

# OPTIMAL RESOURCE ALLOCATION IN COORDINATED MULTI-CELL SYSTEMS

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*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 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.

**Keywords:** MIMO, OFDMA, OFDM, Water filling algorithm, higher energy efficiency.

## I. 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 the 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.

Mathematically, resource allocation corresponds to the selection of a signal correlation matrix for each user. This enables the 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. A detailed outline of this project is given at the end of this section. Mathematical proofs are provided throughout the project to facilitate a thorough understanding of multi-cell resource allocation.

### 1) 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

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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. 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 a 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

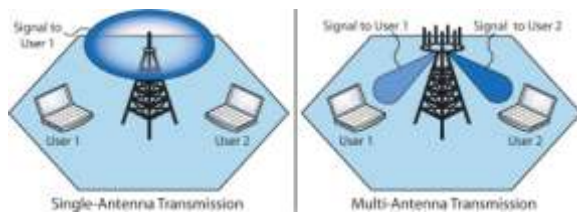
inefficient compared to letting transmitted signals interfere in a controlled way.

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 different relative amplitudes and phases such that the components add up constructively in desired directions and destructively in undesired directions. Herein, steering 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 single-antenna and multi-antenna transmission.

Figure 1.2 Difference between single-antenna and multi-antenna transmission. Illustration of the difference 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 use 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 use which enables simultaneous transmission to multiple spatially separated users with controlled 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 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 downlink where one multi-antenna device transmits to multiple user devices (also known as the broadcast channel) were initially derived. The information-theoretic capacity region is now fully characterized, even under general conditions. The optimal spectral efficiency is achieved by nonlinear interference pre-cancellation 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 cancellation 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.



**Figure. 1.2 Illustration of the difference between**

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. Ideally, this could make the whole network act as one large virtual cell that utilizes all available resources. Such a setup exploits the existence of inter-cell interference, by allowing joint transmission from multiple cells to each 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-cancellation, 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 into the optimization of general multi-cell systems with the 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 differences that should be properly addressed.

## 2) 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 in the user is denoted  $MS_k$  (the abbreviation stands for the mobile station) and is assumed to have a single effective antenna; the case with multiple antennas per user is considered



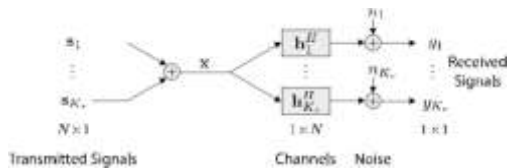
**Figure 1.3 Illustration of the downlink multi-user system in Section 1.2. A base station with  $N$  antennas serves  $K_r$  users.**

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), referring 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<sup>2</sup> and represented in the complex baseband by the dimensionless vector  $h_k \in \mathbb{C}^N$ . The complex-valued element  $[h_k]_n$  describes the channel from the  $n$ th 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  $\{h_k\}_{k=1}^K$  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  $M_k > 1$  antenna that is combined into a single effective antenna (e.g., using receive combining or antenna selection). There are several reasons for making these assumptions: it enables noniterative transmission design, put fewer 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.  $K$  single-antenna users are served by  $N$  antennas.**

Figure 1.3.1 Block diagram of the basic system model for downlink single-cell communications.  $K$  single-antenna users are served by  $N$  antennas is 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  $y_k \in \mathbb{C}$  and is given by the linear input-output model

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

Where  $n_k \in \mathbb{C}$  is the combined vector of additive noise and interference from surrounding systems. It is modeled as a circularly symmetric complex Gaussian distributed,  $n_k \sim \mathcal{CN}(0, \sigma^2)$ , where  $\sigma^2$  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  $x \in \mathbb{C}^N$  1.2 contains data signals intended for each of the users and is given by

$$x = \sum_{k=1}^K s_k \quad 1.2$$

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

$$S_k = E\{s_k s_k^H\} \in \mathbb{C}^{N \times N} \quad 1.3$$

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 that will be used to optimize the performance/utility of the system.

Definition 1.1. Each selection of the signal correlation matrices  $S_1, \dots, S_K$  is called a transmit strategy. The average transmit power allocated to  $MS_k$  is  $\text{tr}(S_k)$  1.3.

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

### 3) Power Constraints

The power resources available for transmission need to be limited somehow to model the inherent restrictions of practical systems. The average transmits power  $\text{tr}(S_k)$  and noise power  $\sigma^2$  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

$$\sum_{k=1}^{K^r} \text{tr}(Q_{lk} S_k) \leq q_l \quad l = 1, \dots, L, \quad 1.4$$

Where  $Q_{lk} \in \mathbb{C}^{N \times N}$  is Hermitian positive semi-definite weighting matrices and the limits  $q_l \geq 0$  for all  $l, k$ . If  $Q_{lk}$  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  $\sum_{i=1}^L Q_{ik}^T > Q^n$ . 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 sectors 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 to each cell sector at 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 has 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 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). 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 are required, which puts huge demands on channel estimation, feedback links, and backhaul networks.

Second, coherent joint transmission (including joint interference cancelation) requires very accurate synchronization<sup>3</sup> 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 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 operated as a single-cell system.



**Figure 1.4 Schematic illustration of static disjoint cooperation clusters.**

Synchronization is very important to enable signal contributions from different base stations to cancel out at non intended 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 offset 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 suffer from out-of-cluster interference. The impact of these drawbacks can be reduced by having different static disjoint cooperation clusters on deferent frequency subcarriers, by increasing the cluster size and serving 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 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 affect the same users. This is very different from the disjointness mentioned above because each base station cooperates with all of its neighbors and forms different cooperation clusters when serving different 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.

## II. SYSTEM DESIGN

### 1)EXISTING SYSTEM:

The Internet of Things (IoT) is an emerging networking paradigm that enhances smart device communications through internet-enabled systems. Due to massive IoT device's connectivity with economic and greenhouse emission effects, energy efficiency poses critical concerns. 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 a tractable convex optimization problem and separated into inner and outer loop subproblems. The paper proposed a joint energy-efficient iterative algorithm, which utilizes successive convex approximation techniques and the 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.

### 2)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.

### 3) BLOCK DIAGRAM:

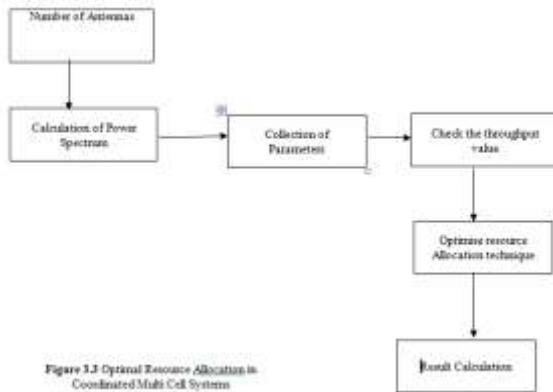


Figure 3.3 Optimal Resource Allocation in Coordinated Multi Cell System

## III. METHODOLOGY

### 1) 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 provides an optimization framework for downlink resource allocation in multi-cell scenarios with  $K_t$  multi-antenna transmitters, which have a total of  $N$  transmit antennas. There are  $K_r$  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

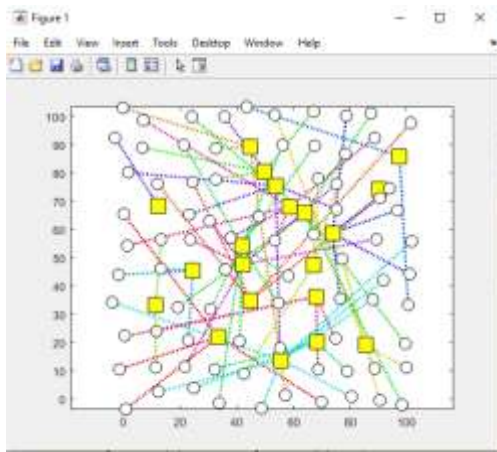
In Heterogeneous Networks, resources (both bandwidth and power) are apportioned by the Macro Base station to multiple User Equipment (UEs) to

provide the maximum possible data 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 the Particle Swarm Optimization (PSO) method. However, this project procures optimal solutions with a lesser number of iterations by properly choosing the 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 the social behavior of swarms. Typically, each particle has a driving velocity that is dictated by past actions and its neighbors. Slowly the particles disperse around, influenced by their counterparts and exploratory behavior. Over time the particles will 'fly' towards the better solutions by using the 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. 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 the solution, whereas a channel response matrix  $H$  with  $K$  rows and  $N$  columns contains the channel gain.

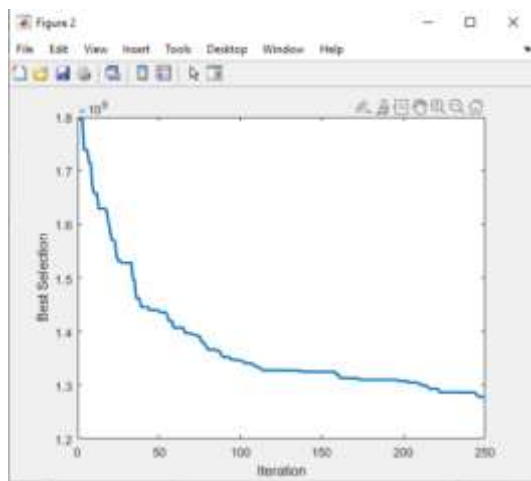
## IV. RESULTS AND DISCUSSION

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



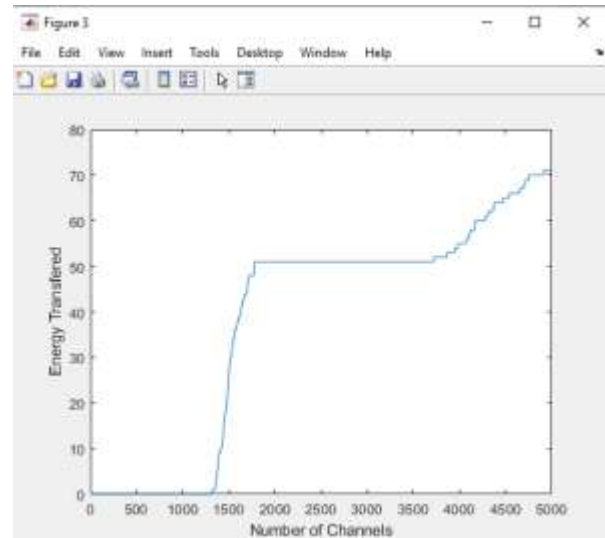
**Figure 5.1 Assignment of Base Station for specific users with respect to Particle Swarm Optimization**

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



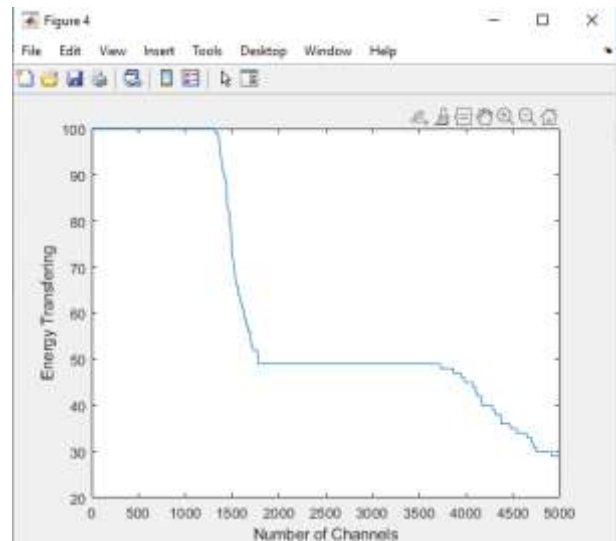
**Figure 5.2 Particle swarm best power selection for individual base station**

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



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

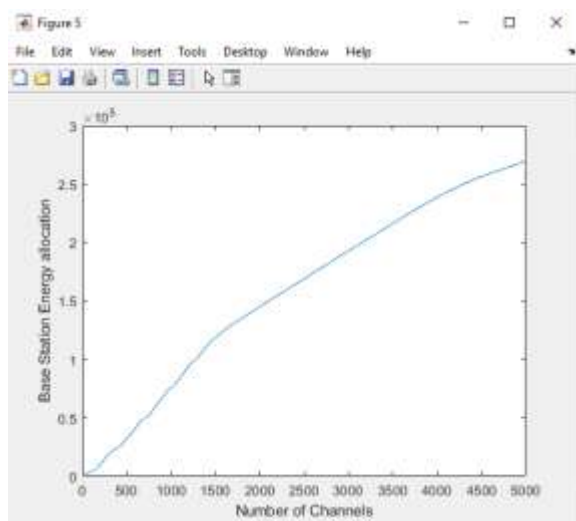
The Current energy transferring level for individual iterations respective to number of channels has been simulated using Matlab programming and the result has been plotted shown in Figure 5.4.



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

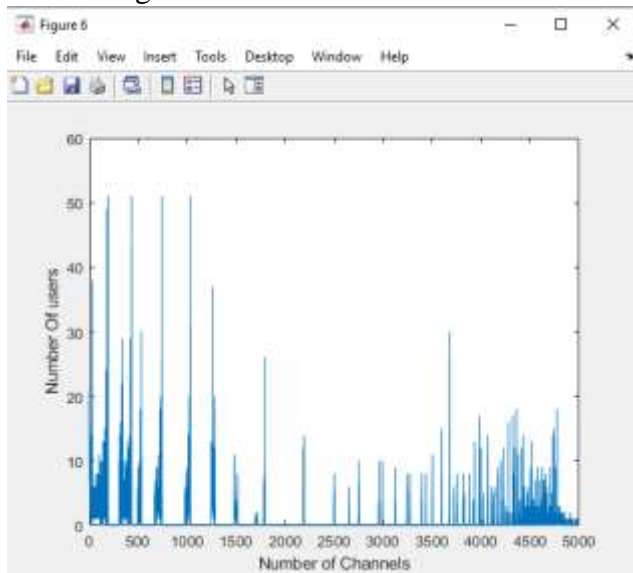
Total Energy allocation for the individual base station has been simulated using Matlab programming and the result has been plotted shown in Figure 5.5.





**Figure 5.5** Total Energy allocation for individual base station

The Total number of users involved in a specific number of channels has been simulated using Matlab programming and the result has been plotted shown in Figure 5.6.



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

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

Sl. No	Number of Channels	Energy Transferred(w)	Base Station	Number of Users
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

## V. CONCLUSION

The performance of multi-cell systems depends on 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.

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