Energy Efficient Infrastructure Sharing in Multi-Operator Mobile Networks

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by

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DECLARATION

I, the undersigned, declare that the thesis comprises my own work in compliance with internationally accepted practices; I have fully acknowledged and referred all materials used in this thesis work.

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Abstract

The rapid development of cellular networks has been urged by the introduction of 3rd Generation (3G) wireless technologies, significantly boosting Ethiotelecom's energy usage and expenditures. Furthermore, mobile data explosion has occurred in recent decades because of an increase in the number of mobile users as well as the rise of bandwidth-hungry applications, hence aiming to utilize the available spectrum as efficiently as possible is a good move. Many researches done on massive MIMO, spectrum sharing, device to device communication (D2D) and GREEN communication shows significant attention in aiding spectrum utilization along with power optimization. In this thesis, motivated by the development of a new Ethiotelecom's business model, infrastructure sharing, which allows emerging MNOs to have their traffic served by other MNOs in the same geographic area, allowing them to share a portion of their network is investigated. This thesis work presents a social dilemma game theoretic framework that allows MNOs to share a portion of their network. Sequential social dilemma and particles swarm algorithm are implemented on OpenAI Gym based adaptable frame work. The algorithm is implemented and optimized for 3 mobile network operator (N = 3), 3 base station sites with 3, 9 and 30 mobile users. Simulation result shows users are connected/linked to nearby base station considering optimization of the utility (reward) function of the MNO (Game players), distance between mobile users and base station sites when the proper cell allocates enough resources. The performance of our simulation is visualized by generating various hypothetical cellular network environments with different number of cell sites and mobile users. A more optimal solution is obtained by adding a particle swarm optimization over it. Simulation results are promising and provide a better direction to the future work.

Keywords: Non-cooperative game, Nash Equilibrium (NE), Sequential social dilemma, Energy saving, Markov game, Particles swarm, CAPEX and OPEX.

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BBU	Base Band Units
RBSs	Radio Base Stations
BW	Band width
BTS	Base Transciever Staion
CaPEX	Capital expenditure
ECG	Energy Consumption Gain
IPD	Iterated Prisoner's Dilemma
MNO	Mibile Network Operator
MDP	Markovian Decision Process
MVNOs	Mobile Virtual Network Operators
MSCs	Mobile Switching Centers
NE	Nash Equilibrium
OpEX	Operationional Expenditure
RRU	Radio Remote Units
RATs	Radio Access Technologies
RRH	Radio Remote Heads
SINR	Signal to Interference and Noise ratio
SSD	Sequential Social Dilemma
UE	User Equipmnet

Chapter1

Introduction and Background

The number of mobile subscriber worldwide is growing at an exponential rate. With more than 44.5 million users in Ethiopia alone [1]. Compared to independent deployments of RAN offering closed access, which would be expensive, multi-operator, RAN sharing possesses the potential for quickly expanding coverage area while significantly reducing the capital expenditures (CapEX) and operational expenditures (OpEX) for mobile network operators (MNOs). A well Multi-operator radio access network(RAN) sharing offers great potential for cost and energy efficient deployment and operation of next-generation millimeter-wave RAN [2]. In telecommunications, sharing resources between operators has been suggested, inparticular with the arrival of the next generation of telecom (5G) in order to extend and improve capacity and coverage of operator's connectivity.

In the last decades, the energy issue has gained a great importance in the field of telecommunications. Several surveys prove that the main energy consuming components are the Base Stations (BSs) [3]. Hence, there is a strong motivation to investigate solutions to bring down the energy consumption and the cost of cellular networks, thus yielding both environmental and financial gains.

In cellular networks, sharing resources across Mobile Network Operators (MNOs) is an appealing approach, such as through roaming, radio access network sharing. Recently, connection marketplaces have been discussed, incorporating financial activities such as trading systems or auctions, whilst alternative solutions may rely on dynamic exchanges and fair provider cooperation. Two key use-cases for collaboration in mobile cellular networks are commonly considered in [4]; network coverage extension and network capacity extension. In the first situation, certain users may be unable to connect due to a gap in their home provider's infrastructure coverage. In the latter instance, there may be too many customers in relation to their home provider's network cell capacity. To address these issues, a provider may wish to work with one or more other providers in order to take advantage of their resources, resulting in closer or less overburdened cells for the users in need.

In this research, motivated by the aforementioned issues and taking into account the rationality of the MNOs and their conflicting interests, a noncooperative Markov game is proposed. Therefore, it can be viewed as a social dilemma, i.e. a situation where Nash equilibria are non-optimal. Operators have no incentive to cooperate despite the fact that cooperation is the optimal global strategy. Besides the expected energy efficiency benefits, the proposed scheme allows the MNOs to significantly reduce their financial costs independently of the strategies of the coexisting MNOs, providing them with the motivations to participate in the game.

1.1 Research Motivation

Currently the enterprise version of mobile communication become historically primarily based totally on complete possession of network infrastructure. With the rate of increase and call for wireless communication offerings globally, they want transfer from the conventional manner of sole network infrastructure to network infrastructure sharing [6]. Rolling out mobile communication offerings in Ethiopia has emerge as interesting to a few providers, especially to the brand new entrants. According to the authority (ECA), the essential purpose underlies in the truth that no service provider, within the framework of coverage and regulation, become now no longer required to perform the deployment of its own infrastructure [5]. Which means sharing infrastructure is highly recommended.

Telecommunication operators are quite recommended to the most volume viable to proportion passive and active infrastructure for the supply of telecommunication service. The authority shall must prescribe directives for the sharing of infrastructure such as preferred technical and industrial terms. The extra infrastructure now no longer best implies a rise in the Capital Expenditures (CapEx), however additionally has an immediate effect at the community strength intake, for this reason resulting in higher Operational Expenditures (OpEx). In particular, using statistics throughout a huge variety of programs money owed for 5.7% of the world's power intake and 1.8 % of world carbon emissions, something that interprets into power payments within the order of 10 billion dollar for the MNOs worldwide [6].

1.2 Statement of the problem

The major challenges in today's radio access networks include cost and energy efficiency. Infrastructure enhancement solves mobile data explosion but still spectrum is scarce. Spectrum enhancement (e.g. mm wave) is can be a solution but still expensive due to spectrum purchasing and research and development. One of the best solution is sharing of RAN resources among mobile network operators (MNOs).

There is a continuous need to install RAN supporting infrastructure in order to effectively care for the increasing users in term of service delivering. A major infrastructure is the RAN base Station containing the Base Transceiver Station (BTS); this is due to the limited available bandwidth, the fading nature of the propagation channel and the mobility and autonomy of the wireless nodes [3]. Hence, there is a strong motivation to investigate solutions to bring down the energy consumption and the cost of cellular networks, thus yielding both environmental and financial gains.

It is already known that our country is going to have multi-operators in the coming years hence it is advantageous to share RAN infrastructure with cost and energy efficiency aspects. RAN sharing possesses the potential for quickly expanding coverage area while significantly reduce cost as well energy. Some users may be unable to connect owing to a lack of coverage by their home provider's infrastructure or because there are too many users in relation to their home provider's network cell capacity. To address these issues, a provider may wish to combine with one or more other providers in order to take advantage of their resources, resulting in closer or less overburdened cells for users in need.

1.3 Objective

1.3.1 General Objective

The main objective of this thesis is to model the optimal Infrastructure Sharing in multi-Operator Mobile Networks with non-cooperative Markov game and show that it can be viewed as a social dilemma approach to save cost and energy.

1.3.2 Specific Objective

The specific aims of the research are:

- Concerns with study of incentives to the mobile network operators to share
  - To improve users quality of service
  - To enhance gains of MNO
- Formulate the problem as a non-cooperative Markov game and show that it can be viewed as a social dilemma, i.e. a situation where Nash equilibria are non-optimal.

Operators have no incentive to cooperate despite the fact that mutual cooperation is the optimal global strategy.

- Formulate the cost analysis taking in to account CAPEX and OPEX, roaming and overhead costs: to assist operators whether infrastructure sharing is profitable or not.
- Build our multi-agent telecom providers frame work based on Environmental features; Number of agents(MNOs), Positions of sites, Number of cells, Mobility of users, Positions of users and Discretization of observation.
- Finally validate the theoretical analysis and assess the effectiveness of the proposed infrastructure-sharing scheme with the aid of simulation experiment.

1.4 Scope of the study

This thesis mainly focuses on to save cost, without compromising the offered Quality of Service and enhance gains of MNOs, by sharing radio access resources. To this end, we propose a non-cooperative Markov game theoretic strategy using our multi-agent telecom provider's framework to decide the optimum sharing of base Stations. Considering cluster of multi-operator cells, while each cell includes BSs of different MNOs; mathematical analysis and simulations demonstrate that the proposed scheme can significantly reduce the energy and cost consumption.

1.5 Contribution of the research

The main contributions of this thesis are summarized as follows:

- Game theory gives insights the most and important theoretic bases for modeling infrastructure sharing and game theory used to inspire practical designs for the operator as it mainly uses as engineering approach in wireless communication.
- Propose a game theoretic algorithm, applicable to realistic centralized networks ruled by multiple operators.
- Formulate the cost analysis taking explicitly into account operational and roaming costs, to assist operators in deciding whether infrastructure sharing will be Profitable.
- This research also could be the starting point to conducted researches on Inter-operator roaming-based infrastructure sharing by game theory in Ethiopia for multi-operator business environment and motivate for further works and used as a reference material for the researchers.

1.6 Literature Review

A number of researches have been conducted in infrastructure sharing among operators and the problem of its coexistence in the same geographical area. In this section, we review some works related to infrastructure sharing between operators operating over the same geographical area. For instance, in the passive RAN sharing scenario, sites, towers, and power supplies of BSs are shared among MNOs, but BSs remain separated. In the active RAN sharing scenario, BSs and backhaul are shared among MNOs.

In [3] a heterogeneous Service Level Agreement (SLA) framework for a shared network is proposed, in which different operators' constraints are addressed utilizing two alternative multi-objective optimization techniques, namely the utility profile and scalarization approaches. Combining these tactics with the notion of generalized fractional programming yields Pareto-optimal solutions. The approach can be used in single carrier or multi-carrier systems that are both noise-limited and interference-limited. Extensive numerical findings show how the operator's particular SLA requirements affect global spectral and energy efficiency. The numerical findings show three network situations, each corresponding to a different SLA, each with its own operator-specific strength efficiency and spectral effectivity limitations.

[7] Introduces a new adaptable framework based on the OpenAI Gym toolkit that allows for the creation of configurable environments for radio resource collaboration. This approach allows for the systematic development and comparison of agents (such as reinforcement learning agents). Then, because multi-player games created by these environments can be thought of as sequential social dilemmas, therefore concentrate on game theory elements. It shows that, despite the fact that each agent has no motivation to cooperate at each phase of such iterated games, mutual cooperation produces better results (in other words, Nash Equilibrium is non optimal).

In [9] Considering the economic impact of cross-carrier MVNOs on the market for cellular records they start by looking at a network choice technique that reduces the expenses of cross-carrier customers. The fees that companion ISPs charge the cross-carrier MVNO and the fees that the cross-carrier MVNO charges its give-up users are then calculated. Although the cross-carrier MVNO may lose money by selling data, it can compensate for this by generating other revenue, such as advertising revenue when users consume additional content. We derive conditions under which the cross-carrier MVNO achieves an income and its users minimize their costs. Finally, using a real-world network quality dataset to simulate users' network choice conduct and demonstrate the advantages of the ISP competition introduced with the aid of the cross-carrier MVNO.

Multi operator infrastructure sharing scenario has been considered in more studies on the past years in the literature. Despite many works trying to justify the use of a game theoretic approach for infrastructure sharing, most of them focus solely on the benefits of sharing. There are various forms of inter-operator RAN sharing. Different levels of RAN sharing have different levels of economic and regulatory considerations. A comprehensive classification and analysis are available in previous work [10] .

Techno-economic model in [10] allows network operators to compete and dynamically select the quality target to deliver to their customers, while simultaneously seeking to maximize their profits. Nash equilibrium (NE) developed in a non-cooperative game, which shows the optimal point for the operators to meet the customers' requirements. Mostly the researchs that have been investigated are based on the concepts of engineering decision that satisfies the QoS requirements of end users, but also an economic one that targets maximizing the profits of all participating operators [11].

In [12] considers an inter-operator RAN sharing scenario where MNOs may have different numbers of deployed mm Wave BSs and users in the beginning. In order to attract more subscribers to mm Wave access services, the MNOs mutually share their BSs by opening the access of their BSs to users of other MNOs. Once a user is associated with the BS of another MNO, it is allocated with a certain amount of bandwidth according to a bandwidth-based service level agreement (SLA) among the MNOs.

In [13] address the trouble of Radio Access Network (RAN) and spectrum sharing in 4G. Cellular networks through that specialize in a case while more than one MNOs plan to set up small cell Base Stations in a geographical place so one can improve their present network infrastructure and advise cooperative game models (with and without transferable utility) to discourse the proposed trouble. If all MNOs contribute with spectrum resources, they decide on constructing a unique shared RAN because of the mixed benefit of spectrum aggregation and the value discount from sharing the network infrastructure; formally, which means that the reference cooperative game has a nonempty core, which makes the grand coalition most desirable to any Sub coalition. The strong division (amongst MNOs) of the shared network infrastructure value relies upon on each network and monetary settings. MNOs with a bigger purchaser base ought to be accounted for a bigger fraction of the network value. Instead, MNOs, which contribute with a bigger spectrum component, are "rewarded" through a decrease value fraction and, in a few cases, now no longer, only they may be exempted from such value however additionally get hold of a part of the alternative MNO character revenues.

[14]Focus on nighttime and sharing strategies of power amongst more than one MNOs with collocated shared network infrastructure and inspire cooperation amongst them via way of means of analyzing relative equity issues. The predominant goal is to allow MNOs, who already share their infrastructure in terms of a green network operation, to in addition lessen their energy Consumption via way of means of sharing (1) the solar energy harvested throughout daylight hours and (2) the harvested power, this is saved in storage devices, e.g. batteries, throughout night time hours. To this end, a bankruptcy game is designed to seize the power sharing interactions amongst MNOs. Taking into attention the power deficits of every MNO for a studied period, they Shapley Value (SV) to decide the quantities of power assigned to every MNO. Focus on nighttime and sharing strategies of power amongst more than one MNOs with collocated shared network infrastructure and inspire cooperation amongst them via way of means of analyzing relative equity issues. The predominant goal is to allow MNOs, who already share their infrastructure in terms of a green network operation, to in addition lessen their energy Consumption via way of means of sharing (1) the solar energy harvested throughout daylight hours and (2) the harvested power, this is saved in storage devices, e.g. batteries, throughout night time hours. To this end, a bankruptcy game is designed to seize the power sharing interactions amongst MNOs. Taking into attention

the power deficits of every MNO for a studied period, they Shapley Value (SV) to decide the quantities of power assigned to every MNO.

[15] In this research, they keep in mind a multi-operator heterogeneous cloud radio get admission to network, wherein operators share their small cells. A method for the power performance of the shared network is usually recommended and a power-green useful resource allocation set of rules is proposed for the person venture and energy allocation in the multi-operator community. The hassle is formulated as a mixed-integer optimization hassle and solved the usage of Lagrange Dual Decomposition method. Numerical effects proved the advantages of sharing in phrases of network power performance, energy intake and customers satisfaction. It additionally confirmed the performance of the proposed set of rules in accomplishing extra energy saving in a multi operator Heterogeneous Cloud RAN.

In [16] introduce a novel scheme primarily based on coalitional game theory to pick out the potential room for cooperation among different MNOs that grant carrier to the equal area. The proposed scheme units the regulations for profitable collaboration and identifies the core formation stipulations (i.e., pricing) for various scenarios with distinctive market and spectrum shares among three operators. There results show that i) cooperation among sub coalitions of MNOs is continually beneficial, yielding each higher revenues and more suitable Quality of Service (QoS) for the end users, and ii) the cooperation of all operators (grand coalition) is worthwhile for given customer pricing in distinct scenarios.

[17],[18] Sequential social dilemmas, like matrix game social dilemmas, have a mixed incentive structure, but agents must learn policies to carry out their strategic goals. It is investigated the dynamics of policies learned by many self-interested autonomous learning agents. Two Markov games are introduced here, each using its own deep Q network: a fruit gathering game and a Wolfpack hunting game. Determine how learnt behavior varies in each domain because of environmental factors such as resource abundance. The studies demon-

strate how rivalry for shared resources can lead to conflict, as well as how the sequential character of real-world social challenges influences cooperation.

Several research works have focused on reducing the number of BSs through optimal or heterogeneous deployment strategies. Recently, in an effort to achieve more drastic energy saving gains, the research community has shifted towards the investigation of BS switching off schemes. These traditional switching off schemes can be taken one step further by considering the emerging business model of infrastructure sharing among multiple MNOs offering service to the same geographical area but we put QOS under question mark.

Therefore, in this work, we consider three operators operating in the same geographical area. The core idea is to increase resource utilization during periods of no connectivity due to a lack of coverage of their home provider's infrastructure. In addition while there may be too many users with respect to the network cell capacity of their home provider. To overcome these problems, a provider may want to collaborate with one or more other providers to benefit from their resources resulting in closer or less load. We considers clusters of three operator cells. Each site has three cells/sectors, while each cell includes BSs of different MNOs.

1.7 Methodology

The major goal of this research is to present a game theoretic radio resource optimal sharing by taking into account the conflicting interests and interactions among MNOs, as well as the various viable courses of action. The game is modeled as a non-cooperative social dilemma Markov game [16].

In order to fulfill the goal of this research, we take the following steps:

Literature review: Regarding the concept and researches done on infrastructure Sharing and Game theory: literature such as books, journals, magazines, and online sources. Other studies that have a direct or indirect relationship to this subject are reviewed in addition to official research.

Simulation frameworks: We use a novel framework to create some fully adaptable RL environments for the simulation of multi-provider cooperation. We decided to adopt the OpenAI Gym toolkit, which is a reference in the study of RL agents and used a python program.

1.8 Thesis Organization

This thesis is organized into five chapters and the remainder of it is organized as follows.Chapter 2 briefly reviews the theoretical background of this thesis; Energy consumption in cellular network, base station architecture and energy consumption and analyze energy efficiency metrics used in cellular networks. Chapter 3, Presents a brief introduction to the basic principles of a game theory and methods to model and analyze infrastructure sharing, along with game formulation of the switching off decision. Chapter 4 focuses on methodology of implementation and Results. validation the theoretical analysis and assess the effectiveness of the proposed infrastructure-sharing scheme with the aid of extensive simulation experiments. We introduce a new performance metric, namely cost efficiency, which connects the network performance with the financial benefits of the MNOs. The results indicate the potential total energy efficiency gains in the network and highlight the individual cost and energy gains for the MNOs. Chapter 5 is the last chapter that we conclude the thesis work and recommend future works based on the study.

Chapter2

Cellular Network Energy Consumption

2.1 Introduction

In this chapter, a basic background for the thesis is provided. Operating with the common BSs or infrastructure sharing of three cellular network operators is considered with the aid of the literature discussions. As stated in the problem statement, the most important problem in the rapid growing cellular network is a continuous need to install RAN supporting infrastructure (The major is BTS) in order to effectively care for the increasing users in term of service delivering which Significantly increasing the energy consumption and the expenditure of the MNO.

According to current estimates, the information and communication technology (ICT) business contributes between 2 and 4% of global carbon emissions. It is worth noting that mobile communication networks, as a subset of the ICT industry, contribute around 0.2 % of total greenhouse gas emissions [14] . Because the number of mobile customers is continually increasing, this percentage could continue to rise year after year. Energy prices account for a considerable amount of network operators' overall expenditures, in addition to environmental concerns (OPEX).

Three different sectors can be considered in a simplified description of a wireless cellular system [19]:

- Mobile Switching Centers (MSCs), which are in charge of switching tasks and serve as a link to the fixed (core) network

- RBSs (Radio Base Stations) constitute the access network and provide a wire-free communication link between mobile terminals and the network's core.

- Mobile terminals, or end-user devices, are typically represented by portable devices.

According to energy measuring methods, the operator's operational expenses (OPEX), which comprise the Mobile Switching Centers (MSCs) and Radio Base Stations, account for nearly 90 percent of the wire-free network power usage (RBSs). Because the total number of base stations is exceedingly large, the heavily distributed radio base stations are the most important elements. As shown in Figure 2.1, there are over 4 million installed Base Transceiver Station (BTS) cabinets in the world now, each consuming approximately 60 TWh per year. Furthermore, CO2 emissions are estimated to be roughly 30 Mt. In general, access radio equipment is to blame for approximately 80 percent of energy consumed by a cellular network.

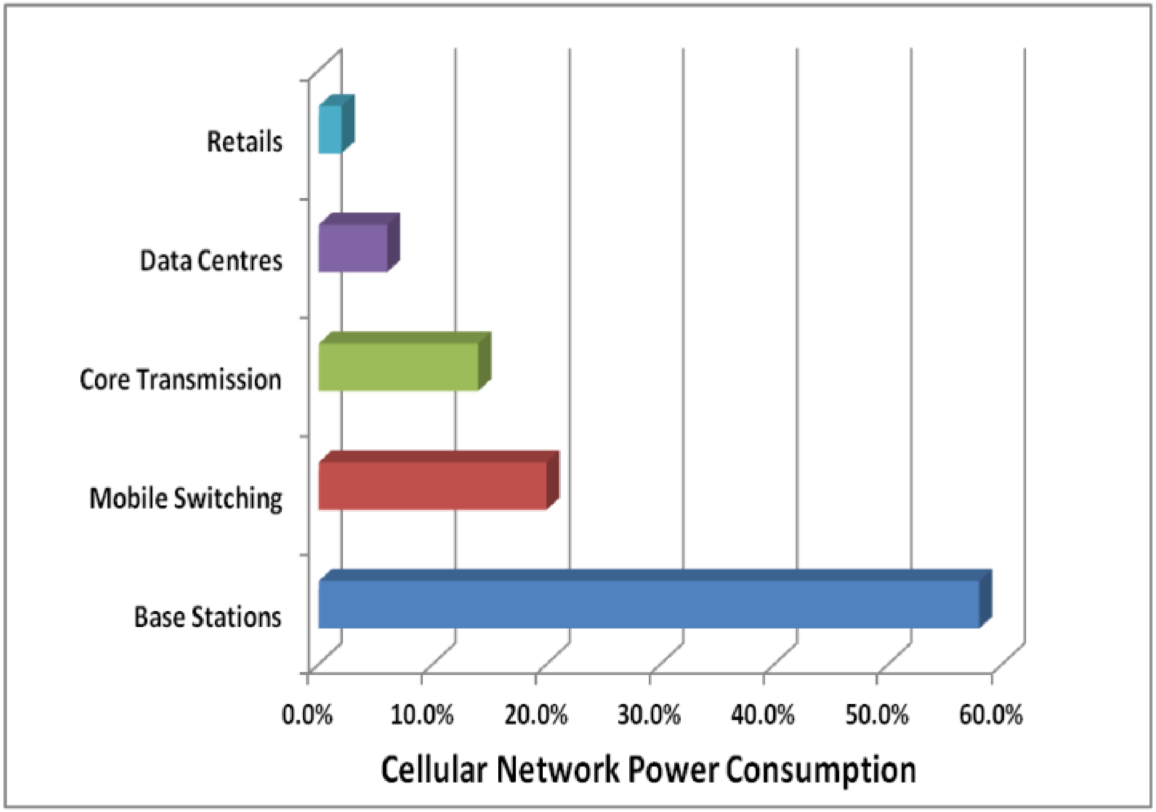

Figure 2.1: Power consumption of cellular network element [17]

2.2 Base stations architecture and energy consumption

Figure 2.1 depicts many power-consuming devices found within a typical base station cabinet in terms of base station design. To begin, overview of each component will be seen and the relative power consumption of each base station piece, as assessed in recent studies. A cellular mobile network consists of three elements, a core network that takes care of switching, base stations providing radio frequency interface and mobile terminals in order to make voice and data connections, of these base station alone contributes 60% to 80% of the whole network energy consumption . Of these cellular networks the energy consumed by the base station components, power amplifier is one of the components which utilizes 65% of energy, based

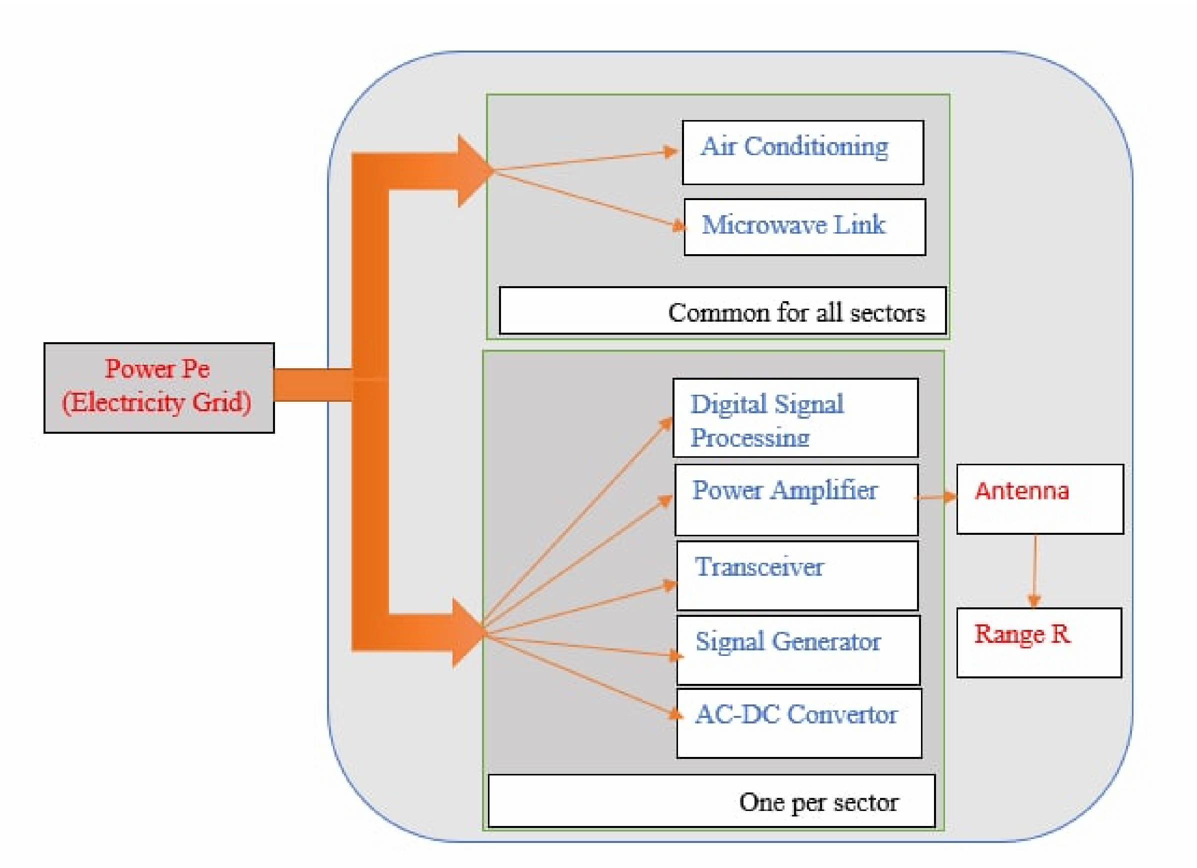

Figure 2.2: Main component of base stations

on the literature review on the problems pertaining to energy consumption of base stations, base station consumes its energy on [17].

- Power supply (5% – 10%)
- Power amplifier (50% – 80%)
- Air conditioning (10% – 30%)
- Signal processing (5% – 15%)

Significant effort has been done on the energy savings of a BS in order to lower the energy consumption of mobile communication networks. The primary idea of work to reduce a BS's energy consumption is to turn off as many of the BS's components as feasible when they are not in use. The BS, for example, can be put to sleep by turning off the electricity to most of

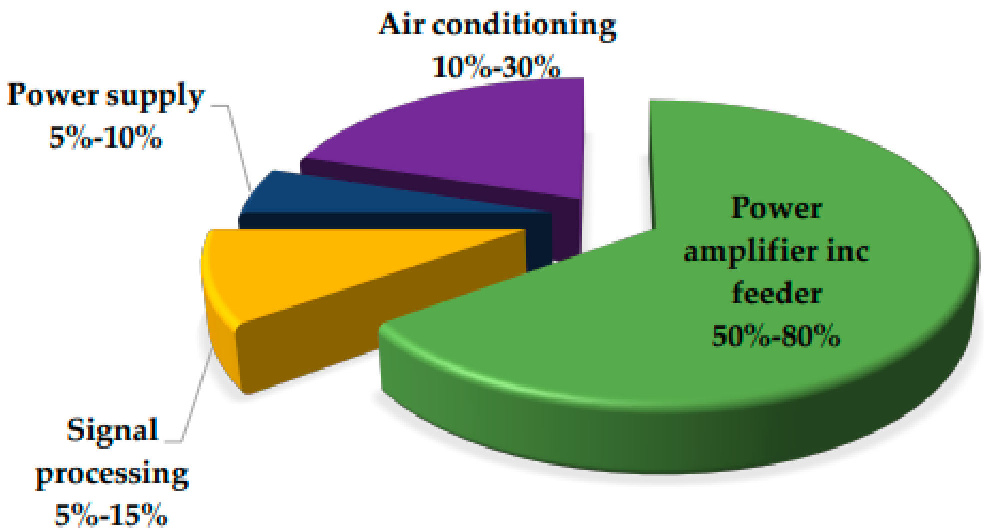

Figure 2.3: Energy consumption distribution in Base stations

its components when they are not being actively used. Furthermore, if a BS has low traffic and neighboring BSs can cover the BS's traffic, the BS can be shut off to save energy more effectively. Because the center BS's user equipment (UEs) can be covered by neighbor BSs with overlapping coverage, the center BS can be shut off to save energy while the UEs are served by neighbor BSs [18].

In an environment where connections between the BS and UE change dynamically, the on/off status of the BS is determined based on context information such as traffic demand and channel state. The greedy-on and greedy-off schemes were proposed in [12], where the state of a BS is changed to either on or off state when a given condition is satisfied, and it was determined that the greedy-on scheme was more effective in terms of energy efficiency. In [20], a traffic-intensity-aware multi-cell cooperation strategy was introduced, in which a BS's state is changed to off state based on its traffic density, which is categorized into peak hour traffic and off-peak traffic, depending on the UE's traffic demand. Furthermore, the coverage gap is filled by neighboring BSs with on-state coverage. However most pervious works did not consider the QoS degradation due to this effect, concentrating on energy saving potential and system capacity issues instead. So studying sharing radio resource related to base station capacity and coverage extension has a better result.

2.3 Energy efficiency metrics used in cellular networks

Energy efficiency measurements defined in two ways: as the ratio of energy production to energy intake in the first place. Second, in terms of performance, with energy efficiency defined as the ratio of a given network's performance to the energy consumed to achieve that performance [21]. Metrics for energy efficiency given at three different levels:

- Component level (for wireless equipment subsystems e.g. power amplifier, antenna, etc.)
- Equipment level (e.g. base stations and wireless terminals)
- System or network level (for a group of equipment that form a network [21].

We need to specify a ratio of energy consumption to a specific network attribute (e.g. data rate, bandwidth, capacity) in order to measure the efficiency of individual equipment. The commonly used Energy Consuming Metric (ECR), which is the ratio of a system's normalized energy consumption to its capacity, measured in [Joule/bit], satisfies this criteria. The ratio of equipment power consumption to effective system throughput [Watt/Gbps] is another way to express this parameter.

$$ECR = \frac{E}{N} = \frac{P}{R} \tag{2.1}$$

Where E is energy required to deliver N bits and R is effective system throughput in bits per second. in 2.1 ECR is commonly used for electronic hardware and the performance of Radio Access Network equipment, particularly base stations respectively. A system with a lower ECR uses less energy than one with a higher ECR. A typical network's traffic load can fluctuate between full-load, half-load, and idle states during the course of a 24-hour period.

As a result, the total power consumption of equipment should be adjusted to account for the network's dynamic nature.The following is a proposed formula for this case in [4]

$$p_{total} = 0.35P_{max} + 0.4P_{50} + 0.25P_{idle} \tag{2.2}$$

where, P_{max}, P_{50}, and P_{idle} correspond to power consumption at 100%, 50%, and % load usage, respectively. Each term's coefficients are statically defined. In this case, the ERC metric is renamed ERC-weighted (ERCW) to account for the various load conditions:

$$ERCW = \frac{(0.35P_{max} + 0.4P_{50} + 0.25P_{idle})}{R} \tag{2.3}$$

The Telecommunication Energy Efficiency Ratio (TEER) proposed by ATIS and the Telecommunication Equipment Energy Efficiency Ratio (TEEER) proposed by Verizons Networks in [4] are two more load-dependent metrics. The following are the definitions for these two metrics:

$$TEER = \frac{Usefulwork}{Power} \tag{2.4}$$

Useful Work can be data rate, throughput etc. and Power is Power consumed by equipment.

$$TEER = \log\frac{(0.35P_{max} + 0.4P_{50} + 0.25P_{idle})}{R} \tag{2.5}$$

The greater the TEER number, the more energy efficient it is. TEEER units are [log(Watts/Gbps)] according to equation 2.5 as well. The aforementioned EE metrics have a significant flaw in that they do not capture all of a system's characteristics. As a result, [4] proposes a new absolute EE metric:

$$dB = \left(\frac{10\log power}{Bitrate}\right)/KT\ln 2 \tag{2.6}$$

The metric in equation 2.6 is expressed in decibels and accounts for the physical features of the system's medium, such as the absolute temperature of the medium T and the Boltzmann constant K, among other things. Low dB values, in general, imply a system that is energy efficient.

Energy efficiency measures, whether at the component, equipment, or system level, play an important part in the drive to design energy efficient solutions. They are as follows:

- They allow us to assess and compare the amount of energy used by various components, equipment, systems, and networks.
- They allow us to define research goals that will help us in our hunt for energy-saving approaches and technologies.
- Energy efficiency measures aid in the analysis of network architecture in order to identify areas of the network that consume more energy, allowing them to replace with more energy efficient components.
- They also assist in quantifying the benefits of adopting or implementing energy efficient strategies in network architecture [22].

According to [21] most energy efficiency metrics have been fully developed at the component level, but defining energy efficiency metrics at the equipment and network level is not easy or straightforward.

The bit per joule measure is one of the most extensively used EE metrics. It is defined as the ratio of total data transferred to total energy spent over a specified time span. Bits per joule or bits per second per watt is the unit of measurement [23].

2.4 Roaming-based Infrastructure Sharing Scheme

The three types of infrastructure sharing include passive sharing of sites, masts, and building premises, active sharing of active network components such as antennas, switches, and backhaul equipment, and roaming-based sharing, in which MNOs share cell coverage for a pre-determined duration [24]. Passive sharing occurs in passive infrastructure such as building premises, sites, and masts.When two or more networks share physical space, it is referred to as passive sharing. Passive sharing is a type of network sharing where two or more networks share physical space. Operators can trade elements of a mobile device's active layer, such as antennas, radio nodes, node controllers, backhaul and backbone transmission. As well as pieces of the core network, in active sharing, a more advanced sort of sharing network (such as switches).

In [23] Roaming is a sort of sharing in which clients of one mobile network operator use the services of another while their own network is unavailable. The two types of roaming are national and international roaming. Since the advent of 2G networks, roaming has been used to essentially extend an operator's geographic coverage by allowing its users to use another operator's network. Customers in countries where the operator does not have a license or a business are served through international roaming. In the United States, roaming is also used on a national level, usually to allow a new entrant to extend coverage to its customers into areas where it does not have a network.

Roaming-based sharing, in the context of network sharing, indicates that one operator relies on the coverage of another operator on a permanent basis for a specific, defined area. Operators working in new locations are always seeking for low-cost solutions to expand coverage and capacity. It will be more open to passive sharing tactics as well. Operators in established areas seek cost savings and new technology options through active sharing opportunities aimed at optimizing access transmission using leased lines and microwave links, whereas operators in emerging markets seek cost savings and new technology options through active sharing opportunities aimed at optimizing access transmission using leased lines and microwave links [25].

Chapter3

Game Theory Approach in Multi-Operator Resources Sharing

3.1 Game Definition

The study of strategic decision-making is known as game theory. It is the study of conflict and cooperation between intelligent rational decision-makers in a formal sense. When the behaviors of numerous individuals (players) are interconnected, game theory concepts apply. Individuals, organizations, groups, corporations, or any combination of these might be considered participants. Game theory can be thought of as a tool for generating, analyzing, and comprehending strategic scenarios.

In general, the instances addressed by game theory is divided into two categories: non-cooperative games and cooperative (coalitional) games.

A game is naturally formalized as a triple of a set of players, a set strategies and a utility function. Utility function represents a players valuation of gains/loss in a game. Players play strategies for the purposes of maximizing their utilities. Usually the strategies are conflicting, i.e., increasing own utility occurs at the expense of other's decreasing utility. Therefore, the players have to be rational while playing strategies as too much greedy approach can harm themselves because of consequences and too much of honesty can let their misuses by greedy opponents. We can represent the game Game G mathematically as :

An **N** player normal form game consists of: A finite set of N players Strategy spaces for the players: $\{S_1, S_2, S_3, \ldots, S_N\}$; Payoff functions for the players: $u_i : S_1 \times S_2 \cdots \times S_N \to \mathbb{R}$

For a two players prisnors dilemma games ,i.e, $N = 2$.

We have $N = 2$ Players with The strategy spaces: $S_1 = S_2 = \{\text{Cooperate}, \text{Defect}\}$ or equivalently $S_1 = S_2 = \{1, 2\}$

The payoff functions mapping an element of $\tilde{s} \in S_1 \times S_2 = \{(1,1), (1,2), (2,1), (2,2)\}$ to $\mathbb{R}$: $u_1(\tilde{s}) = A_{\tilde{s}}$, $u_2(\tilde{s}) = B_{\tilde{s}}$.

3.1.1 Basic Model of the Game

There are two major branches in game theory, cooperative game and non-cooperative game. In this game formulation, players act rationally according to their strategies with the objective to maximize their outcome. However, the strategic profile of players is highly influenced by the regulation imposed by the nature of the environment of the game. Cooperative game provides analytical tools to study the behavior of rational players when they cooperate. In a cooperative-game scenario, the players are allowed to form agreements among themselves that can influence the strategic choices of these players as well as their utilities. Cooperative game in wireless networks is practically unattractive because of excessive overhead signaling and trust issues, but it provides a unique Pareto optimal solution for the problem modeling.

Whereas the non-cooperative game involves a number of players having totally or partially conflicting interests in the outcome of a decision process. The signaling overhead is low, and knowledge of a competitor's CSI is not assumed. It reflects a competitive situation where each player needs to take its decision independently of the other players, given the possible choices of the other players and their effect on the player's objectives or utilities.

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Non-cooperative does not always imply that the players do not cooperate, without centralized control, but it means that any cooperation that might arise must be self-enforcing with no communication or coordination of strategic choices among the players. Repeated game appears when the players have to interact with each other more than one time, and every interaction between the players is called a stage which has utility, and the total utility of the game will be the summation of the utility for each stage in the period of the game for each player individually.

3.1.2 Dynamic Non-Cooperative Game With Complete Information.

We begin with two-player, simultaneous-move games. (Everything we do for two-player games extends easily to three or more players; we consider sequential-move games below.) The timing of such a game is as follows:

1 Player 1 chooses an action a, from a set of feasible actions A1. Simultaneously, player 2 chooses an action a2 from a set of feasible actions A2.

2 After the players choose their actions, they receive payoffs: u1(a1, a2) to player 1 and u2 (al, a2) to player 2.

3.1.3 Prisoners Dilemma

The very common example used to explain a game theory is the prisoner's dilemma. The story tells about two suspects for committing a crime and put into a jail before a trial. The prosecutor believes that they are guilty, but he could not get enough evidence to send them to jail for what they did. The prosecutor offers the prisoners a bargain with two choices to either confess or refuse. The Prisoners Dilemma (PD) is a two-player game used to model a variety of strategic interactions. Each player chooses between cooperation/Confess (C) or defection /Deny (D). Two persons charged with the same crime and held in separate cells. They have no way of Communicating with each other, or, making an agreement beforehand. They are told (at the same time) that: if one of them confesses the crime and the other does not, the confessor will be freed while the other person will get a term of 3 years. If both confess the crime, each will get term of 2 years and if neither confess the crime, each will get a 1-year term. In game theory, we represent such games using a matrix. Instead of months

		Player 2	
		C	D
Player 1	C	-2, -2	0, -3
	D	-3, 0	-1, -1

C: Confess
D: Do not confess

Figure 3.1: Prisoners Dilemma Payoff matrix

in prison, we will be using a positive payoff (a gain) for each of the actions. Therefor this can be written as: The above payoff matrix can be written us:

$$A = \begin{pmatrix} 3 & 0 \\ 5 & 1 \end{pmatrix} \qquad B = \begin{pmatrix} 3 & 5 \\ 0 & 1 \end{pmatrix}$$

The general form is:

```
                     Prisoner A
                 --------------------
                 |Cooperate| Defect |
       |---------|---------|--------|
       |Cooperate| (3, 3)  | (0, 5) |
Prisoner B |---------|---------|--------|
       | Defect  | (5, 0)  | (1, 1) |
       ------------------------------
```

Figure 3.2: Prisoner's Dilemma with Positive Payoff matrix

$$A = \begin{pmatrix} R & S \\ T & P \end{pmatrix} \qquad B = \begin{pmatrix} R & T \\ S & P \end{pmatrix}$$

With the following constraints (Discussed in 3.1.5 for terminology and detail) :

$$\begin{gathered} T > R > P > S \\ 2R > T + S \end{gathered} \tag{3.1}$$

The first constraint ensures that the second action defect dominates the first action cooperate.The second constraint ensures that a social dilemma arises: the sum of the utilities to both players is best when they both cooperate.

This game is a good model of agent (human, etc) interaction: a player can choose to take a slight loss of utility for the benefit of the other play and themselves. As a single one shot game there is not much more to say about the Prisoner's dilemma. It becomes fascinating when studied as a repeated game.

3.1.3.1 Best responses

There are different type of game strategies, that the players can obtain various game resolutions Nash Equilibrium, Max-Min Strategy, Mixed Strategy, Dominant Strategy, Pure Strategy, Best Response and Optimal/sub optimal solution. Nash Equilibrium: In a game theory, Nash Equilibrium (NE) is a concept used to describe the steady state of a game. NE is also called strategic equilibrium, and can be defined as a strategy profile which no player maximizes its utility by unilaterally deviating from this strategy profile. Thus, as long as the other players strategy remains the same no player will change its strategy and get a better payoff.

In a two player game $(A, B) \in \mathbb{R}^{m \times n^2}$ a mixed strategy σ_r^* of the row player is a best response to a column players' strategy σ_c iff:

$$\sigma_r^* = \text{argmax}_{\sigma_r \in S_r} \sigma_r A \sigma_c^T.$$

Similarly a mixed strategy σ_c^* of the column player is a best response to a row players' strategy σ_r iff:

$$\sigma_c^* = \text{argmax}_{\sigma_c \in S_c} \sigma_r B \sigma_c^T.$$

In other words a best response strategy maximise the utility of a player given a known strategy of the other player.

3.1.4 Best responses in the Prisoners Dilemma

Consider the Prisoners Dilemma:

$$A = \begin{pmatrix} 3 & 0 \\ 5 & 1 \end{pmatrix} \qquad B = \begin{pmatrix} 3 & 5 \\ 0 & 1 \end{pmatrix}$$

We can easily identify the pure strategy best responses by underlying the corresponding utilities. For the row player, we will underline the best utility in each column:

$$A = \begin{pmatrix} 3 & 0 \\ \underline{5} & \underline{1} \end{pmatrix}$$

For the column player we underling the best utility in each row:

$$B = \begin{pmatrix} 3 & \underline{5} \\ 0 & \underline{1} \end{pmatrix}$$

Both players best responses are their second strategy.

For a two player game $(A, B) \in \mathbb{R}^{m \times n^2}$, (σ_r, σ_c) is a Nash equilibrium if σ_r is a best response to σ_c and vice versa.

3.1.5 Iterated Prisoners Dilemma (IPD)

Although the PD is a one-round game, it is frequently researched in a way that considers previous outcomes. The Iterated Prisoner's Dilemma is the name given to this recurring version (IPD). The IPD is commonly used to better understand how cooperative behavior evolves from complex dynamics. Each stage game has four possible outcomes: R (Reward for mutual cooperation), P (Penalty for mutual defection), S (Sucker outcome acquired by cooperating with a defecting partner), and T (Temptation outcome achieved by defecting against a cooperator). In PD, both players gain a reward (R) if they collaborate (C). If one of the parties defects (D), the defector receives a bigger payment T, while the naive cooperator receives S, which is normally zero. If both defect, however, both receive a pittance payment P. The game must satisfy two inequalities in 3.1. $T > R > P > S$ ensures that mutual defection is the Nash equilibrium of the game, $2R > T + S$ makes mutual cooperation the global best outcome. In the literature, the conventional values $(T, R, P, S) = (5, 3, 1, 0)$ appear most frequently. The majority of the results are derived in the general case, and when there is a specialization to the customary values, we specify it. The first constraint ensures that the second action Defect dominates the first action Cooperate. The second constraint ensures that a social dilemma arises: the sum of the utilities to both players is best when they both cooperate.

3.2 Social Dilemma

Participants can choose to engage in cooperation, defection, or any combination of the two. A two-player repeated general sum matrix game is a social dilemma when these four payoffs satisfy the following social dilemma inequalities.

- $R > P$: players prefer mutual cooperation (CC) over mutual defection (DD).
- $R > S$:Players prefer mutual cooperation over uni- lateral cooperation (CD).
  - Either $T > R$: Players prefer unilateral defection (DC) to mutual cooperation (greed) or:
  - $P > S$ players prefer mutual defection to unilateral cooperation (fear).

If such a game is iterated, it is called Sequential Social Dilemma (SSD), and then it is relevant to add a condition:
$2R > T + S$: players prefer mutual cooperation over an equal probability of unilateral cooperation and defection. Social dilemma admit non-optimal Nash equilibria in particular (Defect, Defect) in Prisoners Dilemma (where greed and fear are verified).

3.2.1 Continuous Multi-Agents Social Dilemmas

Let us start with the scenario of$N > 2$ agents.Each agent has the option of cooperating or not cooperating with the other agents. This type of action is formalized by a cooperation rate $c_{i,j}$, which specifies the degree of collaboration between agent A_i and agent A_j (0 for total defection and 1 for total cooperation). A definition for a multi-agent continuous social problem is also proposed. Cooperation is assumed ongoing and asymmetric. Assume that each agent A_i earns a reward defined by a gain function $G^i\left(c_{i,0},...,c_{i,N-1},c_{0,i},...,c_{N-1,i}\right)$ That is based on all cooperation degrees from him to other agents $c_{i,k}, k \neq i$ and from other agents to him $c_{k,i}, k \neq i$ Let's use inequaties in 3.1 to define social dilemmas in a multi-agent continuous context. If the scenario is described as a quandary, it means that:

$$\begin{aligned} &\forall j, G^i is \quad decreasing \quad w.r.t \quad c_{i,j} \\ &it \quad exists \quad c_{i,j} \neq 0 \quad such \quad that \quad G^i\left(c_{i,j},c_{j,i}\right) > G^i\left(0,0\right) \end{aligned} \tag{3.2}$$

The first inequality states that each agent is uninterested in cooperating on their own. This can be interpreted as either dread (due to the low value of $c_{j,i}$) or greed (due to the high value of $c_{i,j}$),for sufficiently large value of $c_{j,i}$. The second inequality indicates that the nash equilibrium ($c_{i,j} = 0, \forall i,j$ due to the first inequality) is not optimal, resulting in the dilemma. Let us go over the example in more depth for clarity's sake. with $N = 2$ agents. A1 and A2 earn respectivel $G^1\left(c_{1,2},c_{2,1}\right)$ and $G^2\left(c_{2,1},c_{1,2}\right)$. We can designate specific values,such as the situation then transforms into the classic social dilemma depicted in equation 3.3

$$\begin{aligned} G^1(0,0) = G^2(0,0) = P \\ G^1(1,1) = G^2(1,1) = R \\ G^1(0,1) = G^2(1,0) = S \\ G^1(1,0) = G^2(0,1) = T \end{aligned} \tag{3.3}$$

It's worth noting that displaying payoffs in a table for N ¿ 2 is challenging. However, the payoffs can be represented using a Schelling diagram that shows payoffs as a function of cooperation and the number of other cooperators. The following diagram shown in figure 3.3 illustrates the payoff matrix of repeated games.

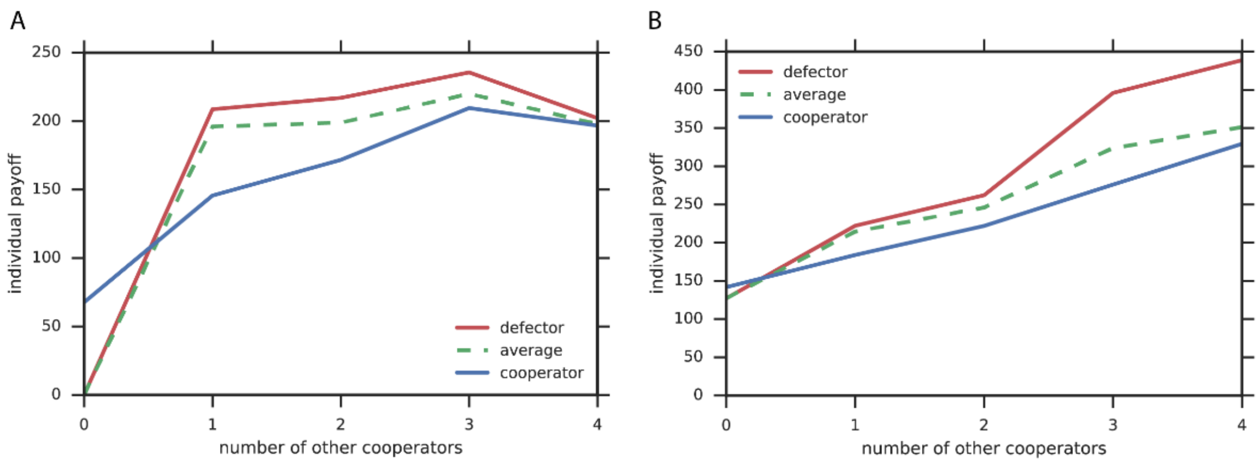

Figure 3.3: Schelling diagram regenerated from [16]

Chapter4

Implementation and Results

4.1 Introduction

In this chapter, we discuss the implementation details of our approach. We will discuss the details of all of the success and failure cases. After implementation detail, we will give an overview of our final proposed model and discuss the evaluated results of our approach and the approaches previously discussed in the related works of chapter one.

Network operators can exchange resources to reach an optimal situation and we consider that their personal interest are driven only by their personal utility. We propose to formulate the problem as a non-cooperative Markov game and show that it can be viewed as a social dilemma, i.e. a situation where Nash equilibria are non optimal. Operators have no incentive to cooperate despite the fact that mutual cooperation is the optimal global strategy.

4.2 System Model

Our network topology consists of a mobile network containing R radio access networks. We also define R for the set Radio access Networks which is expressed as $R = \{1, r, ..., R\}$. The set of clusters in the given network is denoted as $C = \{1, c, ..., C\}$. All set of clusters/cites to choose can from a partition P of R. Note that In conventional architecture, the operation of base station is distributed . That means, each base deployment of base station consists of set of pairs of BBU and a RRH. But in modern cellular networks a C-RAN is introduced. C-RAN stands for Centralized, Collaborative, Cloud, and Clean RAN. In C-RAN, BBUs are moved from site location to a single location. C-RAN has a central office or a super macro site used to aggregate BBUs. Our proposed system of spectrum sharing works only for base station with centralized Radio access network. We use a binary variable $y_{r,c}$ expressed as :

$$\begin{aligned} y_{r,c} &= 1, \quad if \quad RRHr \quad is \quad associated \quad to \quad BBUc \\ y_{r,c} &= 0, \quad otherwise \end{aligned} \tag{4.1}$$

4.2.1 Network Area Decomposition

We partitioned the network area into several smaller zones, and we consider the average number of user equipments (UEs) and radio conditions/received siganl strengths per zone. We can observe figure 4.1 for illustration purpose where set of seven cells is meshed in multiple smaller zones. The average number of UEs located in a zone of index z, associated to a RRH of index r is denoted by $n_{z,r}$. To calculate Signal-to-Interference-plus-Noise ratio

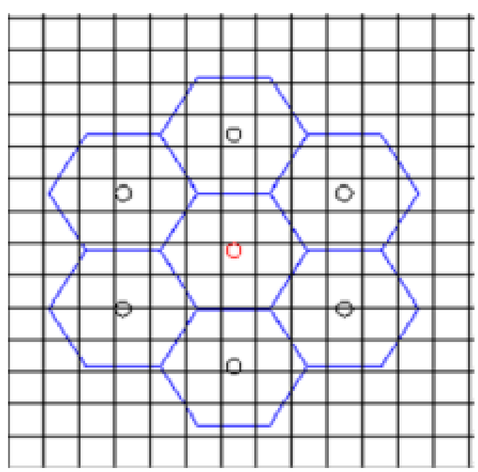

Figure 4.1: Meshed Area [21]

of zone z, associated to RRH r ($SINR_{z,r}$) the average distances between the considered zone and all the cells within the network are calculated. The average distance (D_{avr}) between a RRH of coordinates (x_0, y_0) and all points of coordinates (x, y) belonging to zone z is expressed as follows:

$$D_{avr} = \frac{1}{a^2} \iint_S \sqrt{(x - x_0)^2 \, (y - y_0)^2} \, dx \, dy \tag{4.2}$$

4.2.1.1 States and Reward functions

Regardless of whether the environment changes state in response to an agent action, the environment always computes a scalar reward (the quality of service, for the transmissions made or received by the agent over the bandwidth purchased by its action during the time period specified in its action). We model the goal of the user agent as that of selecting actions at each time step so as to maximize the cumulative (i.e., summed over multiple time steps) expected reward in the long run. Users operator is selection based is based on a policy that maximizes the expected value of the cumulative reward expressed as in 4.3.

$$E\left[\sum_{p=0}^{\infty} \gamma^p R_{t+1+p} | S = s_1\right] \tag{4.3}$$

starting from some state s_1 at time $t = 1$, γ is a discount factor in the range $[0, 1]$ and the reward function for each player is

$$R_p = \sum_{u\varepsilon C_p} \frac{\Gamma_u}{m_u} \exp\left(-\frac{D_u}{D_{max}}\right) \tag{4.4}$$

where C_p is set of customers of P

Γ_u share of radio resources allocated for provider of $U(p)$ in the cell

m_u number of customers of P in the cell u,

D_u distance between u and its connecting antenna and D_{max} is scalling constant.

4.2.1.2 Markov Decision Process

Our mulit agen OPenAI Learning environments is commonly formalized as of Markov Decision Processes (MDP). The goal of the subscribers operator is selecting actions at each time step so as to maximize the cumulative reward in the long run (Reward hypothesis). At each time step t, the agent takes an action drawn PDF S_t that depends on only the present state.Moreover, given $S_t = s$ and action $A_t = a$, the environment changes its state to S_{t+1} and computes a reward R t+1 according to a joint conditional probability distribution on (S_{t+1}, R_{t+1}) which depends only on (s, a) and not the history of states or actions prior to time t. A Markov Game consists of a tuple (S, A, T, R, Ω, O) where:**S** represents set of states,**A** set of actions and **T** represents the transions function given by $S \times A \rightarrow [0, 1]$, Reward function for each player: $r_i : S \times A \rightarrow R$ for player i, Ω Set of obervations for each player **O**: $S \times A \times \omega \rightarrow [0, 1]$ is stochastic observation.

The Objective is to find a policy or Set of gain functions $\pi : S \rightarrow A$ so that cumulated reward **R** is maximised.A Markov game is an SSD when there exist states $s \varepsilon S$.

4.2.1.3 Sequential Social Dilemma Game Formulation

As we have dicussed in chapter 3 a sequential social dilemma is a tuple $\left(M, \pi^c, \pi^d\right)$ where π^c, π^d are disjoint sets of policies(gain functions) for cooperation and defection respectively. M is a Markov game with state space S.The empirical pay off matrix $[R(s), P(s), S(s), T(s)]$is trigered by the policies or gain functions.For the social dilemma discussed in section 3.2 we can designate specific values of pay off matrix the classic social dilemma depicted in equation 3.3. In our game formulation the payoff elements for each $[R(s), P(s), S(s), T(s)]$ isapproximated by cumulative reward function. Where, the expression for the cumulative reward is given by equation 4.3. For individual operators $G^i(c_{i,j}, c_{j,i}) \approx R_i$. R_i the utility function for player i is also given as 4.4. This is our reward or utility function for each players or agents.

4.2.2 Users Association

In our model we assumed all users located in zone z are associated to RRHr when the average distance D_{avr} between z and r is the smallest in comparison with the different distances between zone z and RRHs $r' \neq r$ in the network. While, D_{avr} must follow the following constraint: $D_{avr} \leq D_r$, where D_r denotes the cell radius of the RRH.

4.3 Implementation Frame work

Mobile data explosion experience in the last decades due to both mobile users increase in number and a rising of many bandwidth greedy applications. Hence, for network and coverage extension cooperation of different network is needed. In this thesis resource sharing of among multiple network operator is simulated and tested using a new adaptable frame work based on OpenAI Gym toolkit. Gym is an open source Python library for developing and comparing reinforcement learning algorithms by providing a standard API to communicate between learning algorithms and environments.The Gym environment is customized to generate ideal geographical environments where different base station are deployed and radio resources are shared among them to save operational costs of the radio units.

We have synthesized our own gym environment by defining a python class methods Initialize, Step, Reset and Render used to initialize initial location, initialize mesh steps,visualize the generated environments before and after sharing. Reset class is used to reset the previous parameters of the gym environment at any time.

4.3.1 Open AI Gym Parameters

In the frame work we use preset environments. We also customized and generate our own working environments assuming random number of cell sites, clusters and mobile users. Some terminologies used in the development frame work are explained as follows.

- MNO: In our working frame work an agent (or player) represents a Telecommunication service provider Provider or Mobile Network Operator (MNO)
- Cell sites: individual operator can own multiple base stations or cell sites. Moreover, one cell cite may be divided in to sectors.
- Users: Any mobile users and equipment's around the the any cell sites.Each user is registered for only one network operators
- Radio Resource: For each base stations, and for each cell, the MNO can share a part of its free resources.

Important parameters and features used in the development framework:

- **Action of the game players(MNOs):** Each MNO plays an action which is the partition of its resources for each cell of each site. An action is an array of Number of sites , cells and agents. given by

  $$\sum_{i_{p=1}}^{N} a\left[i_S, k_C, i_P\right] = 1, \forall i_S, \forall k_C$$

  where i_S, k_C, i_P respectively the indices of sites, cells and players.
- **Transaction function :** The users are connected to base stations according to the shares that players allocate to each other. To compute the link, we decided to adopt a particle swarm algorithm. The links are decided in an increasing order of distances of all tuples user sites (u, s) when the proper cell of s allocates enough resources to u's provider. Note that,although this allocation is not optimal, it is rather realistic to model such a cooperative environment.

The selection function is purely a function of the agent's personal history,i.e, locality. A sequential social dilemma game is played among the network operators and particle swarm algorithm is applied after each action. The following learning procedure is applied to the OPenAI gym:

1 . Initialize the cumulative reward for each action (e.g., to zero).

2 . Move an initial action.

3 . Play according to the current action and update its cumulative reward.

4 . Switch to a new action if and only if the total payoff obtained from that action in the latest m iterations is greater than the payoff obtained from the currently chosen action in the same time period.

5 . Go to step 3.

The parameter m in the procedure denotes a finite bound, but the bound may vary.

4.3.2 Simulation Setup and Results

Initially a sequential social dilemma game with two players is modeled and simulated in OpenAI gym toolkit. For a two players sequential social dilemma results have shown that mutual defection is the Nash Equilibrium while the optimal outcome is the mutual cooperation.

A two players sequential social dilemma is extended to be played by three players. Three players (MNO) are modeled and simulated by varying the numbers of cell sites and mobile users. Simulation results shows that due to the availability shared radio resource a mobile user can served by another mobile network operator when if the quality of transmitted signal is better than that of its original service provider. Some predefined environments are shown in figure [4.2].

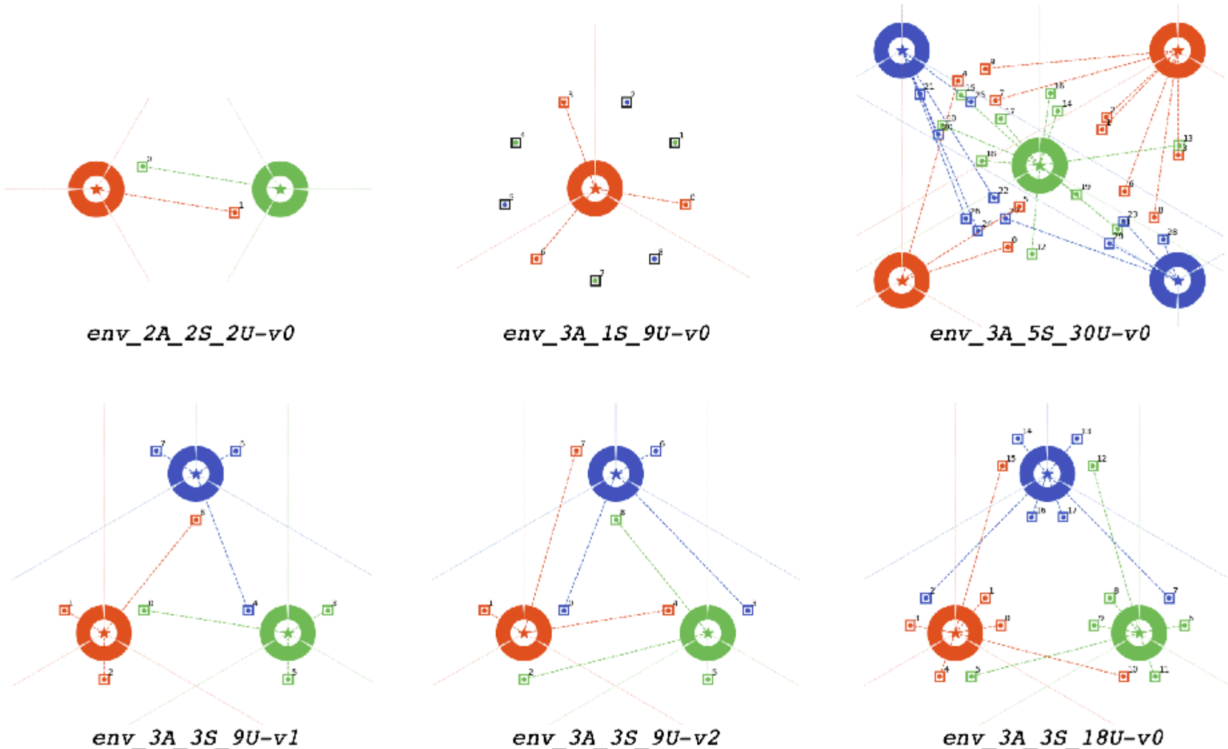

Figure 4.2: Some examples of predefined enviroments

4.3.2.1 Actions and Reward fucntions

For a social dilemma game with greater than two players it is difficult to observe the pay off tables unlike two players prisoners dilemma. Figure 4.3 illustrates the reward fucntions of social dilemma game using schelling diagrams for different actions taken by individual operators. The step action performed by the first agent (Red agent) are given by

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

respectively.

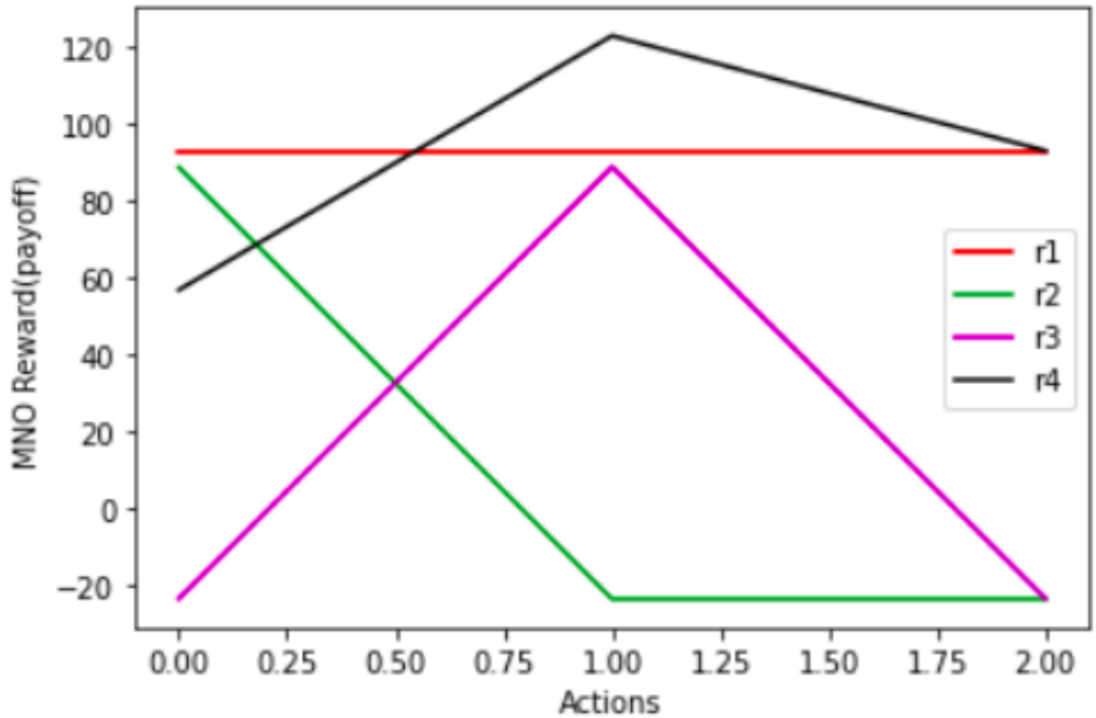

Figure 4.3: Reward function after each step (action) taken by individual MNO

Simulation results of three operators sequential social dilemma for radio resource sharing among different cell sites base station are visualized in the following figures.

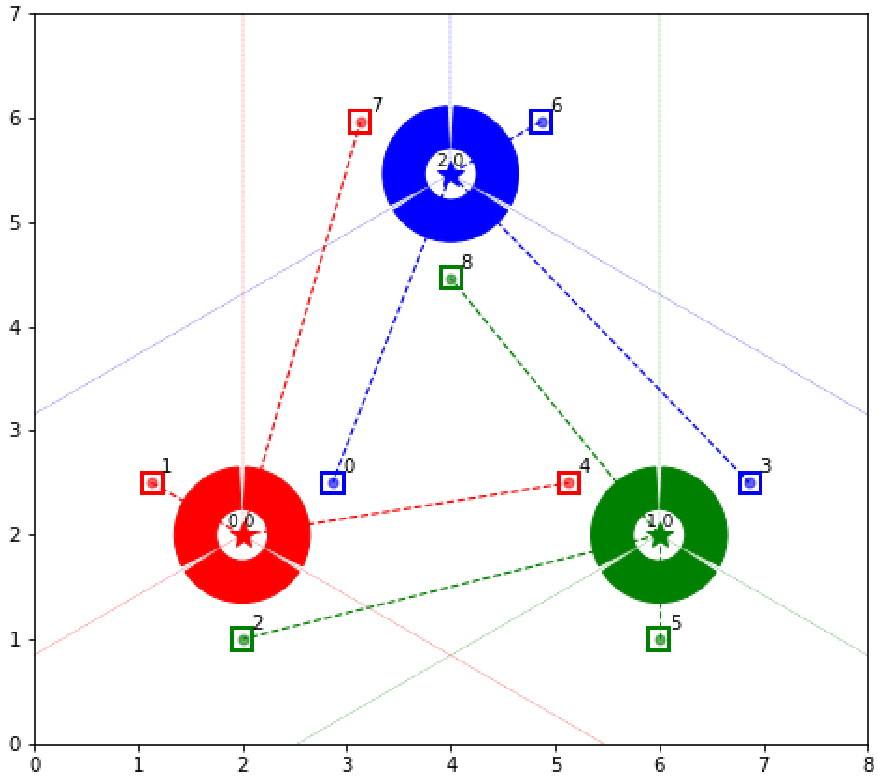

Figure 4.4: Non cooperative (3 MNOs,3 sites and 9 users)

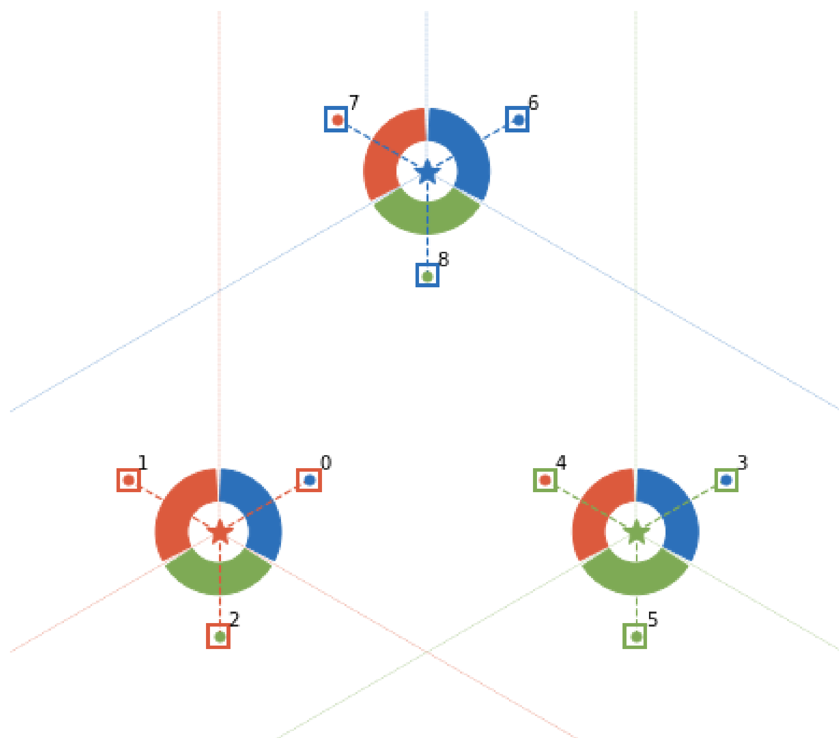

Figure 4.5: 3 MNOs,3 sites and 9 users with shared Resource

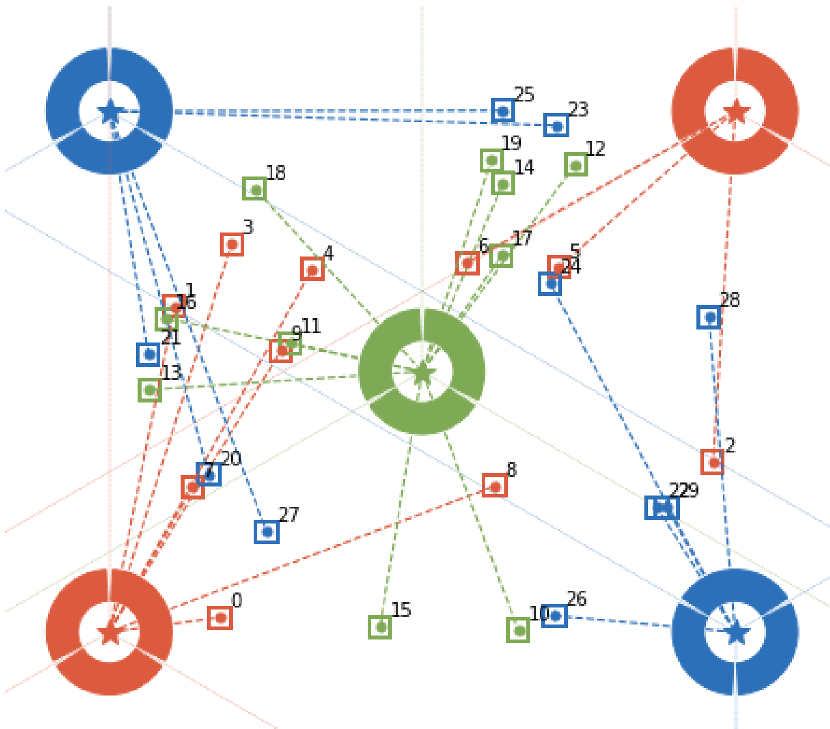

Figure 4.6: Users before sharing (3 agents, 5 sites, 30 users [Random users positions])

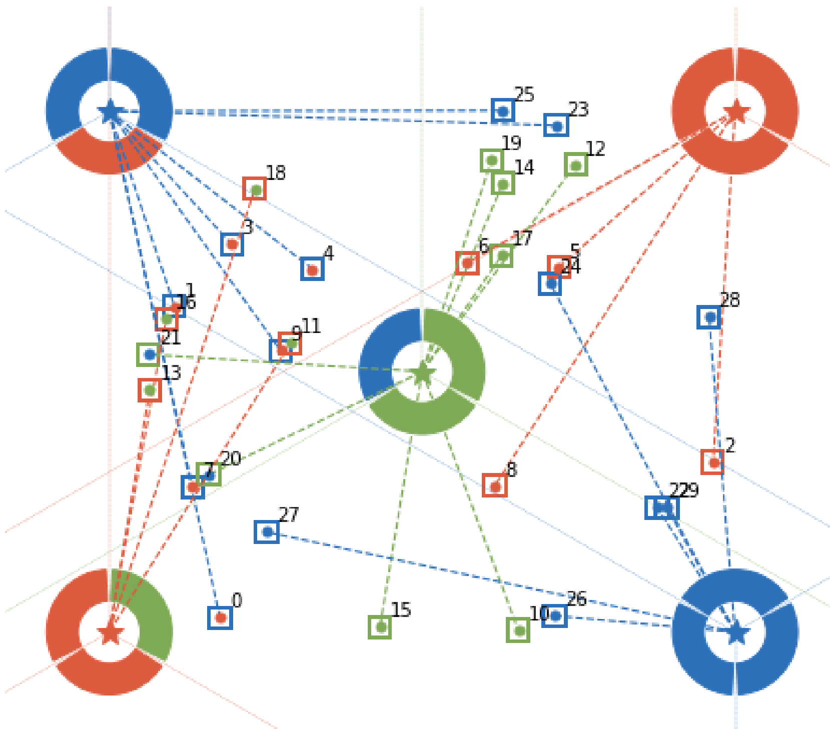

Figure 4.7: Users after optimal Sharing(3 agents, 5 sites, 30 users [Random users positions])

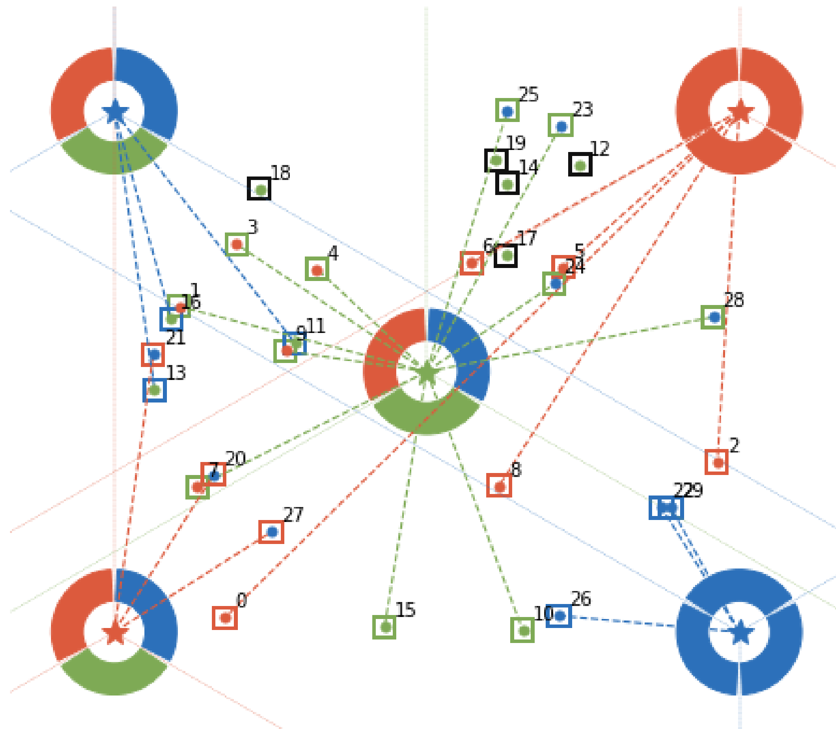

Figure 4.8: Users bad sharing (3 agents, 5 sites, 30 users [Random users positions])

4.3.3 Analysis of Results interms of CAPEX and OPEX

Cost saving is the main triggering factor when for infrastructure sharing. As number of mobile users of one network operator increases deployment of new base staion will become mandatory to serve the new users. Hence, this increases the capital expenditure (CAPEX) which is the cost of site construction and base station purchases. As the number of base stations increases the operational expenditure (OPEX) which covers 60% of the total cost also increases. The increment of OPEX comes from the increased number of power consumption's and other maintainace and operational cost.

Network infrastructure is useful for MNOs to share their resources in order to attain the goal of power consumption reduction and enhanced resource utilization efficiency. If we have ground truth information about the number of users for each network operators and number of migrated users from one operator to other, actual power consumption model for each radio units then, we can calculate the actual cost saving and profits obtained due to network sharing. When MNOs are cooperating, all resources are put together (i.e, BBUs, RRHs and spectrum). If there is cooperation we consider that the power consumption of each MNO is proportional to the number of its subscribed UEs.

Let's assume MNO1, MNO2 and MNO3 has n number of subscribed use equipments (nMNO1, nMNO2 and nMNO3). The new power consumption (PC) for each mobile network operators is given by equation 4.5.

$$\begin{aligned} NewPCofMNO_1 &= P_t \times \frac{nMNO_1}{nMNO_1 + nMNO_2 + nMNO_3} \\ NewPCofMNO_2 &= P_t \times \frac{nMNO_2}{nMNO_1 + nMNO_2 + nMNO_3} \\ NewPCofMNO_3 &= P_t \times \frac{nMNO_3}{nMNO_1 + nMNO_2 + nMNO_3} \end{aligned} \tag{4.5}$$

where P_t is the total power consumption in the system. To quantify all the Total costs,CAPEX and OPEX cost we should have actual data and power consumption models. once we have the data at hand. We can calculate the our total costs and profits using the following general expressions.

$Revenue \approx usertariff \times Guaranteeddatarate \times TotalNumberofsubscriber$

$Cost \approx AverageRANpowerconsumption \times Costofelectricity$

$Profit = Revenue - Cost$

4.3.4 Power consumption modeling of base station

Base Station is the main contributor of energy consumption in cellular mobile communication. The traffic load of base station sginifacnlty with time and space. Therefore, it is important to model and quantify the influence of traffic generated on the power consumption of base station. Althogh there are many many detail and accurate energy consumption models in this research we used simple linear equations to analyse the relationship between input power consumption(P_{IN}) and the radiated power (P_{TX}) for macro and micro base stations.

$$\begin{aligned} P &= a \times P_{Tx} + b \\ P_{ma} &= a_{ma} \times P_{TX,ma} + b_{ma} \\ P_{mi} &= a_{mi} \times P_{TX,mi} + b_{mi} \end{aligned} \tag{4.6}$$

The coefficients a_{ma} and a_{mi} are related to devices whose power consumption is dependent on the average transmit power (PA) and they correspond to power consumption that varies because of PA efficiency, feeder cable losses and cooling processes. On the other hand, the terms b_{ma} and b_{mi} represent power offsets of components which are independent of transmit power and they are generated by signal processes, battery backup and cooling functionalities. For macro base staions power consumptions mainly depends on number of sectors and umber antennnas antennas than traffic load. On the other hand micro base staions has single sectors and single antenna and power consumption mainly depends on number of traffic loads. According to several datasheets of exsiting base staions the transmit power (P_{TX}) which is mainly fucntion of intersite distance varies from 10 - 40W for macro base staions and 100mW - 5W for micro base staons.

CAPEX cost saving comes from the use of less radio and transmission equipments and the existing network whereas the source of OPEX saving are the absence of of site rent, lower site equipment maintenance and less network employee required.

Due to sharing of resources the number of users equipment's varies for each MNO from time to time. Once sharing is done, the new cost function of each MNO is optimized using particle swarm optimization(PSO) algorithm.

4.3.5 Particle swarm Algorithm

Particle Swarm Optimization was proposed in 1995 by Kennedy and Eberhart [18] based on the simulating of social behavior. The algorithm uses a swarm of particles to guide its search. Each particle has a velocity and is influenced by locally and globally best-found solutions. Many different implementations have been proposed in the past and, therefore, it is quite difficult to refer to the correct implementation of PSO. However, the general concepts shall be explained in the following.

Given the following variables:

- $X_d^{(i)}$ d-th coordinate of i-th user position
- $V_d^{(i)}$ d-th coordinate of i-th user velocity
- ω Inertia weight
- $P_d^{(i)}$ d-th coordinate of i-th users personal best
- $G_d^{(i)}$ d-th coordinate of the globally (sometimes also only locally) best solution found.
- c_1 and c_2 Two weight values to balance exploiting the users best $P_d^{(i)}$ and clusters best $G_d^{(i)}$
- r_1 and r_2 Two random values being create for the velocity update

The velocity update is given by:

$$V_d^{(i)} = \omega V_d^{(i)} + c_1 r_1 \left(P_d^{(i)} - X_d^{(i)}\right) + c_2 r_2 \left(G_d^{(i)} - X_d^{(i)}\right) \tag{4.7}$$

The corresponding position value is then updated by:

$$X_d^{(i)} = X_d^{(i)} + V_d^{(i)} \tag{4.8}$$

The social behavior is incorporated by using the globally (or locally) best-found solution in the swarm for the velocity update. Besides the social behavior, the swarm's cognitive behavior is determined by the users personal best solution found. The cognitive and social components need to be well balanced to ensure that the algorithm performs well on a variety of optimization problems. Thus, some effort has been made to determine suitable values for c_1 and c_2.

We implement the partictle swarm optimisation algorithm using the built in python pyswarms module by customising all the parameters. The steps to implement the optimisation algorithm are :

- Initialize an Algorithm: Depending on the optimization problem, different algorithms will perform better or worse on different kind of problems. We can also choose default hyper-parameters

- Define a Termination Criterion: A termination criterion needs to be defined to start the optimization procedure. We terminate our optimisation technique by limiting the number of iterations of the algorithm

- Optimize: The optimisation problem of our utiltiy (pay off fucntion) is solved using the builtin PSO optimiser by customising all the parameters and functions. The objective can be either to minimize or maximize the utility or reward fucntion. In our case our objecive to optimise the connectitvity between mobile user and nearby base stations ,i.e, minimisation problem. The optimiser module has many built optimisation algorithms. Once our problem is formulated there is an option to select the algorithm, initializeand termination values , minization or maximization problem before before optimal or best solutions is obtained.

- Visualization: Analysis and visualization of the solution obatined.

4.3.5.1 PSO Algorithm

Parameters of problem:

- Number of dimensions (d)
- Lower bound (minx)
- Upper bound (maxx)

Hyperparameters of the algorithm:

- Number of particles (N)
- Maximum number of iterations (max_iter)
- Inertia (w)
- Cognition of particle (C1)
- Social influence of swarm (C2)

PSO Algorithm:

```
Step1: Randomly initialize Swarm population of N particles Xi ( i=1, 2, ..., n)

Step2: Select hyperparameter values w, c1 and c2

Step 3: For Iter in range(max_iter):  # loop max_iter times

            For i in range(N):  # for each particle:

               a. Compute new velocity of ith particle

                    swarm[i].velocity =

                         w*swarm[i].velocity +

                         r1*c1*(swarm[i].bestPos - swarm[i].position) +

                         r2*c2*( best_pos_swarm - swarm[i].position)
```

```
                b. If velocity is not in range [minx, max] then clip it
                     if swarm[i].velocity < minx:
                         swarm[i].velocity = minx
                     elif swarm[i].velocity[k] > maxx:
                         swarm[i].velocity[k] = maxx
                            swarm[i].velocity[k] = maxx
                c. Compute new position of ith particle using its new velocity
                     swarm[i].position += swarm[i].velocity
                d. Update new best of this particle and new best of Swarm
                      if swarm[i].fitness < swarm[i].bestFitness:
                         swarm[i].bestFitness = swarm[i].fitness
                         swarm[i].bestPos = swarm[i].position

                      if swarm[i].fitness < best_fitness_swarm
                         best_fitness_swarm = swarm[i].fitness
                         best_pos_swarm = swarm[i].position
             End-for
         End -for
Step 4: Return best particle of Swarm
```

We used third-party library pyrecorder to create an animation for a two dimensional problem easily. 4.9 is an image taken from the aniamtion video. We have reduced the maximum velocity to $maxvelocityrate = 0.025$ for illustration purposes.

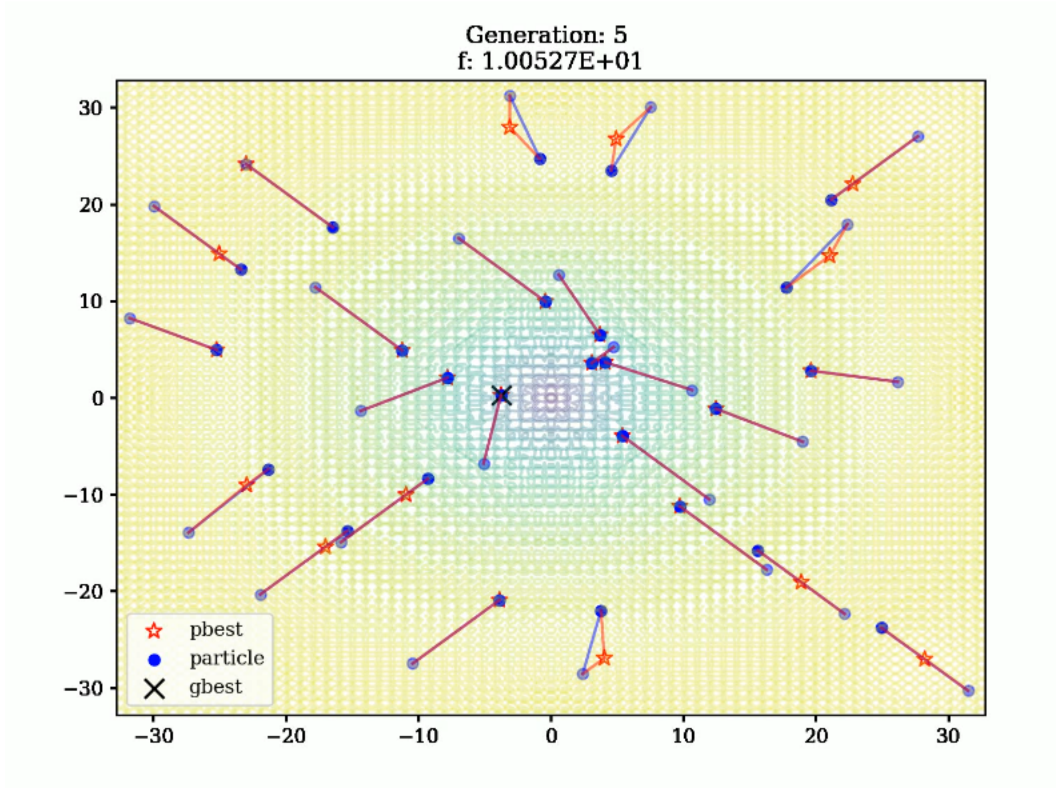

Figure 4.9: Simulation result of PSO

```
from pymoo.factory import get_termination


termination = get_termination("n_gen", 40)
from pymoo.optimize import minimize


res = minimize(problem,
               algorithm,
               termination,
               seed=1,
               save_history=True,
               verbose=True)
```

```
X = res.X

F = res.F
```

The above lisitng generates the result shown in figure 4.10.

n_gen	n_eval	fopt	fopt_gap	favg	f	S	w	c1	c2
1	25	1.44658E+01	1.44658E+01	2.02379E+01	-	-	0.900	2.00000	2.00000
2	50	1.35266E+01	1.35266E+01	1.97739E+01	-4.7E-02	3	0.371	2.00000	2.01638
3	75	1.14201E+01	1.14201E+01	1.91672E+01	-1.9E-02	3	0.388	1.99200	2.03064
4	100	1.14201E+01	1.14201E+01	1.86271E+01	-3.7E-02	3	0.377	1.98117	2.04481
5	125	1.00527E+01	1.00527E+01	1.80550E+01	-3.4E-02	3	0.379	1.96904	2.05841
6	150	9.198073239	9.198073239	1.72000E+01	-1.8E-02	3	0.389	1.95656	2.07171
7	175	6.165163368	6.165163368	1.61546E+01	-2.2E-02	3	0.387	1.94359	2.07677
8	200	4.458590235	4.458590235	1.53917E+01	-2.6E-02	3	0.384	1.93520	2.09201
9	225	3.224030136	3.224030136	1.42653E+01	-2.9E-02	3	0.382	1.92361	2.10241
10	250	3.224030136	3.224030136	1.32361E+01	-2.2E-02	3	0.387	1.91316	2.11580
11	275	2.680781586	2.680781586	1.20881E+01	-1.6E-02	3	0.390	1.90091	2.12124
12	300	2.680781586	2.680781586	1.09364E+01	-1.1E-02	3	0.393	1.89240	2.13110
13	325	2.680781586	2.680781586	1.02814E+01	-1.1E-02	3	0.393	1.88383	2.14308
14	350	2.655340793	2.655340793	9.333864234	-8.4E-03	3	0.395	1.87426	2.15596
15	375	2.564711913	2.564711913	8.055922135	-9.9E-03	3	0.394	1.86311	2.16531
16	400	1.413990992	1.413990992	7.104486704	-1.1E-02	3	0.393	1.85321	2.17554
17	425	1.303095062	1.303095062	6.284893604	-6.2E-03	3	0.396	1.84317	2.18389
18	450	1.303095062	1.303095062	5.013043405	-6.9E-03	3	0.396	1.83431	2.19324
19	475	0.395162286	0.395162286	3.841222442	-5.8E-03	3	0.396	1.82574	2.20342
20	500	0.234340615	0.234340615	3.001679202	-4.7E-03	3	0.397	1.81534	2.20682

Figure 4.10: Iteration of Optimisation

The first two columns are the current generation counter and the number of evaluations so far. For constrained problems, the next two columns show the minimum constraint violation ($cv(min)$) and the average constraint violation ($cv(avg)$) in the current population. This is followed by the number of non-dominated solutions (n_nds) and two more metrics which represents the movement in the objective space.

4.3.5.2 Analysis of Optimisation Convergence

The performance of optimiser and covergence rate should be viusalized .This answer how to define a termination criterion if we solve the problem again. The convergence analysis shall consider two cases, i) the Pareto-front is not known, or ii) the Pareto-front has been derived analytically, or a reasonable approximation exists. Hypervolume is a very well-known performance indicator for multi-objective problems. It is Pareto-compliant and is based on the volume between a predefined reference point and the solution provided. Hypervolume becomes computationally expensive with increasing dimensionality.

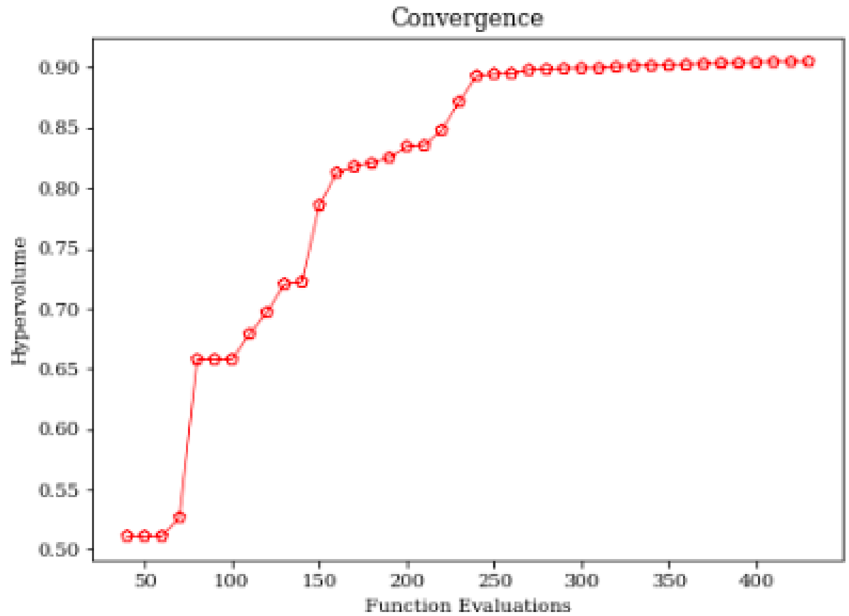

Figure 4.11: Convergence of optimiser

Running metric performance measurement can be applied suitably to indicate the performance of evolutionary many-objective optimization algorithms on problems having more than two objectives. The running metric shows the difference in the objective space from one generation to another and uses the algorithm's survival to visualize the improvement.

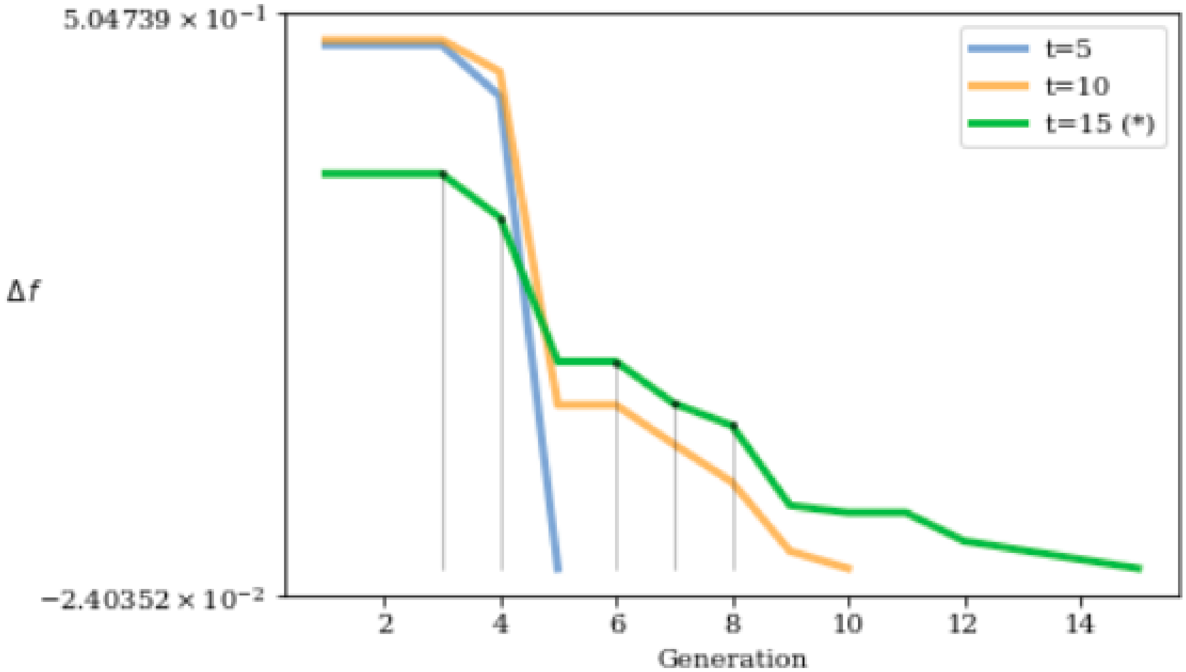

Figure 4.12: Analysis of optimiser using running metric

Figure 4.12 shows plotting until the final population shows the algorithm seems to have more a less converged, and only a slight improvement has been made.

Chapter5

Conclusion, Recommendation and Futre works

In this research we presented and simulated a formalisation of a non-cooperative game to share share radio resources among three operators. We have viewed the problem as a sequential social dilemma in which no network operator is incentive to cooperate (exchanging resources) since Reward or utilities functions are monotonically increasing but doing nothing is non optimal due to the discount factor to penalize late cooperators. Network operators exchange resources to reach an optimal situation and we consider that their personal interest are driven only by their personal utility. A non-cooperative Markov game viewed as a social dilemma, i.e. a situation where Nash equilibria are non optimal. Operators have no incentive to cooperate despite the fact that mutual cooperation is the optimal global strategy.

Estimating future signal strength is complex in mobile network,i.e, mobility plays an important role as the Quality of Service (QoS) offered depends heavily on location learning based models (Open AI gym) have been deployed to improve performance in mobile networks by predicting the best base stations. Realistic environments are generated and customized by the reinforcement learning based openAI Gym toolkit. We showed different resource sharing examples in social dilemma in which MNO has no incentives to collaborate but in the long run mutual cooperation is the optimal solution.

My recommendation for future work is to collect actual data for total power consumptions as well total number of customers registered for each MNO and generate realistic environments derived from our framework to study another robust algorithms for multi-players social dilemmas.

I.

Appendix

Energy Efficient Infrastructure Sharing in Multi-Operator Mobile Networks

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***Abstract*—The rapid development of cellular networks has been urged by the introduction of 3rd Gen- eration (3G) wireless technologies, significantly boosting Ethiotelecom's energy usage and expenditures. Furthermore, mobile data explosion has occurred in recent decades because of an increase in the number of mobile users as well as the rise of bandwidth-hungry appli- cations, hence aiming to utilize the available spectrum as efficiently as possible is a good move. Many researches done on massive MIMO, spectrum sharing, device to device commu- nication (D2D) and GREEN communication shows significant attention in aiding spectrum utilization along with power optimization. In this thesis, motivated by the development of a new Ethiotelecom's business model, infrastructure sharing, which allows emerging MNOs to have their traffic served by other MNOs in the same geographic area, allowing them to share a portion of their network is investigated. This thesis work presents a social dilemma game theoretic framework that allows MNOs to share a portion of their network. Sequential social dilemma and particles swarm algorithm are implemented on OpenAI Gym based adaptable frame work. The algorithm is implemented and optimized for 3 mobile network operator (N = 3), 3 base station sites with 3, 9 and 30 mobile users. Simulation result shows users are connected/linked to nearby base station considering optimization of the utility (reward) function of the MNO (Game players), distance between mobile users and base station sites when the proper cell allocates enough resources. The performance of our simulation is visual- ized by generating various hypothetical cellular network environments with different number of cell sites and mobile users. A more optimal solution is obtained by adding a particle swarm optimization over it. Simulation results are promising and provide a better direction to the future work.**

***Index Terms*—Non-cooperative game, Nash Equilibrium (NE), Sequential social dilemma, Energy saving, Markov game, Particles swarm, CAPEX and OPEX.**

II. INTRODUCTION

The number of mobile subscriber worldwide is growing at an exponential rate. With more than 44.5 million users in Ethiopia alone [1]. Compared to independent deployments of RAN offering closed access, which would be expensive, multi-operator, RAN sharing possesses the potential for quickly expanding coverage area while significantly reducing the capital expenditures (CapEX) and operational expenditures (OpEX) for mobile network operators (MNOs). A well Multi-operator radio access network(RAN) sharing offers great potential for cost and energy efficient deployment and operation of next-generation millimeter-wave RAN (note mm wave is not the main concern of this thesis [2]. In telecommunications, sharing resources between operators has been suggested, inparticular with the arrival of the next generation of telecom (5G) in order to extend and improve capacity and coverage of operator's connectivity. In the last decades, the energy issue has gained a great importance in the field of telecommunications. Several surveys prove that the main energy consuming components are the Base Stations (BSs) [3]. Hence, there is a strong motivation to investigate solutions to bring down the energy consumption and the cost of cellular networks, thus yielding both environmental and financial gains.2 In cellular networks, sharing resources across Mobile Network Operators (MNOs) is an appealing approach, such as through roaming, radio access network sharing. Recently, con- nection marketplaces have been discussed, incorporating financial activities such as trading systems or auctions, whilst alternative solutions may rely on dynamic exchanges and fair provider cooperation. Two key use-cases for collaboration in mobile cellular networks are commonly considered in [4]. Network coverage extension and network capacity extension. In the first situation, certain users may be unable to connect due to a gap in their home provider's infrastructure coverage. In the latter instance, there may be too many customers in relation to their home provider's network cell capacity. To address these issues, a provider may wish to work with one or more other providers in order to take advantage of their resources, resulting in closer or less over-burdened cells for the users in need. In this research, motivated by the aforementioned issues and taking into account the rationality of the MNOs and their conflicting interests, a noncooperative Markov game is proposed. Therefore, it can be viewed as a social dilemma, i.e. a situation where Nash equilibria are non-optimal. Operators have no incentive to cooperate despite the fact that cooperation is the optimal global strategy. Besides the expected energy efficiency benefits, the proposed scheme allows the MNOs to significantly reduce their financial costs independently of the strategies of the coexisting MNOs, providing them with the motivations to participate in the game.

III. PROBLEM STATEMENT

The major challenges in today's radio access networks include cost and energy efficiency. In- frastructure enhancement solves mobile data explosion but still spectrum is scarce.

Spectrum enhancement (e.g. mm wave) is can be a solution but still expensive due to spectrum pur- chasing and research and development. One of the best solution is sharing of RAN resources among mobile network operators (MNOs). There is a continuous need to install RAN supporting infrastructure in order to effectively care for the increasing users in term of service delivering. A major infrastructure is the RAN base Station containing the Base Transceiver Station (BTS); this is due to the limited available bandwidth, the fading nature of the propagation channel and the mobility and autonomy of the wireless nodes [3]. Hence, there is a strong motivation to investigate solutions to bring down the energy consumption and the cost of cellular networks, thus yielding both environmental and financial gains. It is already known that our country is going to have multi-operators in the coming years hence it is advantageous to share RAN infrastructure with cost and energy efficiency aspects. RAN sharing possesses the potential for quickly expanding coverage area while significantly reduce cost as well energy. Some users may be unable to connect owing to a lack of coverage by their home provider's infrastructure or because there are too many users in relation to their home provider's network cell capacity. To address these issues, a provider may wish to combine with one or more other providers in order to take advantage of their resources, resulting in closer or less overburdened cells for users in need.

IV. LITERATURE REVIEW

A number of researches have been conducted in infrastructure sharing among operators and the problem of its coexistence in the same geographical area. In this section, we review some works related to infrastructure sharing between operators operating over the same geographical area. For instance, in the passive RAN sharing scenario, sites, towers, and power supplies of BSs are shared among MNOs, but BSs remain separated. In the active RAN sharing scenario, BSs and backhaul are shared among MNOs. In [3] a heterogeneous Service Level Agreement (SLA) framework for a shared network is proposed, in which different operators' constraints are addressed utilizing two alterna- tive multi-objective optimization techniques, namely the utility profile and scalarization approaches. Combining these tactics with the notion of generalized fractional programming yields Pareto-optimal solutions. The approach can be used in single carrier or multi-carrier systems that are both noise-limited and interference-limited. Extensive numerical findings show how the operator's particular SLA requirements affect global spectral and energy ef- ficiency. The numerical findings show three network situations, each corresponding to a different SLA, each with its own operator-specific strength efficiency and spectral effectivity limitations. [7] Introduces a new adaptable framework based on the OpenAI Gym toolkit that allows for the creation of configurable environments for radio resource collaboration. This approach allows for the systematic development and comparison of agents (such as reinforcement learning agents). Then, because multi-player games created by these environments can be thought of as sequential social dilemmas, therefore concentrate on game theory elements. It shows that, despite the fact that each agent has no motivation to cooperate at each phase of such iterated games, mutual cooperation produces better results (in other words, Nash Equilibrium is non optimal). In [9] Considering the economic impact of cross-carrier MVNOs on the market for cellular records they start by looking at a network choice technique that reduces the expenses of cross- carrier customers. The fees that companion ISPs charge the cross-carrier MVNO and the fees that the cross-carrier MVNO charges its give-up users are then calculated. Although the cross-carrier MVNO may lose money by selling data, it can compensate for this by generating other revenue, such as advertising revenue when users consume additional content. We derive conditions under which the cross-carrier MVNO achieves an income and its users minimize their costs. Finally, using a real-world network quality dataset to simulate users' network choice conduct and demonstrate the advantages of the ISP competition introduced with the aid of the cross-carrier MVNO.Multi operator infrastructure sharing scenario has been considered in more studies on the past years in the literature [10]. Despite many works trying to justify the use of a game theoretic approach for infrastructure sharing, most of them focus solely on the benefits of sharing. There are various forms of inter-operator RAN sharing. Different levels of RAN sharing have different levels of economic and regulatory considerations. A comprehensive classification and analysis are available in previous work. Techno-economic model in [10] allows network operators to compete and dynamically select the quality target to deliver to their customers, while simultaneously seeking to maximize their profits. Nash equilibrium (NE) developed in a non-cooperative game, which shows the optimal point for the operators to meet the customers' requirements. Mostly the papers that have been investigated are based on the concepts of engineering decision that satisfies the QoS requirements of end users, but also an economic one that targets maximizing the profits of all participating operators [11]. In [12] considers an inter-operator RAN sharing scenario where MNOs may have different numbers of deployed mm Wave BSs and users in the beginning. In order to attract more subscribers to mm Wave access services, the MNOs mutually share their BSs by opening the access of their BSs to users of other MNOs. Once a user is associated with the BS of another MNO, it is allocated with a certain amount of bandwidth according to a bandwidth-based service level agreement (SLA) among the MNOs.

V. METHODOLOGY

The major goal of this paper is to present a game theoretic radio resource optimal sharing by taking into account the conflicting interests and interactions among MNOs, as well as the various viable courses of action. The game is modeled as a non-cooperative social dilemma Markov game [13]. In order to fulfill the goal of this research, we take the following steps:

A. Literature review

Regarding the concept and researches done on infrastructure Sharing and Game theory: literature such as books, journals, magazines, and online sources. Other studies that have a direct or indirect relationship to this subject are reviewed in addition to official research.

B. Simulation frameworks

We use a novel framework to create some fully adaptable RL environments for the simulation of multi-provider cooperation. We decided to adopt the OpenAI Gym toolkit, which is a reference in the study of RL agents and used a python program.

VI. System Model

Our network topology consists of a mobile network containing R radio access networks. We also define R for the set Radio access Networks which is expressed as R = 1, r, ..., R. The set of clusters in the given network is denoted as C = 1, c, ..., C. All set of clusters/cites to choose can from a partition P of R. Note that In conventional architecture, the operation of base station is distributed . That means, each base deployment of base station consists of set of pairs of BBU and a RRH. But in modern cellular networks a C-RAN is introduced. C-RAN stands for Centralized, Collaborative, Cloud, and Clean RAN. In C-RAN, BBUs are moved from site location to a single location. C-RAN has a central office or a super macro site used to aggregate BBUs. Our proposed system of spectrum sharing works only for base station with centralized Radio access network. We use a binary variable $y_{r,c}$ expressed as :

$$\begin{aligned} y_{r,c} &= 1, \quad if \quad RRHr \quad is \quad associated \quad to \quad BBUc \\ y_{r,c} &= 0, \quad otherwise \end{aligned} \tag{1}$$

A. Network Area Decomposition

We partitioned the network area into several smaller zones, and we consider the average number of user equipments (UEs) and radio conditions/received siganl strengths per zone. We can observe figure 1 for illustration purpose where set of seven cells is meshed in multiple smaller zones. The average number of UEs located in a zone of index z, associated to a RRH of index r is denoted by $n_{z,r}$. To calculate Signal-to-Interference-plus-Noise ratio of zone z, associated to RRH r $(SINR_{z,r})$ the average distances between the considered zone and all the cells within the network are calculated. The average distance (D avr) between a RRH of coordinates (x_0, y_0) and all points of coordinates (x, y) belonging to zone z is expressed as follows:

$$D_{avr} = \frac{1}{a^2} \iint_S \sqrt{(x-x_0)^2 (y-y_0)^2}\, dx\, dy \tag{2}$$

B. States and Reward functions

Regardless of whether the environment changes state in response to an agent action, the environment always computes a scalar reward (the quality of service, for the transmissions made or received by the agent over the bandwidth purchased by its action during the time period specified in its action). We model the goal of the user agent as that of selecting actions at each time step so as to maximize the cumulative (i.e., summed over multiple time steps) expected reward in the long run. Users operator is selection based is based on a policy that maximizes the expected value of the cumulative reward expressed as in 3.

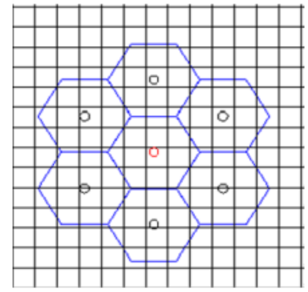

Fig. 1. Meshed Area

$$E\left[\sum_{p=0}^{\infty} \gamma^p R_{t+1+p} | S = s_1\right] \tag{3}$$

starting from some state s_1 at time $t = 1$, γ is a discount factor in the range $[0, 1]$ and the reward function for each player is

$$R_p = \sum_{u \varepsilon C_p} \frac{\Gamma_u}{m_u} \exp\left(-\frac{D_u}{D_{max}}\right) \tag{4}$$

where C_p is set of customers of *P*
Γ_u share of radio resources allocated for provider of $U(p)$ in the cell
m_u number of customers of *P* in the cell *u*,
D_u distance between *u* and its connecting antenna and D_{max} is scalling constant.

VII. IMPLEMENTATION AND RESULTS

Initially a sequential social dilemma game with two players is modeled and simulated in OpenAI gym toolkit. For a two players sequential social dilemma results have shown that mutual defection is the Nash Equilibrium while the optimal outcome is the mutualcooperation.

A two players sequential social dilemma is extended to be played by three players. Three players (MNO) are modeled and simulated by varying the numbers of cell sites and mobile users. Simulation results shows that due to the availability shared radio resource a mobile user can served by another mobile network operator when if the quality of transmitted signal is better than that of its original service provider. Some predefined environments are shown in figure [2]. Simulation results of three operators sequential social dilemma for radio resource sharing among different cell sites base station are visualized in the following figures.

A. Actions and Reward fucntions

For a social dilemma game with greater than two players it is difficult to observe the pay off tables unlike two players

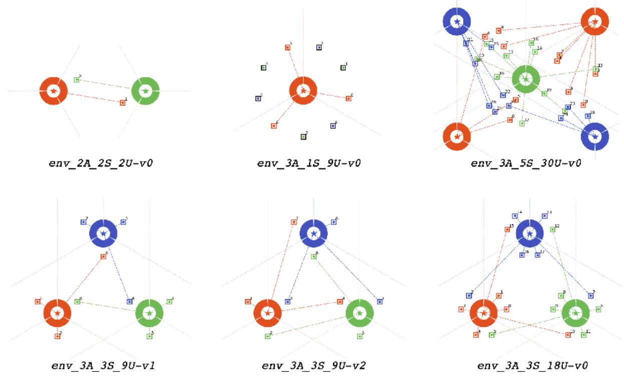

Fig. 2. Some examples of predefined enviroments

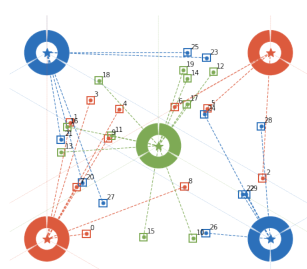

Fig. 3. Users before sharing (3 agents, 5 sites, 30 users [Random users positions])

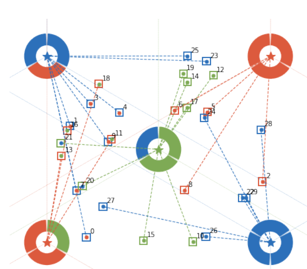

Fig. 4. Users after optimal Sharing(3 agents, 5 sites, 30 users [Random users positions])

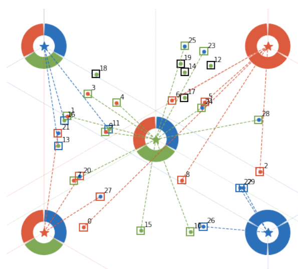

Fig. 5. Users bad sharing (3 agents, 5 sites, 30 users [Random users positions])

prisoners dilemma. Figure 6 illustrates the reward fucntions of social dilemma game using schelling diagrams for different actions taken by individual operators. The step action performed by the first agent (Red agent) are given by

$$\begin{bmatrix}1 & 0 & 0\\1 & 0 & 0\\1 & 0 & 0\end{bmatrix}, \begin{bmatrix}0 & 1 & 0\\0 & 1 & 0\\0 & 1 & 0\end{bmatrix}, \begin{bmatrix}0 & 0 & 1\\1 & 0 & 0\\0 & 1 & 0\end{bmatrix}, \begin{bmatrix}0 & 1 & 0\\1 & 0 & 0\\1 & 0 & 0\end{bmatrix}$$

respectively.

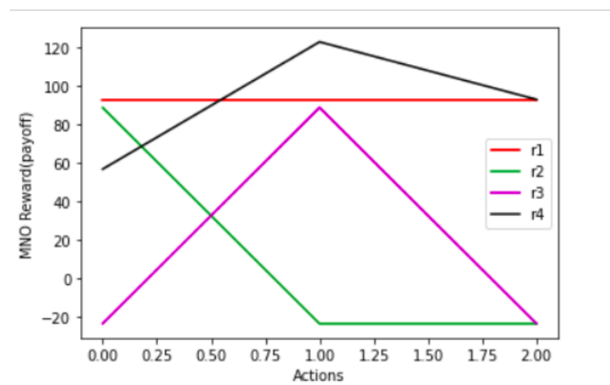

Fig. 6. Reward function after each step (action) taken by individual MNO

B. Analysis of Results interms of CAPEX and OPEX

Cost saving is the main triggering factor when for infrastructure sharing. As number of mobile users of one network operator increases deployment of new base staion will become mandatory to serve the new users. Hence, this increases the capital expenditure (CAPEX) which is the cost of site construction and base station purchases. As the number of base stations increases the operational expenditure (OPEX) which covers 60 percent of the total cost also increases. The increment of OPEX comes from the increased number of power consumption's and other maintainace and operational cost. Network infrastructure is useful for MNOs to share their resources in order to attain the goal of power consumption reduction and enhanced resource utilization efficiency. If we have ground truth information about the number of users for each network operators and number of migrated users from one operator to other, actual power consumption model for each radio units then, we can calculate the actual cost saving and profits obtained due to network sharing. When MNOs are cooperating, all resources are put together (i.e, BBUs, RRHs and spectrum). If there is cooperation we consider that the power consumption of each MNO is proportional to the number of its subscribed UEs. Let's assume MNO1, MNO2 and MNO3 has n number of subscribed use equipments (nMNO1, nMNO2 and nMNO3). The new power consumption for each mobile network operators is given by equation 5.

$$\begin{aligned} PCofMNO_1 &= P_t \times \frac{nMNO_1}{nMNO_1 + nMNO_2 + nMNO_3} \\ PCofMNO_2 &= P_t \times \frac{nMNO_2}{nMNO_1 + nMNO_2 + nMNO_3} \\ PCofMNO_3 &= P_t \times \frac{nMNO_3}{nMNO_1 + nMNO_2 + nMNO_3} \end{aligned} \quad (5)$$

where P_t is the total power consumption in the system. To quantify all the Total costs,CAPEX and OPEX cost we should have actual data and power consumption models. once we have the data at hand. We can calculate the our total costs and profits using the following general expressions.

$Revenue \approx usertariff \times Guaranteeddatarate \times TotalNumberofsubscriber$
$Cost \approx AverageRANpowerconsumption \times Costofelectricity$
$Profit = Revenue - Cost$

C. Power consumption modeling of base station

Base Station is the main contributor of energy consumption in cellular mobile communication. The traffic load of base station sginifacnlty with time and space. Therefore, it is important to model and quantify the influence of traffic generated on the power consumption of base station. Althogh there are many many detail and accurate energy consumption models in this research we used simple linear equations to analyse the relationship between input power consumption(P_{IN}) and the radiated power (P_{TX}) for macro and micro base stations.

$$\begin{aligned} P &= a \times P_{Tx} + b \\ P_{ma} &= a_{ma} \times P_{TX,ma} + b_{ma} \\ P_{mi} &= a_{mi} \times P_{TX,mi} + b_{mi} \end{aligned} \quad (6)$$

The coefficients a_{ma} and a_{mi} are related to devices whose power consumption is dependent on the average transmit power (PA) and they correspond to power consumption that varies because of PA efficiency, feeder cable losses and cooling processes. On the other hand, the terms b_{ma} and b_{mi} represent power offsets of components which are independent of transmit power and they are generated by signal processes, battery backup and cooling functionalities.For macro base staions power consumptions mainly depends on number of sectors and umber antennnas antennas than traffic load. On the other hand micro base staions has single sectors and single antenna and power consumption mainly depends on number of traffic loads. According to several datasheets of exsiting base staions the transmit power (P_{TX}) which is mainly fucntion of intersite distance varies from 10 - 40W for macro base staions and 100mW - 5W for micro base staons. CAPEX cost saving comes from the use of less radio and transmission equipments and the existing network whereas the source of OPEX saving are the absence of of site rent, lower site equipment maintenance and less network employee required.

Due to sharing of resources the number of users equipment's varies for each MNO from time to time. Once sharing is done, the new cost function of each MNO is optimized using particle swarm optimization(PSO) algorithm.

D. Particle Swarm Algorithm (PSO)

Particle Swarm Optimization was proposed in 1995 by Kennedy and Eberhart [14] based on the simulating of social behavior. The algorithm uses a swarm of particles to guide its search. Each particle has a velocity and is influenced by locally and globally best-found solutions. Many different implementations have been proposed in the past and, therefore, it is quite difficult to refer to the correct implementation of PSO. However, the general concepts shall be explained in the following. Given the following variables:

- $X_d^{(i)}$ d-th coordinate of i-th user position
- $V_d^{(i)}$ d-th coordinate of i-th user velocity
- ω Inertia weight
- $P_d^{(i)}$ d-th coordinate of i-th users personal best
- $G_d^{(i)}$ d-th coordinate of the globally (sometimes also only locally) best solution found.
- c_1 and c_2 Two weight values to balance exploiting the users best $P_d^{(i)}$ and clusters best $G_d^{(i)}$
- r_1 and r_2 Two random values being create for the velocity update

The velocity update is given by:

$$V_d^{(i)} = \omega V_d^{(i)} + c_1 r_1 \left(P_d^{(i)} - X_d^{(i)}\right) + c_2 r_2 \left(G_d^{(i)} - X_d^{(i)}\right) \quad (7)$$

The corresponding position value is then updated by:

$$X_d^{(i)} = X_d^{(i)} + V_d^{(i)} \quad (8)$$

The social behavior is incorporated by using the globally (or locally) best-found solution in the swarm for the velocity update. Besides the social behavior, the swarm's cognitive behavior is determined by the users personal best solution found. The cognitive and social components need to be well balanced to ensure that the algorithm performs well on a variety of optimization problems. Thus, some effort has been made to determine suitable values for c1 and c2.

: Note :- We used third-party library pyrecorder to create an animation for a two dimensional problem easily. 7 is an image taken from the aniamtion video. We have reduced the maximum velocity to $maxvelocityrate = 0.025$ for illustration purposes. The above listing generates the result shown in figure 8. The first two columns are the current generation counter and the number of evaluations so far.

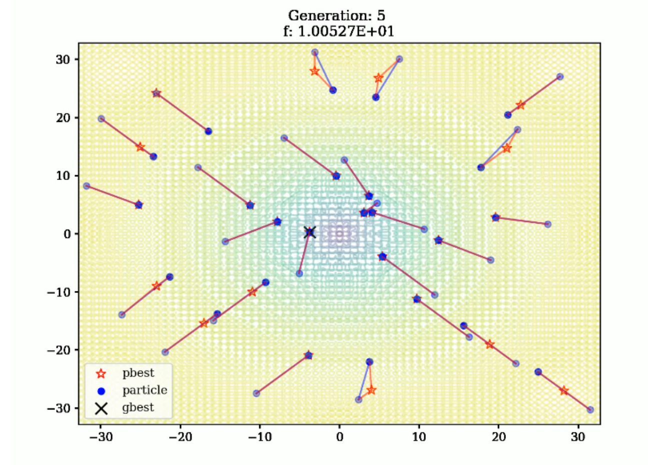

Fig. 7. Simulation result of PSO

n_gen	n_eval	fopt	fopt_gap	favg	f	S	w	c1	c2
1	25	1.44658E+01	1.44658E+01	2.02379E+01	-	-	0.900	2.00000	2.00000
2	50	1.35266E+01	1.35266E+01	1.97739E+01	-4.7E-02	3	0.371	2.00000	2.01638
3	75	1.14201E+01	1.14201E+01	1.91672E+01	-1.9E-02	3	0.388	1.99200	2.03064
4	100	1.14201E+01	1.14201E+01	1.86271E+01	-3.7E-02	3	0.377	1.98117	2.04481
5	125	1.00527E+01	1.00527E+01	1.80550E+01	-3.4E-02	3	0.379	1.96904	2.05841
6	150	9.198073239	9.198073239	1.72000E+01	-1.8E-02	3	0.389	1.95656	2.07171
7	175	6.165163368	6.165163368	1.61546E+01	-2.2E-02	3	0.387	1.94359	2.07677
8	200	4.458590235	4.458590235	1.53917E+01	-2.6E-02	3	0.384	1.93520	2.09201
9	225	3.224030136	3.224030136	1.42653E+01	-2.9E-02	3	0.382	1.92361	2.10241
10	250	3.224030136	3.224030136	1.32361E+01	-2.2E-02	3	0.387	1.91316	2.11580
11	275	2.680781586	2.680781586	1.20881E+01	-1.6E-02	3	0.390	1.90091	2.12124
12	300	2.680781586	2.680781586	1.09364E+01	-1.1E-02	3	0.393	1.89240	2.13110
13	325	2.680781586	2.680781586	1.02814E+01	-1.1E-02	3	0.393	1.88383	2.14308
14	350	2.655340793	2.655340793	9.333864234	-8.4E-03	3	0.395	1.87426	2.15596
15	375	2.564711913	2.564711913	8.055922135	-9.9E-03	3	0.394	1.86311	2.16531
16	400	1.413990992	1.413990992	7.104486704	-1.1E-02	3	0.393	1.85321	2.17554
17	425	1.303095062	1.303095062	6.284893604	-6.2E-03	3	0.396	1.84317	2.18389
18	450	1.303095062	1.303095062	5.013043405	-6.9E-03	3	0.396	1.83431	2.19324
19	475	0.395162286	0.395162286	3.841222442	-5.8E-03	3	0.396	1.82574	2.20342
20	500	0.234340615	0.234340615	3.001679202	-4.7E-03	3	0.397	1.81534	2.20682

Fig. 8. Iteration of Optimisation

For constrained problems, the next two columns show the minimum constraint violation $(cv(min))$ and the average constraint violation $(cv(avg))$ in the current population. This is followed by the number of non-dominated solutions $(n_n ds)$ and two more metrics which represents the movement in the objective space.

VIII. Conclusion

In this research we presented and simulated a formalisation of a non-cooperative game to share share radio resources among three operators. We have viewed the problem as a sequential social dilemma in which no network operator is incentive to cooperate (exchanging resources) since Reward or utilities functions are monotonically increasing but doing nothing is non optimal due to the discount factor to penalize late cooperators. Network operators exchange resources to reach an optimal situation and we consider that their personal interest are driven only by their personal utility. A non-cooperative Markov game viewed as a social dilemma, i.e. a situation where Nash equilibria are non optimal. Operators have no incentive to cooperate despite the fact that mutual cooperation is the optimal global strategy. Estimating future signal strength is complex in mobile network,i.e, mobility plays an important role as the Quality of Service (QoS) offered depends heavily on location learn- ing based models (Open AI gym) have been deployed to improve performance in mobile networks by predicting the best base stations. Realistic environments are generated and customized by the reinforcement learning based openAI Gym toolkit. We showed different resource sharing examples in social dilemma in which MNO has no incentives to collaborate but in the long run mutual cooperation is the optimal solution.

IX. Recommendation and Futre works

My recommendation for future work is to collect actual data for total power consumptions as well total number of customers registered for each MNO and generate realistic environ- ments derived from our framework to study another robust algorithms for multi-players social dilemmas.

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