Optimal Resource Allocation in Coordinated Multi-Cell Systems for Green Communications and Networking

Ms.R.KANMANI[1st]
Assistant Professor (Sr.Gr)
ECE Department
Sri Ramakrishna Institute of Technology
Coimbatore, India
E-mail: kanmani.ece@srit.org

Dr.S.MARY PRAVEENA [2nd]
Associate Professor
ECE Department
Sri Ramakrishna Institute of Technology
Coimbatore, India
E-mail: marypraveena.ece@srit.org

Mr.M.SARAVANAKUMAR [3rd]
Assistant Professor
CSE Department
Jansons Institute of Technology
Coimbatore, India
E-mail: saravanakumar.m@jit.ac.in

Abstract: The use of multiple antennas at base stations is a key component in the design of cellular communication systems that can meet high-capacity demands in the downlink. Under ideal conditions, the gain of employing multiple antennas is well-recognized: the data throughput increases linearly with the number of transmit antennas if the spatial dimension is utilized to serve many users in parallel. The practical performance of multi-cell systems is, however, limited by a variety of no idealities, such as insufficient channel knowledge, high computational complexity, heterogeneous user conditions, limited backhaul capacity, transceiver impairments, and the constrained level of coordination between base stations. This proposed paper presents a general framework for modeling different multi-cell scenarios, including clustered joint transmission, coordinated beam forming, interference channels, cognitive radio, and spectrum sharing between operators.

Keywords: MIMO, OFDMA, OFDM, PSO Algorithm, higher energy efficiency.

1. INTRODUCTION

This section describes a general framework for modeling different types of multi-cell systems and measuring their performance both in terms of system utility and individual user performance. The framework is based on the concept of dynamic cooperation clusters, which enables unified analysis of everything from interference channels and cognitive radio to cellular networks with global joint transmission. The concept of resource allocation is defined as allocating transmit power among users and spatial directions, while satisfying a set of power constraints that have physical, regulatory, and economic implications. A major complication in resource allocation is the inter-user interference that arises and limits the performance when multiple users are served in parallel. Resource allocation is particularly complex when multiple antennas are employed at each base station. However, the throughput, user satisfaction, and revenue of multi-cell systems can be greatly improved if we understand the nature of multi-cell resource allocation and how to exploit the spatial domain to obtain high spectral efficiencies[3].

Mathematically, resource allocation corresponds to the selection of a signal correlation matrix for each user. This enables computation of the corresponding signal-to-interference-and-noise ratio (SINR) of each user. For a given resource allocation, this section describes divergent ways of measuring the performance experienced by each user and the inherent conflict between maximizing the performance of different users. The performance region and channel gain regions are defined to illustrate this conflict. These regions provide a bridge between user performance and system utility. Resource allocation is then naturally formulated as a multi-objective optimization problem and the boundary of the performance region represents all efficient solutions.This section formulates the general optimization problem, discusses the different solution strategies taken in later sections, and derives some basic properties of the optimal solution and the performance region[4]. A detailed outline of this project is given at the end of this section. Mathematical proofs are provided throughout the paper to facilitate a thorough understanding of multi-cell resource allocation.

Introduction to Multi-Antenna Communications

The purpose of communication is to transfer data between devices through a physical medium called the channel. This project focuses on wireless communications, where the data is sent as electromagnetic radio waves propagating through the environment between the devices (e.g., air, building, trees, etc.). The wireless channel distorts the emitted signal, adds interference from other radio signals emitted in the same frequency band, and adds thermal background noise. As the radio frequency spectrum is a global resource used for many things (e.g., cellular/computer networks, radio/television broadcasting, satellite services, and military applications) it is very crowded and spectrum licenses are very expensive, at least in frequency bands suitable for long-range applications. Therefore, wireless communication systems should be designed to use their assigned frequency resources as efficiently as possible, for example, in terms of achieving high spectral efficiency (bits/s/Hz) for the system as a whole. This becomes particularly important as cellular networks are transitioning from low-rate voice/messaging services to high-rate low-latency data services. The overall efficiency and user satisfaction can be improved by dynamic allocation and management of the available resources, and service providers can even share spectrum to further improve their joint spectral efficiency.

The spectral efficiency of a single link (from one transmitter to one receiver) is fundamentally limited by the available transmit power, but the spectral efficiency can potentially be improved by allowing many devices to communicate in parallel and thereby contribute to the total spectral efficiency[9]. This approach will however create inter-user interference that could degrade the performance if not properly controlled. As the power of electromagnetic radio waves attenuates with the propagation distance, the traditional way of handling interference is to only allow simultaneous use of the same resource (e.g., frequency band) by spatially well-separated devices. As the radio waves from a single transmit antenna follow a fixed radiation pattern, this calls for division of the landscape into cells and cell sectors. By applying fixed frequency reuse patterns such that adjacent sectors are not utilizing the same resources, interference can be greatly avoided. This near-orthogonal approach to resource allocation is, however, known to be inefficient compared to letting transmitted signals interfere in a con-trolled way.

In contrast to classical resource allocation with single-antenna transmitters, modern multi-antenna techniques enable resource allocation with precise spatial separation of users. By steering the data signals toward intended users, it is possible to increase the received signal power (called an array gain) and at the same time limit the interference caused to other non-intended users. The steering is tightly coupled with the concept of beamforming in classic array signal processing; that is, transmitting a signal from multiple antennas using diff erent relative amplitudes and phases such that the components add up constructively in desired directions and destructively in undesired directions. Herein, steering basically means to form beams in the directions of users with line-of-sight propagation and to make multipath components add up coherently in the geographical area around non-line-of-sight users. The beamforming resolution depends on the propagation environment and typically improves with the number of transmit antennas. The ability to steer signals toward intended users ideally enables global utilization of all spectral resources, thus

1.2 Introduction

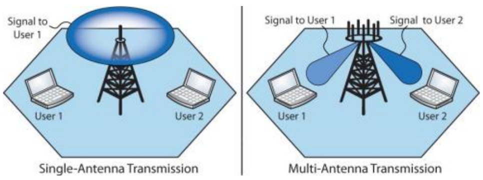

Figure. 1.2 Illustration of the difference between

single-antenna and multi-antenna transmission.

Figure 1.2 Diff erence between single-antenna and multi-antenna transmission Illustration of the diff erence between single-antenna and multi-antenna transmission. With a single antenna, the signal propagates according to a fixed antenna pattern (e.g., equally strong in all directions) and can create severe interference in directions where the intended user is not located. For example, interference is caused to User 2 when User 1 is served. With multiple antennas, the signal can be steered toward the intended user which enables simultaneous transmission to multiple spatially separated users with con-trolled inter-user interference. Removing the need for cell sectoring and fixed frequency reuse patterns. This translates into a much higher spectral efficiency but also more complex implementation constraints as described later in this section.

The seminal works of provide a mathematical motivation behind multi-antenna communications; the spectral efficiency increases linearly with the number of antennas (if the receiver knows the channel and has at least as many antennas as the transmitter). The initial works considered point-to-point communication between two multi-antenna devices a scenario that is fairly well-understood today. Encouraging results for the single-cell down-link where one multi-antenna device transmits to multiple user devices (also known as the broadcast channel) were initially derive. The information-theoretic capacity region is now fully characterized, even under general conditions. The optimal spectral efficiency is achieved by nonlinear interference pre-cancelation techniques, such as dirty paper coding. The single-cell scenario is more challenging than point-to-point since the transmitter needs to know the channel directions of the intended users to perform nonlinear interference precancelation or any sensible linear transmission. Thus, sufficient overhead signaling needs to be allocated for estimation and feedback of channel information. On the other hand, high spectral efficiency can be achieved in single-cell scenarios while having low-cost single-antenna user devices and non-ideal channel conditions (e.g., high antenna correlation, keyhole-like propagation, and line-of-sight propagation) this is not possible in point-to-point communication.

The multi-cell downlink has attracted much attention, since the system-wide spectral efficiency can be further improved if the frequency reuse patterns are replaced by cooperation between transmitters. Ide-ally, this could make the whole network act as one large virtual cell that utilizes all available resources. Such a setup actually exploits the existence of inter-cell interference, by allowing joint transmission from multiple cells to each and every user. Unlike the single-cell scenario, the optimal transmit strategy is unknown even for seemingly simple multi-cell scenarios, such as the interference channel where each transmitter serves a single unique user while interference is coordinated across all cells. Part of the explanation is that interference pre-cancelation, which is optimal in the single-cell case, cannot be applied between transmitters in the interference channel. Among the schemes that are suboptimal in the capacity-sense, linear transmission is practically appealing due to its low complexity, asymptotic optimality (in certain cases), and robustness to channel uncertainty. The best linear transmission scheme is generally difficult to obtain, even in those single-cell scenarios where the capacity region is fully characterized. Recent works have however derived strong parameterizations and these will be described.

This project provides theoretical and conceptual insights on the optimization of general multi-cell systems with linear transmission. To this end, the project first introduces a mathematical system model for the single-cell downlink. This model serves as the foundation when moving to the multi-cell downlink, which has many conceptual similarities but also important diff erences that should be properly addressed.

1.3 System Model: Single-Cell Downlink

Consider a single-cell scenario where a base station with N antennas communicates with K_r user devices, as illustrated inKth user is denoted MS_k (the abbreviation stands for mobile station) and is assumed to have a single eff ective antenna1; the case with multiple antennas per user is considered

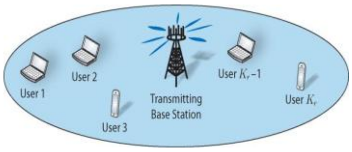

Figure 1.3 Illustration of the downlink multi-user system in Section 1.2. A base station with *N* antennas serves *Kr* users.

This scenario can be viewed as the superposition of several multiple-input single-output (MISO) links, thus it is also known as the MISO broadcast channel or multi-user MISO communication. It is also frequently described as multi-user MIMO (multiple-input multiple-output), refer-ring to that there are K_r receive antennas in total, but we avoid this terminology as it creates confusion.

The channel to MS_k is assumed to be flat-fading[2] and represented in the complex baseband by the dimensionless vector $h_k \in C^N$. The complexvalued element $[h_k]_n$ describes the channel from the nth transmit antenna; its magnitude represents the gain (or rather the attenuation) of the channel, while its argument describes the phase-shift created by the channel. We assume that the channel vector is quasi-static; that is, constant for the duration of many transmission symbols, known as the coherence time. The collection of all channel vectors $\{hk\}Krk = 1$is known as the channel state information (CSI) and is assumed perfectly known at the base station. We also assume that the transceiver hardware is ideal, without other impairments than can

This means that MS_k is equipped with either a single antenna or $M_k > 1$ antennas that are combined into a single eff ective antenna (e.g., using receive combining or antenna selection). There are several reasons for making these assumptions: it enables noniterative transmission design, put less hardware constraints on the user devices, requires less channel knowledge at the transmitter, and is close-to-optimal under realistic conditions.

Flat fading means that the frequency response is flat, which translates into a memoryless channel where the current output signal only depends on the current input signal.

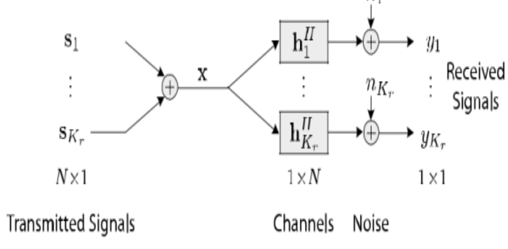

Figure 1.3.1 Block diagram of the basic system model

for downlink single-cell communications. Kr single-antenna users are served by N antennas.

Figure 1.3.1Block diagram of the basic system model for downlink single-cell communications. Kr single-antenna users are served by N antennas be included in the channel vector and background noise. These assumptions are idealistic, but simplify the conceptual presentation in this and subsequent sections. It is generally impossible to find perfect models of reality, or as famously noted in “Remember that all system models are wrong.” Therefore, the goal is to formulate a model that enables analysis and at the same time is accurate enough to provide valuable insights. Relaxations to more realistic conditions and assumptions are provided.

Under these assumptions, the symbol-sampled complex-baseband received signal at MS_k is $y_k \in C$ and is given by the linear input–output model

$$y_k = h_k^H x + n_k \qquad 1.1$$

Where$n_k \in C$ is the combined vector of additive noise and interference from surrounding systems. It is modeled as circularly symmetric complex Gaussian distributed, nk~ CN (0, σ2), where σ2 is the noise power. This input–output model is illustrated in Figure 1.3. In a multi-carrier system, for example, based on orthogonal frequency-division multiplexing (OFDM), the input–output model (1.1) could describe one of the subcarriers. For brevity, we concentrate on a single subcarrier in Sections 1–3, while the multi-carrier case is discussed.

The transmitted signal x ∈CN 1.2 contains data signals intended for each of the users and is given by

$$X = \sum_{k=1}^{Kr} S_k \qquad 1.2$$

Where$s_k \in C^N$ is the signal intended for MS_k. These stochastic data signals are modeled as zero-mean with signal correlation matrices

$$S_k = E\{s k_{s_k}^H\} \in C^{N\times N} \qquad 1.3$$

This transmission approach is known as linear multi-stream beam forming (rank (S_k) is the number of streams) and the signal correlation matrices are important design parameters which will be used to optimize the performance/utility of the system.

Definition 1.1. Each selection of the signal correlation matrices $S1,...,Sk_r$ is called a transmit strategy. The average transmit power allocated to MS_k is tr (S_k)1.3 .

The only transmit strategies of interest are those that satisfy the power constraints of the system, which are defined next.

1.4 Power Constraints

The power resources available for transmission need to be limited some-how to model the inherent restrictions of practical systems. The average transmit power tr(Sk) and noise power σ2 are normally measured in mill watt [mW], with dBm as the corresponding unit in decibels. We assume that there are L linear power constraints, which are defined as

$$\sum_{k=1}^{Kr} \mathrm{tr}(Q_{lk} S_k) \le q_l l = l \dots\dots, L, \qquad 1.4$$

Where$Q_{lk} \in C^{N\times N}$ are Hermitian positive semi-definite weighting matrices and the limits ql ≥ 0 for all l, k. If Q_{lk}1.4 is normalized and dimensionless, then q_l is measured in mW and serves as an upper bound on the allowed transmit power in the subspace spanned by Q_{lk}. To ensure that the power is constrained in all spatial directions, these matrices satisfy $\sum_{l=1}^{L} Q^{lr} > Q^n$These constraints are given in advance and are based on, for example, physical limitations e.g., to protect the dynamic range of power amplifiers.

In traditional multi-cell systems, each user belongs to one cell at a time and resource allocation is performed unilaterally by its base station. This is enabled by having frequency reuse patterns such that cell sec-tors utilizing the same resources cause negligible interference to each other. The single-cell system model, defined in the previous section, can therefore be applied directly onto each cell sectorat least if the negligible interference from distant cell sectors is seen as part of the additive background noise. Accordingly, the base station can make autonomous resource allocation decisions and be sure that no uncoordinated interference appears within the cell.

A different story emerges in multi-cell multi-antenna scenarios where all base stations are simultaneously using the same frequency resources (to maximize the system-wide spectral efficiency). The counterpart of SDMA in multi-cell systems have been given many names, including co-processing, cooperative processing, network MIMO, coordinated multi-point (CoMP), and multicell processing. It is based on the same idea of exploiting the spatial dimensions for serving multiple users in parallel while controlling the interference. Network MIMO is particularly important for users that experience channel gains on the same order of magnitude from multiple base stations (e.g., cell edge users). The initial works in assumed perfect co-processing at the base stations and modeled the whole network as one large multi-user MISO system where the transmit antennas happen to be distributed over a large area; all users were served by joint transmission from all base stations and the multi-cell characteristics were essentially reduced to just constraining the transmit power per antenna array or antenna, instead of the total transmit power (as traditionally assumed for single-cell systems)[4]. The optimal spectral efficiency under these ideal conditions can be obtained from the single-cell literature, in particular. Although mathematically convenient, this approach leads to several implicit assumptions that are hard to justify in practice. First, global CSI and data sharing is required, which puts huge demands on the channel estimation, feed-back links, and backhaul networks.

Second, coherent joint transmission (including joint interference cancelation) requires very accurate synchronization3 between base stations and increases the delay spread potentially turning flat-fading channels into frequency-selective. Third, the complexity of centralized resource allocation algorithms is infeasible in terms of computations, delays, and scalability. On the other hand, the early works on the multi-cell downlink provide (unattainable) upper bounds on the practical multi-cell performance.

Various alternative models have been proposed to capture multi-cell-specific characteristics. The CSI requirements were reduced in by using the so called Wyner model from where interference only comes from immediate neighboring cells; see Example 1.1 for details. This enables relatively simple analysis, but the results can also be oversimplified another approach is to divide base stations into static disjoint cooperation clusters. Each cluster is basically operated as a single-cell system.

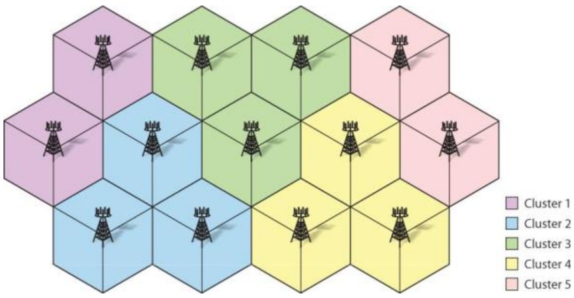

Figure1.4 Schematic illustration of static disjoint cooperation clusters.

Synchronization is very important to enable signal contributions from deferent base stations to cancel out at nonintended users. Precise phase-synchronization can potentially be achieved and maintained by sending a common reference signal to the base stations from a master oscillator, using reference clocks that are phase-locked to the GPS, or by estimating and feeding back the off set at the users.

If the clusters are sufficiently small (e.g., cell sectors connected to the same eNodeB in an LTE system), this approach enables practical channel acquisition, coordination, and synchronization within each cluster. Networks with static clusters unfortunately provide poor spectral efficiency when the user distribution is heterogeneous and suff er from out-of-cluster interference. The impact of these drawbacks can be reduced by having diff erent static disjoint cooperation clusters on deferent frequency subcarriers, by increasing the cluster size and serve each user by a subset of its base stations, by having frequency reuse patterns in the cluster edge area, and by changing the disjoint clusters over time. These approaches can however be viewed as treating the symptoms rather than the actual problem, namely the formation of clusters based on a base station-perspective. Steps toward more dynamic and flexible multi-cell coordination were taken in by creating clusters from a user-centric perspective. This means that the set of base stations that serve or reduce interference to a given user is based on the particular needs of this user.

Consequently, each base station has its own unique set of users to coordinate interference toward and serves a subset of these users with data. Each base station coordinates its resource allocation decisions with exactly those base stations that aff ect the same users. This is very deferent from the disjointness mentioned above, because each base station basically cooperates with all of its neighbors and forms diff erent cooperation clusters when serving diff erent users. The geographical location of a user has a large impact on the clustering but the desirable cooperation and coordination also change with time, for example, based on user activity levels, mobility of users, and macroscopic conditions such as congestion in certain areas. This project considers dynamic cooperation clusters of this user-centric type and the framework includes the scenarios described above as special cases.

2.SYSTEM DESIGN-
EXISTING SYSTEM:

Internet of Things (IoT) is an emerging networking paradigm that enhances smart device communications through internet-enabled systems. Due to massive IoT devices connectivity with economic and greenhouse emission effects, the energy efficiency poses critical concerns[1]. Under imperfect channel state information (CSI), this paper investigates joint optimization of user selection, power allocation and the number of activated Base Station (BS) antennas of multiple IoT devices considering the transmit power and different quality of service (QoS) requirements in combinatorial mode to maximize energy efficiency. The optimization problem formulated is a non-convex mixed-integer nonlinear programming, which is NP-hard with no practical solution. The primal optimization problem is transformed into tractable convex optimization problem and separated into inner and outer loop sub problems[2]. The paper proposed joint energy efficient iterative algorithm, which utilizes successive convex approximation technique and Lagrangian dual decomposition method to achieve near-optimal solutions with guaranteed convergence. Simulation results are provided to evaluate the proposed algorithm and its significant performance gain over the baseline algorithms in terms of energy efficiency maximization.

3. PROPOSED SYSTEM:

The use of multiple antennas at base stations is a key component in the design of cellular communication systems that can meet high-capacity demands in the downlink. Under ideal conditions, the gain of employing multiple antennas is well-recognized: the data throughput increases linearly with the number of transmit antennas if the spatial dimension is utilized to serve many users in parallel. The practical performance of multi-cell systems is, however, limited by a variety of non-idealities, such as insufficient channel knowledge, high computational complexity, heterogeneous user conditions, limited backhaul capacity, transceiver impairments, and the constrained level of coordination between base stations. This proposed system presents a general framework for modeling different multi-cell scenarios, including clustered joint transmission, coordinated beamforming, interference channels, cognitive radio, and spectrum sharing between operators.

BLOCK DIAGRAM:

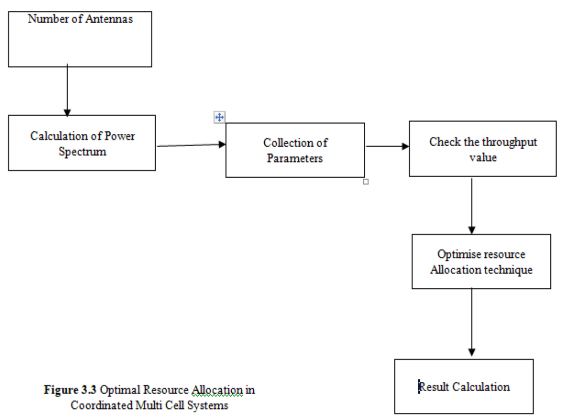

Figure 3.3 Optimal Resource Allocation in Coordinated Multi Cell Systems

METHODOLOGY

3.a Optimal Resource Allocation

Resource allocation in multi-cell multi-antenna systems can be described as the maximization of a system utility function by allocating transmit power among users and spatial directions. The allocation should satisfy a set of power constraints that have physical, regulatory, and economic implications. The book pro-vides an optimization framework for downlink resource allocation in multi-cell scenarios with Kt multi-antenna transmitters, which have a total of N transmit antennas. There are Kr single-antenna receiving users. The framework can describe transmitter cooperation scenarios, including global joint transmission, dynamic cooperation clusters, interference channels, coordinated beamforming, and cognitive radio. These scenarios are characterized by the design parameters which are diagonal matrices with zeros and ones on the main diagonal. One means that the corresponding antenna might send data to the user

In Heterogeneous Networks, resources (both bandwidth and power) are apportioned by the Macro Base station to multiple User Equipment’s (UEs) with the intention of providing maximum possible date rate to all UEs. Concurrently, UE’s received power has to be above its receiver sensitivity. In addition, cross-tier co-channel interference to the nearest Base station must be limited. This resource allocation problem is solved using Particle Swarm Optimization (PSO) method. However, this project procures optimal solution with lesser number of iterations by properly choosing minimum and maximum possible powers in PSO.

PSO is a population-based evolutionary computation technique initialized with a population of random solutions, referred to, as particles. The evolutionary algorithm is inspired by social behavior of swarms. Typically, each particle has a driving velocity which is dictated by past actions and its neighbors. Slowly the particles disperse around, influenced by its counterparts and exploratory behavior. Over time the particles will ‘fly’ towards the better solutions by using information of the best particle and local best result to adjust the trajectory. PSO requires position and velocity values as part of the initial population[7]. To define the Optimal resource allocation problem for PSO to evaluate, the goal is to minimize the power load sustained by the base station. First, the matrices of position and velocity are obtained to store updated values at each time step. Each particle owns an array of velocities and positions. A matrix of N sub-carriers (rows) by P particles (columns) is used to represent the form of solution, whereas a channel response matrix H with K rows and N columns contains the channel gain.

4. RESULTS AND DISCUSSION

Optimal resource allocation has been simulated with particle swarm optimization using Matlab programming. The Assignment of Base Station for specific users with respect to Particle Swarm Optimization has been simulated and result has been plot as shown in Figure 5.1 Block Diagram.

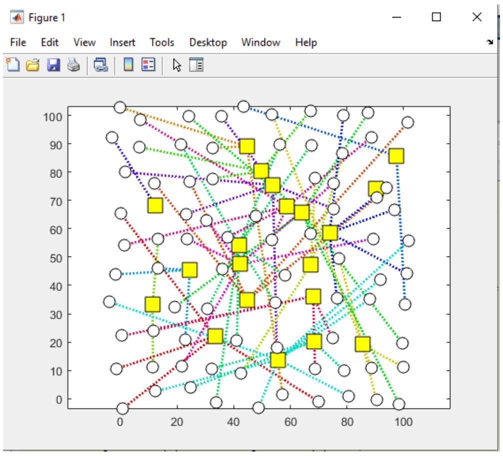

Figure 5.1 *Assignment of Base Station for specific users with respective to Particle Swarm Optimization*

Particle swarm best power selection for individual base station has been simulated using Matlab programming and result has been plot as shown in Figure 5.2.

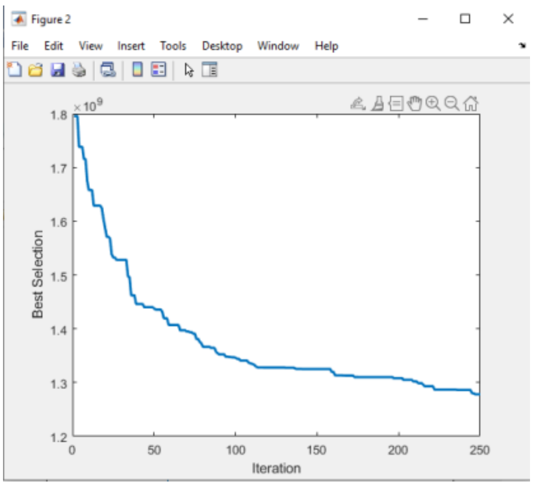

Figure 5.2 *Particle swarm best power selection for individual base station*

Total energy transferred in a single base station with total number of channels has been simulated using Matlab programming and result has been plot as shown in Figure 5.3.

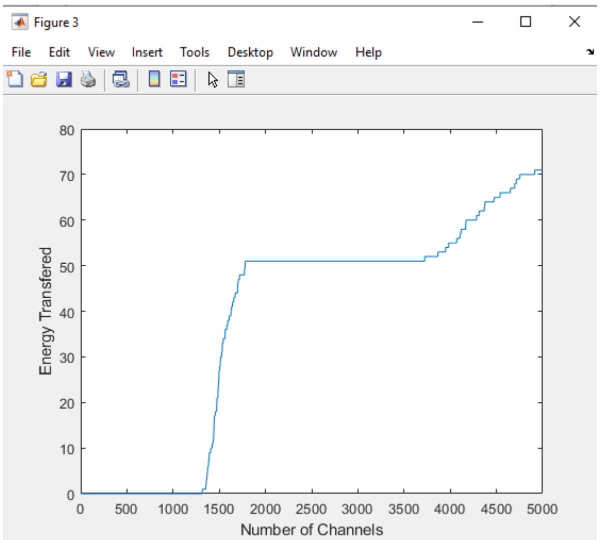

Figure 5.3 *Total energy transferred in a single base station with total number of channels*

Current energy transferring level for individual iterations with respective to number of channels has been simulated using Matlab programming and result has been plot shown in Figure 5.4.

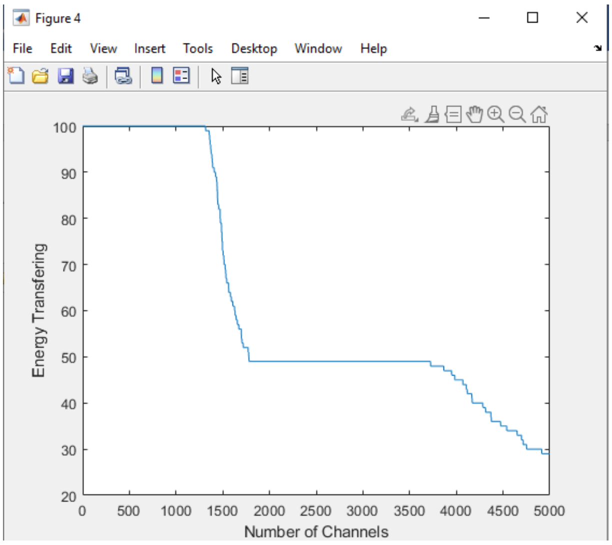

Figure 5.4 *Current energy transferring level for individual iterations with respective to number of channels*

Total Energy allocation for individual base stationhas been simulated using Matlab programming and result has been plot shown in Figure 5.5.

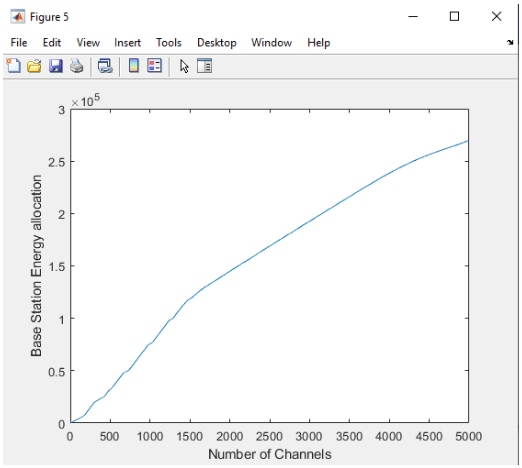

Figure 5.5*Total Energy allocation for individual base station*

Total number of users involved in specific number of channels has been simulated using Matlab programming and result has been plot as shown in Figure 5.6.

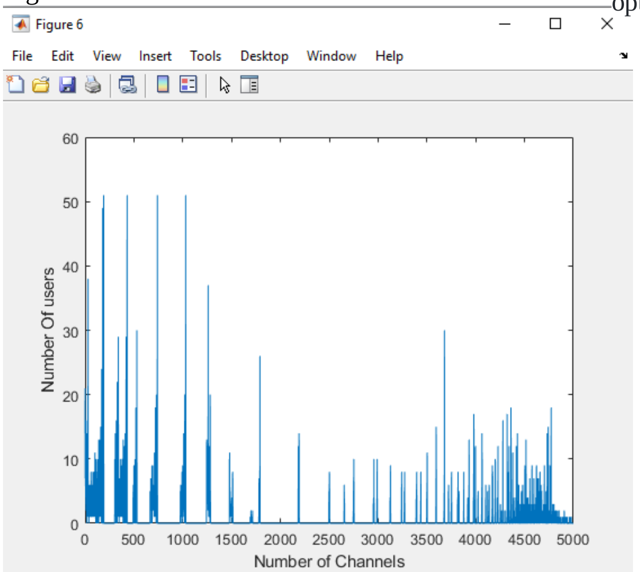

Figure 5.6 *Total number of users involved in specific number of channels*

Sl. No	Number of Channels	Energy Transferred (w)	Base Station	Number of User
1.	500	0	2.4	30
2.	1000	0	6.7	51
3.	1500	22	11.4	11
4.	2000	51	14.3	9
5.	2500	51	16.7	8
6.	3000	51	19.74	11
7.	3500	57	21.86	29
8.	4000	60	23.85	18
9.	4500	65	26.4	14
10.	5000	74	26.85	1

TABLE 5.1*Total number of users involved in specific number of channels*

5.CONCLUSION

The performance of multi-cell systems depends on the resource allocation; that is, how the time, power, frequency, and spatial resources are divided among users. A comprehensive characterization of resource allocation problem categories is provided, along with the signal processing algorithms that solve them. The inherent difficulties are revealed: (a) the overwhelming spatial degrees-of-freedom created by the multitude of transmit antennas; and (b) the fundamental tradeoff between maximizing aggregate system throughput and maintaining user fairness. This project provides a pragmatic foundation for resource allocation where the system utility metric can be selected to achieve practical feasibility. The structure of optimal resource allocation is also derived, in terms of beamforming parameterizations and optimal operating points.

REFERENCES

[1] OmidYazdani, Mehdi Monemi, GhasemMirjalily, "Fast Globally Optimal Transmit Antenna Selection and Resource Allocation Scheme in mm Wave D2D Networks", IEEE Transactionson Mobile Computing, Volume: 21, Issue: 2, 01 February 2022.

[2] AtefehRezaei, Ata Khalili, Jalal Jalali, HosseinShafiei, "QingqingWuEnergy-Efficient Resource Allocation and Antenna Selection for IRS-Assisted Multicell Downlink Networks" IEEE Wireless Communications Letters (Volume: 11, Issue: 6, June 2022).

[3] DelinGuo, Lan Tang, Xinggan Zhang, "Resource Allocation Scheme in Multi-Antenna Systems With Hybrid Energy Supply" IEEE Wireless Communications Letters (Volume: 10, Issue: 3, March 2021).

[4] James AduAnsere, Guangjie Han, Li Liu, Yan Peng, Mohsin Kamal, "Optimal Resource Allocation in Energy-Efficient Internet-of-Things Networks With Imperfect CSI"IEEE Internet of Things Journal Volume: 7, Issue: 6, June 2020.

[5] Feng Wang, Hong Xing, JieXu, "Optimal Resource Allocation for Wireless Powered Mobile Edge Computing with Dynamic Task Arrivals",ICCIEEE International Conference on Communications (ICC),2019.

[6] Marie-Josepha Youssef, Joumana Farah, Charbel Abdel Nour, Catherine Douillard, "Resource Allocation for Mixed Traffic Types in Distributed Antenna Systems Using

NOMA", IEEE 88th Vehicular Technology Conference (VTC-Fall),2018.
[7] JieLiu, QiangGao, "User pairing and resource allocation for multi-antenna users in uplink multiuser MIMO system", 10th International Conference on Communications and Networking in China (China Com),2015.
[8] Yao Yao, Mustafa Mehmet-Ali, "Optimal resource allocation in distributed broadband wireless communication systems", IEEE 23rd International Symposium on Personal Indoor and Mobile Radio Communications,2012.
[9] Huiling Zhu, Jiangzhou Wang, "Resource allocation in OFDMA-based distributed antenna systems", IEEE/CIC International Conference on Communications in China (ICCC),2013.
[10] Rui Zhang, "Optimal Dynamic Resource Allocation for Multi-Antenna Broadcasting With Heterogeneous Delay-Constrained Traffic", IEEE Journal of Selected Topics in Signal Processing Volume: 2, Issue: 2, April 2008.

AUTHOR'S BIOGRAPHIES

Dr. S.MaryPraveena received her Ph.D degree in 2012 in Faculty of Information and Communication Engineering, Anna University, Chennai. She received her M.E degree in Applied Electronics from Sathyabama University, Chennai in the year of 2007 and her B.E.degree in Electronics and Communication Engineering from Sri Krishna College of Engineering and Technology, Bharathiar University, Coimbatore in the year of 2003.She is having totally 14 years of teaching experience. Currently she is working as a Associate Professor in ECE department of Sri Ramakrishna Institute of Technology, Coimbatore. She is a life member of ISTE. She has published around 25 technical papers in referred National and International level Journals an also published 10 technical papers in various National and International level conferences.

Ms.R.Kanmani received her M.Tech. degree in Advanced Communication Systems from SASTRA University, Thanjavur in the year 2009 . She received her B.E. degree in Electronics and Communication Engineering from P.R Engineering College, Thanjavur under Anna University, Chennai in the year 2007. Currently she is working as Assistant Professor in ECE Department at Sri Ramakrishna Institute of Technology, Coimbatore. She is having 10 years of teaching experience. She is a Life member of ISTE. She has presented papers in National and International Conferences. She has published her papers in International Journals. Her field of interest includes Wireless Communication and Wireless Sensor Networks.

Mr.M.Saravanakumar received his M.E. degree in Network Engineering from Anna University, Coimbatore in the year 2009 . He received his B.Tech. degree in Information Technology from Maharaja Engineering College, Coimbatore under Anna University, Chennai in the year 2006. Currently she is working as Assistant Professor in CSE Department at Jansons Institute of Technology, Coimbatore. He is having 12 years of teaching experience. He has presented papers in National and International Conferences. He has published his papers in International Journals. His field of interest includes Cloud computing, Machine Learning and Artificial Intelligence.