and fed to the Algorithm 4.1. The throughput is the final throughput for that particular frame.
Figure 4.3. D2D Throughput versus the Rate Requirement of the cellular users.

The figure 4.3 depicts the sum throughput versus the rate requirement of the cellular users. When the rate requirements of the cellular users are low, the sum throughput of the device users tends to be high. When $R_i^2 = \gamma_i$, and, the minimum rate requirement of cellular users is increased, the device power must be lowered furthermore. This lesser device power results in lesser device throughput for the given single cell network. When the network has 2 D2D pairs, the sum throughput is observed to be greater than when the network has 4 D2D pairs. This is because with the increase in the number of devices in the network, a particular device experiences more interference from the fellow devices leading to lesser device throughput. The NOMA scheme performs better than the OMA scheme because the bandwidth is divided into $M$ units. This division of bandwidth leads to a lower throughput for the OMA scheme as compared to the NOMA scheme.
Figure 4.4. D2D Throughput versus the Energy Conversion Efficiency of the DTX

The figure 4.4. depicts the relationship between the sum device throughput and the energy conversion efficiency of the device transmitters. With the decreasing energy efficiency of the devices, the amount of energy harvested by the device received decreases, which affects the device power when the device is transmitting. The device power decreases leading to a lower device throughput. The NOMA scheme performs better than the OMA scheme in this scenario as well, the reason being the division of bandwidth in the OMA scheme which isn’t there in the NOMA scheme. The interference from the fellow D2D pairs results in lower device power for a particular D2D pair. As the number of devices increases in a network, the sum throughput of devices decreases.
Figure 4.5. D2D Throughput versus the Path Loss Exponent.

The figure 4.5. gives the relationship between the D2D throughput and path loss exponent. As the path loss exponent increases, the distance dependent loss increases. The increase in this loss is responsible for the decrease in D2D throughput along with the increase in the path loss exponent. The NOMA scheme performs better in this scenario as well because of the division of bandwidth in the OMA scheme. As the number of D2D users increase in the network, the mutual interference between the D2D pairs increase thus, leading to lower D2D throughput.

4.7. Summary

This chapter presents the discussion about time switching scheme enabled D2D pairs underlaying a NOMA based cellular network. A resource allocation problem aimed at
maximizing the sum throughput of devices is formulated under the constraint of guaranteeing the rate requirements of cellular users. The formulated problem is further reformulated and analyzed using rigorous mathematical calculations. The results are obtained using simulations and the NOMA scheme is compared with the OMA scheme.
Chapter 5: **D2D Throughput Prediction Using Deep Learning**

### 5.1. Introduction

In the previous two chapters, PS-SWIPT enabled D2D communications and TS-SWIPT enabled D2D communications were studied. The resource allocation problems with the objective of maximizing the D2D throughput were formulated under the constraint of satisfying the rate requirements of cellular users. Though the conventional optimization algorithms achieve high performance, but they take significant number of iterations to achieve the target which greatly increases the computation cost and time. To address this challenge, deep learning approaches are gaining attention throughout academia and industry. Deep learning is proven to effectively estimate the channel and examine various parameters such as path loss, fading and other random variables exclusive to the wireless channel thus giving better performances for large datasets [52]. This chapter focuses on using feed forward neural networks (FFNN)- a kind of deep neural network (DNN) to predict the D2D throughput. The main aim of this chapter is to show that when the same set of inputs is fed to an optimization algorithm and an already trained FFNN, the FFNN can process the newer inputs in much less time and give comparatively accurate results. The FFNN offers a much simpler architecture as compared to other major deep learning neural networks and is also efficient, therefore, is chosen to model the problem.

The remainder of the chapter is organized as follows. Section 5.2 gives an overview of the architecture of the neural network. Sections 5.3, 5.4, 5.5 give the overview of the optimization, training and testing stage respectively and section 5.6 gives the numerical results and discussion.
5.2. Neural Networks

Deep Learning is an artificial intelligence technique that mimics the workings of the human brain. Neural networks are integral part of deep learning. Like human brains, the neural networks also contain interconnected units known as neurons. The neurons are grouped into three different layers, namely, input layer, hidden layer or hidden layers, and the output layer.

Most of the literatures use three main categories of neural networks – artificial neural network (ANN), convolutional neural network (CNN) and the recurrent neural network (RNN). The CNNs are mostly suited for image and video processing applications. The RNNs are mostly suited for time series data, text data and audio data. The ANNs are mostly suited for tabular data. Since the ANNs follow the simplest architecture and are used for tabular data, they can be conveniently used for this thesis’s application.

5.2.1 Input Layer

The input layer is the first layer and, as the name suggests, it receives the input data and forwards it to the further layers.

5.2.2. Hidden Layers

In an artificial neural network, the hidden layers come in between the input layer and the output layer. The hidden layer consists of neurons which take in a set of weighted inputs and produce an output using an activation function. Each connection between neurons relates to a weight. The weight of each input value decides its importance in calculating the output for a neural network. For most cases, the starting weights are random.
The hidden layers model the complex data due to the neurons/nodes they possess, thus, processing the information given by the input layer by performing mathematical calculations on them. For the neural network, the number of hidden layers and the number of neurons associated with a particular hidden layer is challenging to decide.

5.2.3. Output Layer

The output layer is the final layer of the neural network. This layer is the pathway to get the desired output out of the model with the help of processed data. The number of neurons for the output layer are the same as the outputs required from the existing neural network.

**Figure 5.1. Architecture of a feed forward neural network (FFNN).**

The fig. 5.1. gives the architecture of a feed forward neural network used for the thesis. The layer with blue colored neurons (first layer) serves as the input layer. The number of nodes for the channel vectors \(|h|\) is \(K(1 + C) + C^2 + 2C\) and the number of nodes for the DTX maximum transmit power vector \(\{P_{D_{c_{max}}}\}\) is \(C\), where \(K\) is the number of cellular users present in the cell and \(C\) denotes the number of device pairs in the cell. The
subsequent layers are hidden layers which perform mathematical operations on the inputs provided to them with the help of activation function which is “ReLU” in this case and the biases. Finally, the 
\((B + 1)^{th}\) or the output layer gives the output (device throughput) after operating on all inputs from the \(B^{th}\) layer. The time complexity of the FFNN is given as 
\(O(B \times A^2 \times (C^2 + 3C + K(1 + C)))\), excluding the complexity for training the FFNN.

The feed forward neural network (FFNN) calculates the output with the following steps:

1. Initialize the input layer

2. Calculate the output of hidden layer in order from 1 to \(B\):
   a) Calculate \(f_i^k = b_i^k - 1 + \sum_{j} w_{ij}^k u_j^{k-1}\) for \(i = 1, 2, \ldots, a_k\).
   b) Calculate \(u_j^k = g(f_i^k)\) for \(i = 1, 2, \ldots, a_k\).

3. Calculate the output of output layer:
   a) Calculate \(u = u_1^{B+1} = f_1^{B+1} = b_1^B + \sum_{j} w_{j1}^B u_j^{k-1}\).

where, \(f_i^k = \) product sum plus bias for perceptron \(i\) in \(k^{th}\) layer, \(b_i^k = \) bias for perceptron \(i\) in \(k^{th}\) layer, \(w_{ij}^k = \) weight for perceptron \(i\) in \(k^{th}\) layer for incoming node \(i\) in \((k-1)^{th}\) layer, \(u_j^k = \) output for node \(i\) in \(k^{th}\) layer, \(a_k = \) number of nodes in \(k^{th}\) layer, \(g(x) = \) activation function for the hidden layers, \(u_j^k = \) output for node \(j\) in \(k^{th}\) layer.

5.2.4. Activation Function

An activation function or a transfer function in a neural network defines the way of how the weighted sum of the input is transformed into an output from a neuron or neurons in the layer of the network. It is crucial to choose the correct activation function for a neural network as the activation function has a noteworthy impact on deciding the performance of the neural network. In most cases, the hidden layers use the same activation function,
and the output layer uses a different activation function for transforming the weighted inputs into an output depending on the type of the output expected by the model.

Activation functions are usually differentiable, and this is important because the neural networks are trained using backpropagation of the error algorithm which requires the derivatives to update the weights in the model. Though there are many types of activation functions, but only a small number of activation functions are used for hidden and output layers. The most common ones used are Rectified Linear Activation (ReLU), Logistic, Hyperbolic Tangent.

The activation function used in this work is ReLU for both hidden and output layer as it is an ideal choice for regression models. The rectified linear unit activation function is a piecewise linear activation that will output the input directly if the input is positive, otherwise, the output will be zero.

The ReLU function is calculated as follows:

$$ y = \max(0.0, x) $$

This implies that when the input value ($x$) is negative, then a value of 0.0 is returned, else a value of $x$ is returned.

The rectified linear activation function makes it easy to train the model and helps achieve better performance. It helps to overcome vanishing gradient problem thus allowing models to learn faster and perform better.
5.2.5. Optimizers

An optimizer in deep learning is basically an algorithm or method which is used to minimize an error or loss function to maximize the efficiency of production. Optimizers help in changing the learning rates and weights in a neural network to reduce the loss [53]. There are different types of optimizers, the relevant ones are being discussed here:

1. Gradient Descent: Gradient Descent is an optimization algorithm which finds a local minimum of a differentiable function. Gradient descent is used to find the values of function’s coefficients to minimize a cost function. The method finds the derivative of the loss function for finding the minima. A variable $a$ is updated by the gradient descent method such that

$$a_{new} = a_{old} - \mu \frac{\partial f_{loss}}{\partial (a_{old})}$$  \hspace{1cm} (5.2)

where, $\mu$ is the learning rate, $f_{loss}$ is the loss function, $a_{new}$ is the updated variable after applying the gradient descent and $a_{old}$ is the old value of the variable before applying the gradient descent algorithm. Though the advantage of gradient descent is that it is easy to implement and easy to compute, but the algorithm needs to calculate over the whole dataset to change the weights of the network. If the dataset is large, then the time of implementation increases for the FFNN. Also, the gradient descent requires large memory to operate on the whole dataset.

2. Stochastic Gradient Descent: A variant of the gradient descent where the model tries to update the weights frequently. Unlike the gradient descent method where the model updates weights once after going over the whole dataset the stochastic gradient descent method updates the weight after going over each row in the entire dataset. Since the model parameters are frequently updated, they have high variance, and the
loss functions have fluctuations at different intensities. Also, the stochastic gradient
descent uses a specific rate for updating the weights which does not change during
the training. Though the stochastic gradient descent takes less time to converge and
requires less memory but, because of frequently updating the model parameters, they
have high variance, and the method may shoot even after reaching global minima.

3. Adam: The Adam (Adaptive Momentum Estimation) algorithm basically is a
combination of two algorithms that themselves are extensions to the stochastic
gradient descent. These two algorithms are Adaptive Gradient Algorithm and Root
Mean Square Propagation. Adaptive Gradient Algorithm (AdaGrad) keeps a learning
rate specific to each network weight and hence, improves performance on sparse
gradients. The Root Mean Square Propagation (RMSProp) also maintains a learning
rate specific to each network weight. The learning rates are adapted based on recent
magnitudes of the gradients.

    The Adam has both the benefits of using AdaGrad and RMSProp. Instead of fixing
the learning rate of each parameter on the basis of the mean, the optimizer also takes
the uncentred variance into account. Adam updates the weights inversely proportional
to the L2 norm of the previous gradients.

4. Adamax: This work utilizes Adamax which is an optimizer based on Adam and more
broadly an extension to the gradient descent algorithm. Unlike the Adam, the Adamax
algorithm updates the weights to the infinite norm of the previous gradients.

5.2.5.1 Learning Rate

    When using the gradient descent algorithm, steps are needed to be taken to reach to the
local minimum. The step size is known as the learning rate. An appropriate value of
learning rate is to be decided for the algorithm to converge. If the value of the learning rate is high, the learning might surpass the minima whereas if the value of the learning rate is too low, it might get infinitely stuck at the minimum or take too long to converge.

5.3. Optimization Stage

In chapters 3 and 4, two optimization problems were formulated considering maximizing the throughput of power splitting SWIPT enabled device and time switching SWIPT enabled devices guaranteeing the minimum rate requirements of cellular devices respectively. The problems were solved using rigorous mathematical analysis and finally the throughputs were obtained using the gradient descent method. The data for training the feed forward neural network is obtained in the optimization stage.

For the resource allocation problems considering PS SWIPT enabled D2D communications, the channel vectors \( \{ |h| \} \) and the device maximum transmit power vector corresponding to a particular channel condition \( \{ P_{D_{max}} \} \) are treated as inputs and the corresponding optimal device throughput obtained in chapter 3 through the gradient method is taken as the output.

For the resource allocation problems considering TS SWIPT enabled D2D communications, the channel vectors \( \{ |h| \} \) and the device maximum transmit power vector corresponding to a particular channel condition \( \{ P_{D_{c_{max}}} \} \) are treated as inputs and the corresponding sum device throughput obtained in chapter 4 through the gradient method is taken as the output.

For each of the receiver architectures, 10,000 data points are taken in total i.e. the number of rows in the dataset is 10,000. The number of columns depend upon the number
of user equipment present in the network cell as all the channel coefficients are taken into consideration.

Once the data is generated through the optimization problems, the data is pre-processed before being fed to the FFNN. Pre-processing of data is a crucial step as it transforms the raw feature vectors into a suitable representation used by downstream estimators [54]. Standardization is a common requirement for neural networks as their performance might not be good if the individual features do not look like standard normally distributed data. Standardization refers to the scaling of features such that the values are centred around the mean where the resultant distribution has a unit standard deviation. Therefore, the original data is standardized before being fed to the neural network.

Fig. 5.2. shows the functioning of the current feed forward neural network. The input and output data are taken from the optimization algorithm discussed in chapters 3 and 4. The FFNN is trained using the data obtained from the optimization algorithms in the training stage and the corresponding outputs are obtained as the neural network learns from the trend obtained from the optimization algorithm. The trained neural network is given entirely unknown values, or the test set, and outputs are obtained, and the performance of the feed forward neural network is evaluated from the testing stage.
5.4. Training Stage

After solving the respective resource allocation problems of maximizing the throughput of PS-SWIPT enabled D2D communications and TS-SWIPT enabled D2D communications, the data is obtained for the training stage. The dataset is split into two parts: the training dataset for the training stage and the test dataset for the testing stage. The training set is taken 80% of the total dataset.

With the data obtained from the resource allocation problems, the FFNN is trained using backpropagation and the training stage is based on updating the weights and biases of the FFNN by optimizing the mean squared error using the “Adamax” algorithm.

5.5. Testing Stage

The data for the testing stage is prepared the same way as the training stage. The test set is taken 20% of the total dataset.

The testing data is passed through the trained network and the results are compared with the output using the conventional optimization algorithm.
5.6 Numerical Results and Discussion

This section provides the explanation of the results obtained through the FFNN as compared to the conventional optimization algorithm. The simulation parameters and network parameters are described in this section. The system specifications on which the programs are run are Intel(R) Core (TM) i3-6100 CPU @3.70 GHz; installed RAM is 16 Gb.

For the PS SWIPT enabled D2D communications, as the rate requirements increase, the throughput decreases. The reason is given in chapter 3. The neural network has four hidden layers with 10 neurons each. The number of epochs is taken to be 150. The hidden layers use the ReLU activation function. The loss function is taken as the mean squared error. The results are shown in fig. 5.3. and fig. 5.6.

The figure 5.3. gives a comparison between the predicted results and test results. The fig. 5.4. gives a comparison of the optimization time and the test set prediction time of the neural network. It can be observed that for the same number of predictions (2000), the gradient descent takes 37 minutes whereas the test set results can be obtained in 3 minutes. Therefore, it can be proved that optimization algorithms are way less efficient and takes comparatively more time as compared to the feed forward neural network.
Figure 5.3. The comparison between test set results and predicted data results for PS SWIPT receiver architecture for 4 CUs and 2 CUs respectively.

Table 5.1. Percentage (%) error between the test set values and the predicted values

<table>
<thead>
<tr>
<th>Rate Requirement of the cellular users</th>
<th>Percentage error for 4 cellular users (%) error</th>
<th>Percentage error for 2 cellular users (%) error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>7.1</td>
<td>2.1</td>
</tr>
<tr>
<td>0.2</td>
<td>1.29</td>
<td>2.66</td>
</tr>
<tr>
<td>0.3</td>
<td>6.74</td>
<td>1.356</td>
</tr>
<tr>
<td>0.4</td>
<td>0.5</td>
<td>8.01</td>
</tr>
<tr>
<td>0.5</td>
<td>1.4</td>
<td>15.07</td>
</tr>
</tbody>
</table>
The table 5.1. presents the percentage error between the mean test set values and the mean predicted values for fig. 5.3.

![Comparison between optimization times and FFNN](image)

**Figure 5.4.** The comparison between the optimization times and the time taken by the FFNN for the PS SWIPT enabled D2D communications.

The figures 5.3 and 5.4 gives the comparison between the predicted test set results from the feed forward neural network (FFNN) and the test results from the conventional optimization algorithms for PS SWIPT enabled D2D communications. Fig. 5.4. gives the comparison between optimization times and the FFNN. The FFNN is 92% faster than the conventional optimization techniques. As it is clearly visible from the results, the feed forward neural network gives an excellent performance on the test when trained with the dataset obtained from the optimization algorithms. Table 5.1 gives the percentage error between the test set values and the FFNN predicted values for both figs. 5.3 and 5.4.
5.5. gives the rationale behind the selection of 10 neurons for this configuration. The training and test MSE are obtained on normalized data. Theoretically, the best neural network configuration is obtained when the value of testing and training MSE should be equal and minimum as compared to other configurations. Practically, a “good fit” for the data is obtained when the testing error is slightly higher than the training error. If the training MSE is lower than the value of test MSE, it means there is a problem of overfitting. Therefore, the aim is to have the testing and training MSE equal or at least at a minimum difference from each other after the final epoch. Therefore, fig. 5.5 shows the variation of MSE with the number of neurons in each layer of the neural network. As the number of neurons increases from 2 to 12, the MSE for the training data decreases. Initially at 2 neurons, the test MSE is considerably higher as compared to the training MSE and the trend continues till 6 neurons. At 6 neurons, the training and the test MSE are almost equal but at 10 neurons, the training and test MSE are equal and at a minimum value than all other configurations therefore, 10 neuron is the best configuration. Thus, the optimal configuration selected is 10 neurons.

To check how the neural network performs on a totally new dataset, a trained neural network is given a new set of input data (10,000 data points) for 4 CUs and the output is obtained. For the rate requirement of cellular user at 0.1 bps/Hz, 0.3 bps/Hz, 0.5 bps/Hz the percentage errors between the values of average throughput by the conventional optimization algorithm and the FFNN on the same input data are 6.77%, 1.75% and 3.46% respectively. Thus, the FFNN gives a good estimate on a new dataset as well. This implies that once an FFNN is trained with a particular dataset it will be able to judge the output for a new set of inputs.
Figure 5.5. Variation of MSE with the number of neurons.

The figure 5.6. shows the variation of MSE with the number of hidden layers. Each hidden layer has 10 neurons. For the PS SWIPT enabled D2D communications, the neural network performs well on the training set with 1, 2, 3 and 5 hidden layers but fails to perform well on the training set and therefore gives high MSE. The best results are obtained when number of hidden layers are 4.
For the PS SWIPT enabled D2D communications, for the increasing energy conversion efficiency, the throughput increases. The reason is given in chapter 3. A feed forward neural network is trained using the data obtained from the optimization algorithm. The test set is taken 20% of the total dataset. The neural network has four hidden layers with 10 neurons each. The number of epochs is taken to be 100. The hidden layers use the “ReLU” activation function. The loss function is taken as the mean squared error. The results are shown in fig. 5.7.
Table 5.2. Percentage (%) error between the test set values and the predicted values

<table>
<thead>
<tr>
<th>Energy Conversion Efficiency of the DTX</th>
<th>Percentage error for 4 cellular users (%) error</th>
<th>Percentage error for 2 cellular users (%) error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>5.3</td>
<td>5.02</td>
</tr>
<tr>
<td>0.8</td>
<td>1.85</td>
<td>2.62</td>
</tr>
<tr>
<td>0.7</td>
<td>4.4</td>
<td>0.7</td>
</tr>
<tr>
<td>0.6</td>
<td>13.08</td>
<td>3.5</td>
</tr>
<tr>
<td>0.5</td>
<td>9.7</td>
<td>3.92</td>
</tr>
</tbody>
</table>
Figure 5.7. The comparison between test set results and predicted data results for PS SWIPT receiver architecture for 4 CUs and 2 CUs respectively.

Fig. 5.7. compares the test set results and predicted data results for PS SWIPT receiver architecture for 4 CUs and 2 CUs and the table 5.2. gives the percentage error of the test set results and the predicted results. It can be very well seen that the FFNN gives good results as compared to the optimization algorithms.

For the TS SWIPT enabled D2D communications, for the increasing energy conversion efficiency, the throughput increases, and when the rate requirement increases, throughput decreases. The reason is given in chapter 4. A feed forward neural network is trained using the data obtained from the optimization algorithm. The test set is taken 20% of the total dataset. The neural network has five hidden layers with 15 neurons each. The number of epochs is taken to be 200. The hidden layers use the “ReLU” activation function. The loss
function is taken as the mean squared error. The results are shown in fig. 5.8. and fig. 5.10. Tables 5.3. and 5.4. give the percentage error between the actual values and the predicted values in fig. 5.8. and fig 5.10. respectively.

To check how the neural network performs on a totally new dataset, a trained neural network is given a new set of input data (10,000 data points) for 4 CUs and the output is obtained. For the energy conversion efficiency at 90%, 70%, 50% the percentage errors between the values of average throughput by the conventional optimization algorithm and the FFNN on the same input data are 6.77%, 1.68% and 5.01% respectively. Thus, the FFNN gives a good estimate on a new dataset as well. This implies that once an FFNN is trained with a particular dataset it will be able to judge the output for a new set of inputs.

Figure 5.8. The comparison between test set results and predicted data results for TS SWIPT receiver architecture for 2 D2Ds and 4 D2Ds respectively.
**Table 5.3. Percentage (%) error between the test set values and the predicted values**

<table>
<thead>
<tr>
<th>Rate Requirement of the cellular users</th>
<th>Percentage error for 2 D2D users (% error)</th>
<th>Percentage error for 4 D2D users (% error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>3.97</td>
<td>5.29</td>
</tr>
<tr>
<td>0.2</td>
<td>3.21</td>
<td>8.31</td>
</tr>
<tr>
<td>0.3</td>
<td>5.9</td>
<td>8.08</td>
</tr>
<tr>
<td>0.4</td>
<td>4.86</td>
<td>33.50</td>
</tr>
<tr>
<td>0.5</td>
<td>13.92</td>
<td>14.92</td>
</tr>
</tbody>
</table>

**Figure 5.9. The comparison between optimization time and FFNN time for TS SWIPT enabled D2D communications**
Fig. 5.8. gives the relation between the D2D throughput and the rate requirement of cellular users. For both the FFNN and conventional optimization technique, the throughput decreases with the rate requirement of the cellular users.

Fig. 5.8. and fig. 5.9. gives the comparison of test set results and predicted data for TS SWIPT receiver architecture for 4 D2D pairs and 2 D2D pairs respectively. Due to the more complex data when dealing with 4 D2D and 2 D2D pairs, the results showcase more percentage error good when 1 D2D pair is taken for PS scheme. Also, fig. 5.9. shows that the time needed for conventional optimization technique is considerably more than FFNN. The FFNN is 93.33 % faster than the conventional optimization technique.

To check how the neural network performs on a totally new dataset, a trained neural network is given a new set of input data (10,000 data points) for 2 D2D and the output is obtained. For the rate requirement of cellular user at 0.1 bps/Hz, 0.3 bps/Hz, 0.5 bps/Hz the percentage errors between the values of average throughput by the conventional optimization algorithm and the FFNN on the same input data are 5.57%, 9.72% and 1.96% respectively. Thus, the FFNN gives a good estimate on a new dataset as well. This implies that once an FFNN is trained with a particular dataset it will be able to judge the output for a new set of inputs.

Table 5.4. Percentage (%) error between the test set values and the predicted values

<table>
<thead>
<tr>
<th>Energy conversion efficiency of DTX</th>
<th>Percentage error for 2 D2D users (% error)</th>
<th>Percentage error for 4 D2D users (% error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0.9</td>
<td>1.7</td>
</tr>
<tr>
<td>0.8</td>
<td>2.09</td>
<td>5.11</td>
</tr>
</tbody>
</table>
Table  

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>2.25</td>
<td>2.84</td>
</tr>
<tr>
<td>0.6</td>
<td>9.51</td>
<td>0.5</td>
</tr>
<tr>
<td>0.5</td>
<td>5.75</td>
<td>4.2</td>
</tr>
</tbody>
</table>

**Figure 5.10.** The comparison between test set results and predicted data results for TS SWIPT receiver architecture for 2 D2Ds and 4 D2Ds respectively.

Fig. 5.10. gives the relationship between D2D throughput and the energy conversion efficiency. The throughput increases with the energy conversion efficiency as stated in chapter 4.

To check how the neural network performs on a totally new dataset, a trained neural network is given a new set of input data (10,000 data points) for 2 D2D and the output is obtained. For the energy conversion efficiency at 90%, 70%, 50% the percentage errors between the values of average throughput by the conventional optimization algorithm and
the FFNN on the same input data are 5.57%, 5.84% and 2.53% respectively. Thus, the FFNN gives a good estimate on a new dataset as well. This implies that once an FFNN is trained with a particular dataset it will be able to judge the output for a new set of inputs.

The reason for the selection of 15 neurons for TS SWIPT enabled D2D communications is similar to the selection of 10 neurons as explained for the PS SWIPT enabled D2D communications and can be seen from Fig. 5.11. Similarly, the reason for selecting 5 hidden layers is shown in Fig 5.12.

![Figure 5.11. Variation of MSE with the number of neurons with TS SWIPT enabled D2D communications.](image)

Figure 5.11. Variation of MSE with the number of neurons with TS SWIPT enabled D2D communications.
Figure 5.12. Variation of MSE with the number of hidden layers with TS SWIPT enabled D2D communications.

5.7. Summary

The chapter is aimed at testing the benefits of deep learning over the conventional optimization algorithms. First, a brief overview of the neural network and its components is given. Second, an idea of how the system operates is also given. Input and output dataset is taken from optimization algorithms. The dataset is fed into a neural network to train it. Finally, the trained neural network is used to predict results for the test data. The results are found to be very close to the ones from the optimization algorithms, and the times are way less for FFNN than the conventional optimization techniques.
Chapter 6: **Conclusion and Future Work**

6.1. **Thesis Conclusions**

The thesis studied resource allocation problems for TS and PS SWIPT enabled D2D communications underlaying NOMA cellular networks. The resource allocation problems were first formulated with the objective of maximizing the throughput of the SWIPT (PS and TS) enabled devices keeping the constraint that the rate requirements of the cellular users are satisfied. The problems were mathematically solved and simplified in a way where the gradient descent method could be applied easily to solve the problems. The results were obtained varying the different network parameters.

For the PS and TS SWIPT enabled D2D communications, the rate requirement of cellular users should be designed to be low. The lower the rate requirement of the cellular users, the higher the D2D throughput. Also, the D2D throughput depends on the environment in which the devices are present. This is an important observation in the use case of D2D where the cellular users are present in some remote area such as a desert area where the received BS signal strength is poor. In this case, the cellular users can search for a device nearby and establish a link with the device to relay its information to the BS. Since, the environment is a free space, there is efficient communication between the devices. Highly obstructed areas in the cities aren’t fit to support D2D communication as the rates become considerably less in these scenarios. Also, results are obtained considering the geographical position of the devices. The throughput observes a considerable gain of almost 100% when the devices are placed closely (2m) rather than being placed at a comparatively far off distance (10m). This observation is crucial in highlighting the importance of geographical positioning of the devices. Also, the design of circuit
electronics plays a major role in determining the D2D throughput. Highly efficient ICs deployed in energy harvesting circuits will result in better D2D throughput.

Also, the density of the network matters in deciding the D2D throughput. The results for PS SWIPT enabled devices were obtained varying the number of cellular users. The increase in the cellular users affected the D2D throughput such that the throughput decreased as compared to when the cellular users were more. This implies that dense networks will lead to lower throughputs and might not support D2D communications with proper rate requirement. For the TS SWIPT D2D communications, the effect of multiple D2D pairs were studied. It was found that even as the D2D pairs increase in the network, the D2D communications had lower rates. Hence, dense networks will decrease the performance of the D2D communications. In all the scenarios, the NOMA based network offers a much better performance than the OMA based network.

The conventional optimization algorithms solve the problem iteratively exploiting the mathematical structure of the problem. This takes long simulation times and is not computationally efficient. Deep learning approaches take 90-92% less time as compared to the conventional optimization algorithms because they are computationally efficient and give almost the same results. Though deep learning approaches prove to be much better as compared to conventional optimization algorithms, yet a dataset is needed to implement the deep learning approaches. The dataset that is used in this thesis is a synthetic dataset generated by solving optimization problems in chapters 3 and 4.

6.2. Engineering Significance and Impact of the Thesis Findings

The constant upgrade in the conventional networks is garnering a lot of attention from the industry and the academia. Furthermore, attention is being paid to create battery less
devices which will contribute to an eco-friendlier world. Thus, the work done in this thesis is relevant to the adoption of SWIPT enabled D2D communications in real life practical scenarios.

In Chapters 3 and 4, the formulated optimization problems aim to integrate the PS-SWIPT enabled D2D communications and the TS-SWIPT enabled D2D communications respectively in the network without letting the performance of cellular communications deteriorate. The locations of the devices, the rate requirement of the cellular users, the design of the circuit electronics and the feasibility of these communications based on environment and density of the network can be evaluated by the engineers based on the results obtained in this thesis.

Chapter 5 shows the importance of adopting deep learning in calculating the optimal values for a particular set of network scenarios. It is shown that neural networks once trained can give excellent results on a new set of network scenarios and would occupy less computation times thus efficiently utilizing resources and enabling faster communications. Thus, engineers can train neural networks based on appropriate data and conveniently use neural networks to predict the entities they aim to.

6.3. Suggestions for Future Work

Even though this thesis covers a lot of aspects, yet this work can be extended to include more practical scenarios. Following points can be considered in the future to extend this work:

1) Imperfect channel conditions: The work considers perfect channel conditions but in practical scenarios, the perfect channel state information (CSI) is not available. The results should be obtained considering imperfect channel state information
(CSI). The error in channel coefficients propagates through the optimization algorithm in this case. Thus, imperfect channel state information (CSI) can be incorporated with this work, and it can be seen what happens to the performance for D2D communications if perfect channel conditions are not known to the devices.

2) Configurations of SWIPT receivers: This thesis and most of the literature consider PS and TS SWIPT receiver architectures. Separate receiver architecture and antenna switching architecture have not been studied as widely as the TS and PS architectures. Therefore, an extension of this work is to study separate receiver and antenna switching architecture enabled D2D communications underlaying NOMA based network.

3) Considering multi cell scenario: This work considers a single cell scenario and thus accounts only for intra-cell interference. If multi-cell scenarios will be considered, the inter-cell interference will play a role in deciding the D2D throughput. Therefore, a complex resource allocation optimization problem which includes the effect of devices in the multi-cells in the network should be studied.

4) Comparisons of different deep learning approaches: This work considers feed forward neural network (FFNN) to estimate the D2D throughput given the input. Other types of neural networks such as the long-short term memory (LSTM), nonlinear autoregressive exogenous model (NARX) can be deployed to fit in the data and obtain the D2D throughput and it can be seen which neural network type actually takes the least time and is most accurate in predicting the D2D throughput.
Thus, the adoption of 5G technology has a lot of scope for the existing network. The technologies central to 5G can lead to improved data rates, throughputs, spectral efficiency, lower latency thus fulfilling the demands of the users and help to combat the ever-increasing number of devices and data demands.
References


APPENDIX

APPENDIX A: Proof of Theorem 3.1

We assume that, for the optimal solution of (3.16) \((\varepsilon^*, \lambda^*, \rho_D^*)\), constraints (3.7), (3.8), and (3.12) hold. Let us assume that there exists at least one strict inequality in (3.17), \(R_k^2(\lambda^*, \rho_D^*) > \gamma_k\) and for all cellular uses except \(CU_k\), \(R_i^2(\lambda^*, \rho_D^*) \geq \gamma_i\). We construct a new solution \((\bar{\varepsilon}, \bar{\lambda}, \bar{\rho}_D)\) where \(\bar{\varepsilon} = \varepsilon^*, \bar{\lambda} = \lambda^*, \bar{\rho}_D = \rho_D^*\). Now, for \(CU_k\), suppose that \(R_k^2(\bar{\lambda}, \bar{\rho}_D) = \gamma_k\). Using (3.10) and (3.14b) and solving for \(\bar{\lambda}_k\) gives:

\[
\bar{\lambda}_k = \frac{(2\gamma_k - 1)\left[\sum_{k=1}^{|\mathcal{K}|} |h_k|^2 \rho_{BS} + |h_{D,j}|^2 \rho_D + 1\right]}{\rho_D + 1}
\]

\(\Rightarrow R_k^2(\bar{\lambda}, \bar{\rho}_D) < R_k^2(\lambda^*, \rho_D^*) \Rightarrow \bar{\lambda}_k < \lambda_k\).

Now if we set \(\bar{\lambda}_i < \lambda_i^*\) for all \(i \in \mathcal{Q}\) then from (3.13) it follows that \(R_k^2(\bar{\lambda}, \bar{\rho}_D) > R_k^2(\lambda^*, \rho_D^*)\) for all \(i \in \mathcal{Q}\). Similarly, for the D2D users it can be concluded from (3.13) that \(R_D^2(\bar{\lambda}, \bar{\rho}_D) > R_D^2(\lambda^*, \rho_D^*)\). That is, the throughput of the solution \((\bar{\varepsilon}, \bar{\lambda}, \bar{\rho}_D)\) will be higher than that of the optimal solution \((\varepsilon^*, \lambda^*, \rho_D^*)\) which is a contradiction.

Hence it is proved that, \(R_i^2 = \gamma_i\) for all \(i \in \mathcal{Q}\).

APPENDIX B: Proof of Theorem 3.2

Now since we have proved that \(R_i^2 = \gamma_i\)

\[
\frac{\rho_{BS} \lambda_i}{\sum_{k=1}^{i-1} \lambda_k \rho_{BS} + \sigma_i \rho_D + \zeta_i} = \psi_i
\]

where \(\psi_i, \sigma_i, \zeta_i\) are defined in (3.20). For \(i=1, \sum_{k=1}^{i-1} \lambda_1 \rho_{BS} = 0\)

Therefore, for all the other cellular users apart from \(CU_i\), let us assign \(A_i = \sum_{j=1}^i \lambda_i \rho_{BS}\) and \(A_{i-1} = \sum_{j=1}^{i-1} \lambda_j \rho_{BS}\). Therefore,
\[ A_i = A_{i-1} + \psi_i(A_{i-1} + \sigma_i \rho_D + \zeta_i) \]  
(B.2)

Generalizing the equation becomes
\[ A_i = \prod_{j=2}^{i}(1 + \psi_j)A_1 + \sum_{j=1}^{i} \left\{ \prod_{u=j+1}^{i}(1 + \psi_u) \psi_j(\sigma_j \rho_D + \zeta_j) \right\} \]  
(B.3)

Now, for \( j + 1 > i, \prod_{u=j+1}^{i}(1 + \psi_u) = 1. \)

Also,
\[ \lambda_i = \frac{A_i - A_{i-1}}{\rho_{BS}} \]  
(B.4)

Hence, in general for \( i \geq 2, \) we can calculate
\[ \sum_{i=1}^{K} \lambda_i = \frac{\sum_{j=1}^{K} \left\{ \prod_{u=j+1}^{K}(1 + \psi_u) \psi_j(\sigma_j \rho_D + \zeta_j) \right\}}{\rho_{BS}} \]

Hence, Theorem 2 is proved.

**APPENDIX C: Proof of Convexity**

The objective function (3.26a) increases with \( \rho_D, \) we set optimal solution as \( \rho_D^* = \frac{\bar{C}}{\bar{D}}. \) Now, let us rewrite our objective function (substituting the optimal solution in 3.26(a)) as
\[ \max_{\epsilon} U_D(\epsilon) = \frac{\epsilon}{2} \log_2 \left( \frac{m_1 \epsilon^2 + m_2 \epsilon + m_3}{n_1 \epsilon + n_2} \right) \]  
(C.1)

where \( m_1 = -|h_D|^2 \bar{C}, \) \( m_2 = j\bar{C} + |h_D|^2(\bar{C} + \bar{D}), m_3 = \bar{S} - |h_D|^2 \bar{D} - j\bar{D}, n_1 = j\bar{C}, n_2 = \bar{S} - j\bar{D} \)

The double differential with respect to \( \epsilon \)
\[ \nabla_{\epsilon}^2 U_D = \Gamma \left( \frac{G\epsilon^4 + X\epsilon^3 + Y\epsilon^2 + Z\epsilon + W}{(n_1 \epsilon + n_2)^2 (m_1 \epsilon^2 + m_2 \epsilon + m_3)^2} \right) \]  
(C.2)

where,
\[ G = -m_1^2 n_1^2 \]
\[ X = -4m_1^2 n_1 n_2 \]
\[ Y = 4m_1 m_3 n_1^2 - 4m_1 m_2 n_1 n_2 - 2m_1^2 n_2^2 \]
\[ Z = 4m_1 m_3 n_1 n_2 - 2m_1 m_2 n_2^2 - 2m_2^2 n_1 n_2 + 2m_2 m_3 n_1^2 \]
\[ W = 2m_1 m_3 n_2^2 + m_3^2 n_1^2 - m_2^2 n_2^2 \]

For our objective function to be concave the numerator should be less than 0 which is the case here and hence the optimization problem (3.26) becomes convex optimization problem.

**APPENDIX D: Proof of Theorem 4.1**

The constraint given is \( \tau_{Sc} + \tau_{Ec} \leq T \)

\( \tau_{Ec}^* \) = optimal energy harvesting time

\( \tau_{Sc}^* \) = optimal transmission time from DTX and DRX

It is assumed that

\[ \tau_{Sc}^* + \tau_{Ec}^* < T. \]  \hspace{1cm} (D.1)

Since the assumptions holds for constraints (4.7), (4.8), (4.12), (4.16)

An intermediate solution can be constructed \( (\bar{\tau}_{Sc}, \bar{\tau}_{Ec}, \bar{\alpha}, \bar{P}_{Dx}) \) such that

\[ \bar{\tau}_{Sc} + \bar{\tau}_{Ec} = T. \]  \hspace{1cm} (D.2)

Also assume that,

\[ \bar{\tau}_{Ec} = \frac{\tau_{Ec}^* \cdot \tau_{Sc}^*}{\tau_{Ec}^* + \tau_{Sc}^*} \]  \hspace{1cm} (D.3)

and,
\[
\bar{\tau}_{Sc} = \frac{\tau_{Sc}^*}{\tau_{Ec} + \tau_{Sc}^*},
\]

and, \( \bar{\lambda} = \lambda^*, \bar{\rho}_{DC} = \rho_{DC}^* \)

The objective is to maximize the sum throughput of D2D communication

\[
\max_{\tau_{E}, \tau_{S}, \lambda, \rho_{DC}} \sum_{c=1}^{C} U_{DC} = \sum_{c=1}^{C} \tau_{Sc}^2 R_{Dtc}^2,
\]

The achievable rate of D2D c link can be achieved as

\[
R_{Dtc}^2 = \log_2 (1 + SINR_{Dtc}^2).
\]

The SINR is given as

\[
SINR_{Dtc}^2 = \frac{|h_{Dc}|^2 \rho_{DC}}{\sum_{i=1}^{N} \lambda_i |h_{B,DrC}|^2 \rho_{BS} + \sum_{l=1, l \neq c}^{L} |h_{Dtl,DrC}|^2 \rho_{DL} + 1}.
\]

Since, the SINR does not depend on \( \tau_{Ec} \) and \( \tau_{Sc} \). Therefore irrespective of values of \( \tau_{Ec} \) and \( \tau_{Sc} \) the rate remains the same.

\[
R_{Dtc}^2(\bar{\lambda}, \bar{\rho}_{DC}) = R_{Dtc}^2(\lambda^*, \rho_{DC}^*).
\]

Now, it can be said that \( \bar{\tau}_{Sc} > \tau_{Sc}^* \)

Therefore,

\[
U_{DC}(\bar{\lambda}, \bar{\rho}_{DC}, \bar{\tau}_{Sc}, \bar{\tau}_{Ec}) > U_{DC}(\lambda^*, \rho_{DC}^*, \tau_{Sc}^*, \tau_{Ec}^*).
\]

Hence, the assumption \( \tau_{Sc}^* + \tau_{Ec}^* < T \) is contradicted. And therefore, it can be said that

\[
\tau_{Sc}^* + \tau_{Ec}^* = T.
\]

Let us prove that the optimal solution to problem (4.19) satisfies (4.20). From (4.15b):

\[
R_{i}^{2*} = \gamma_i.
\]

From (4.14b), the equation for \( R_{i}^2 \) (achievable rate for cellular users in second phase) is

\[
R_{i}^2 = \log_2 (1 + SINR_{i,i}^2).
\]
We assume that, for the optimal solution \((\lambda^*, \rho_{DC}^*, \tau_{Sc}^*, \tau_{Ec}^*)\), constraints (4.8), (4.9), and (4.14) holds

\[
SINR_{i,j}^2 = \frac{|h_i|^2 \lambda_j \rho_{BS}}{\sum_{k=1}^{j-1} \lambda_k |h_i|^2 \rho_{BS} + \sum_{c=1}^{C} |h_{DC,c}|^2 \rho_{DC} + 1}.
\]

Let us assume that there exists at least one strict inequality in (4.18)

\[
R_i^2(\lambda^*, \rho_{DC}^*) > \gamma_k.
\]

and, for all \(i \in \mathbb{N}\) except \(k\)

\[
R_i^2(\lambda^*, \rho_{DC}^*) \geq \gamma_i.
\]

A new solution is constructed \((\tilde{\tau}_{Ec}, \tilde{\tau}_{Sc}, \tilde{\rho}_{DC}, \tilde{\lambda})\) where \((\tilde{\tau}_{Sc} = \tau_{Sc}^*, \tilde{\tau}_{Ec} = \tau_{Ec}^*, \tilde{\rho}_{DC} = \rho_{DC}^*, \tilde{\lambda}_i = \lambda_i^*)\).

Now, for \(CU_k\), suppose that \(R_k^2(\tilde{\lambda}, \tilde{\rho}_{DC}) = \gamma_k\). Using (4.14b) and (4.11) gives

\[
2\gamma_k - 1 = \frac{|h_i|^2 \rho_{BS} \lambda_j}{\sum_{i=1}^{j-1} \lambda_i |h_i|^2 \rho_{BS} + \sum_{c=1}^{C} |h_{DC,c}|^2 \rho_{DC} + 1}.
\]

Solving for \(\tilde{\lambda}_k\)

\[
\tilde{\lambda}_k = \frac{(2\gamma_k - 1) \sum_{i=1}^{j-1} \lambda_i |h_i|^2 \rho_{BS} + \sum_{c=1}^{C} |h_{DC,c}|^2 \rho_{DC} + 1}{|h_i|^2 \rho_{BS}}.
\]

Here, we have assumed

\[
R_k^2(\tilde{\lambda}, \tilde{\rho}_{DC}) = \gamma_k,
\]

\[
R_k^2(\tilde{\lambda}, \tilde{\rho}_{DC}) < R_k^2(\lambda^*, \rho_{DC}^*),
\]

\[
\tilde{\lambda}_k < \lambda_k^*.
\]

Now if we set \(\tilde{\lambda}_k < \lambda_k^*\) for all \(i \in \mathbb{N}\), then from (4.11) it follows that

\[
R_k^2(\tilde{\lambda}, \tilde{\rho}_{DC}) > R_k^2(\lambda^*, \rho_{DC}^*).
\]
for all \( i \in \mathbb{N} \). Similarly, for the D2D users \( \bar{\lambda}_k < \lambda'_k \), since, it can be concluded from (4.10) that

\[
R_{Dtc}^2(\bar{\lambda}, \bar{\rho}_{DC}) > R_{Dtc}^2(\lambda^*, \rho^*_{DC}). \tag{D.22}
\]

That is, the throughput of the solution \((\bar{\lambda}, \bar{\rho}_{DC}, \bar{\tau}_{Sc}, \bar{\tau}_{Ec})\) will be bigger than that of the optimal solution \((\lambda^*, \rho^*_{DC}, \tau^*_{Sc}, \tau^*_{Ec})\) which is a contradiction.

Hence it is proved that, \( R_i^2 = \gamma_i \) for all \( i \in \mathbb{N} \).

APPENDIX E: Proof of Theorem 4.2

Now since we have proved that \( R_i^2 = \gamma_i \),

\[
\log_2(1 + SINR_{i,l}) = \gamma_i. \tag{E.1}
\]

\[
2^{\gamma_k} - 1 = \frac{|h_d|^2 \rho_{BS} \lambda_i}{\sum_{k=1}^{\lambda_i} \lambda_k |h_{d,k}|^2 \rho_{BS} + \sum_{c=1}^{C} |h_{DC,c}|^2 \rho_{DC} + 1}. \tag{E.2}
\]

\[
\zeta_i = \frac{\rho_{BS} \lambda_i}{\sum_{k=1}^{\lambda_i} \lambda_k \rho_{BS} + \sum_{c=1}^{C} \psi_{c,1} \rho_{DC} + \delta_i}. \tag{E.3}
\]

Substituting \( i = 1 \),

\[
\zeta_1 = \frac{\rho_{BS} \lambda_1}{\sum_{k=1}^{\lambda_1} \lambda_k \rho_{BS} + \sum_{c=1}^{C} \psi_{c,1} \rho_{DC} + \delta_1}. \tag{E.4}
\]

Clearly

\[
\sum_{k=1}^{0} \lambda_k \rho_{BS} = 0. \tag{E.5}
\]

Hence

\[
\lambda_1 = \frac{\zeta_1 (\sum_{c=1}^{C} \psi_{c,1} \rho_{DC} + \delta_1)}{\rho_{BS}}. \tag{E.6}
\]

Now, for all other CUs apart from CU\(_i\), \( \sum_{k=1}^{j-1} \lambda_k \rho_{BS} \) will attain some positive values.
Therefore, for all other cellular users apart from $CU_i$

$$\lambda_i = \frac{\left(\sum_{k=1}^{i-1} \lambda_k \rho_{BS} + \sum_{c=1}^{i} \psi_{c,i} \rho_{DC} + \delta_i \right) \zeta_i}{\rho_{BS}}. \quad (E.7)$$

Assign $A_i = \sum_{j=1}^{i} \lambda_j \rho_{BS}$ and $A_{i-1} = \sum_{j=1}^{i-1} \lambda_j \rho_{BS}$

Clearly,

$$A_i = A_{i-1} + \lambda_i \rho_{BS}. \quad (E.8)$$

$$A_i = A_{i-1} + \left(\sum_{k=1}^{i-1} \lambda_k \rho_{BS} + \sum_{c=1}^{i} \psi_{c,i} \rho_{DC} + \delta_i \right) \zeta_i$$

$$A_i = A_{i-1} + \left(A_{i-1} + \sum_{c=1}^{i} \psi_{c,i} \rho_{DC} + \delta_i \right) \zeta_i. \quad (E.9)$$

Generalizing the equation, we can see that

$$A_i = \prod_{j=2}^{i} (1 + \psi_j) A_1 + \sum_{j=1}^{i} \left[\prod_{u=j+1}^{i} (1 + \zeta_u) \right] \zeta_j \left(\sum_{c=1}^{i} \psi_{c,j} \rho_{DC} + \delta_j \right). \quad (E.10)$$

Now, for $j+1 > i$, $\prod_{u=j+1}^{i} (1 + \zeta_u) = 1$

$$\lambda_i = \frac{A_i - A_{i-1}}{\rho_{BS}}. \quad (E.11)$$

Hence, in general for $i \geq 2$, we can calculate

$$\lambda_i = \frac{\sum_{k=1}^{i-1} \left[\prod_{u=k+1}^{i} (1 + \zeta_u) \zeta_k \left(\sum_{c=1}^{i} \psi_{c,j} \rho_{DC} + \delta_j \right) \right] + \sum_{c=1}^{i} \psi_{c,i} \rho_{DC} + \delta_j}{\rho_{BS}}.$$

Hence, theorem 2 is proved.