İSTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

A GAME-THEORETIC APPROACH TO UPLINK POWER CONTROL IN CDMA NETWORKS

M.Sc. Thesis by
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Programme : Telecommunication Engineering

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CDMA AĞLARINDA YUKARI YÖNDEKİ GÜÇ KONTROLÜ İÇİN OYUN KURAMI YAKLAŞIMI

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FOREWORD

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ABBREVIATIONS

AWGN	: Additive White Gaussian Noise
BER	: Bit Error Rate
BS	: Base Station
CDMA	: Code-Division Multiple-Access
DCPC	: Distributed Constrained Power Control
DPC	: Distributed Power Control
DS	: Direct Sequence
DS-CDMA	: Direct-Sequence Code-Division Multiple-Access
DSSS	: Direct Sequence Spread Spectrum
FER	: Frame Error Rate
IEEE	: The Institute of Electrical and Electronics Engineers
MIMO	: Multiple-Input and Multiple-Output
MPA	: Minimum Power Assignment
MS	: Mobile Station
NGPC	: Non-cooperative Game-theoretic Power Control
OFDMA	: Orthogonal Frequency-Division Multiple Access
PB	: Power Balancing
PCB	: Power Control Bit
PN	: Pseudo Noise
QoS	: Quality-of-Service
RRM	: Radio Resource Management
SIR	: Signal-to-Interference Ratio
SNR	: Signal-to-Noise Ratio
SS	: Spread-Spectrum
SSMA	: Spread Spectrum Multiple Access
UMTS	: Universal Mobile Telecommunications System

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SUMMARY

In wireless communication networks, fundamental resources that are bandwidth (spectrum) and power are limited. For this reason, efficient use of these resources becomes important. Therefore, power control is an essential requirement for radio resource management in the design of wireless systems, especially in direct-sequence code-division multiple-access (DS-CDMA) systems. Since DS-CDMA system is interference-limited, when a user acts selfishly to improve its quality-of-service (QoS) requirements by increasing its individual transmit power at the uplink that causes unnecessary interference to other users in the cell. QoS depends on the signal-to-interference ratio (SIR) and achieving a high SIR requires a high transmit power, though, resulting in a lower bit-error rate (BER) and thus higher throughput. Additionally, increasing the transmit power of a user expedites its battery drain, which reduces the satisfaction of the mobile user. Hence, SIR and transmit power become valuable commodities, thus a wireless user prefers to obtain high SIR and to consume low energy. Finding a good balance between two conflicting objectives is the main focus of the power control component of radio resource management in CDMA networks. Power control has mainly used to reduce co-channel interference and to guarantee SIR, resulting better QoS.

In this thesis, one of the most common approaches to power control in wireless communication networks which is power balancing, also called SIR balancing is considered. Power balancing algorithms are simple and most of them can be implemented distributively, but have the disadvantage that convergence can be slow and it is guaranteed only if every mobile's target SIR is feasible.

In recent years, an alternative approach based on game theory has been used to study power control in data networks. In this thesis, the application of game theory for studying uplink power control in DS-CDMA network is considered. Power control problem is modeled as a *N*-person non-cooperative game in which each mobile user tries to maximize its own utility without any deal among the users. A utility function is defined for each user, which represents the user's choice with respect to the SIR and the transmitter power. For a proper utility function, it is shown that there exists an optimum operating point referred to as a "Nash equilibrium" that is unique.

Furthermore, power balancing algorithm and game theoretic approach to uplink power control were implemented and analyzed based on power versus number of iterations. A comparison of simulation results are carried out. The game theoretic power control algorithm was shown to give better results compared to SIR balancing power control algorithm.

CDMA AĞLARINDA YUKARI YÖNDEKİ GÜÇ KONTROLÜ İÇİN OYUN KURAMI YAKLAŞIMI

ÖZET

Kablosuz iletişim ağlarında temel kaynaklar olan bant genişliği (spektrum) ve güç sınırlıdır. Bu nedenle, bu kaynakların verimli kullanımı önem kazanmıştır. Bu yüzden DS-CDMA türü çoklu erişimin kullanıldığı sistemlerde telsiz kaynaklarının yönetiminde güç kontrolü önemli bir gerekliliktir. DS-CDMA sistemi girişim kısıtlı olduğundan dolayı, herhangi bir kullanıcı bencilce hareket ederek, kullanıcıdan erişim noktasına olan kendi iletim gücünü arttırarak, kendi servis kalitesini arttırılabilir. Ancak bu artış diğer kullanıcılara için istenmeyen girişime sebebiyet verir. Servis kalitesi, sinyal girişim oranına (SIR) bağlıdır ve yüksek SIR elde etmek için yüksek iletim gücüne ihtiyaç vardır, bununla beraber bit hata oranı (BER) düşmekte ve böylece daha yüksek bir veri aktarımı elde edilmektedir. Ayrıca, kullanıcının iletim gücünü arttırması, pil tüketimini hızlandırmakta bu da kullanıcının memnuniyetini azaltmaktadır. Bu sebeple, SIR ve iletim gücü değerlerinin mobil kullanıcılar için önem kazanmaya başlar ve kullanıcılar bir yandan yüksek SIR elde etmek isterken aynı zamanda düşük enerji tüketmek ister. Bu iki çelişen amaç arasında iyi bir denge kurmak, DS-CDMA ağlarında telsiz kaynaklarının yönetiminin bir parçası olan güç kontrolünün ana odak noktasıdır. Güç kontrolü çoğunlukla ortak kanal girişimini azaltmak ve SIR değerini garanti altına alarak daha iyi bir servis kalitesi elde etmek amacıyla kullanılır.

Bu tez çalışmasında, kablosuz haberleşme şebekelerinde güç kontrolü için en genel yaklaşımlardan biri olan güç dengeleme veya diğer adıyla SIR dengeleme yaklaşımı incelenmiştir. Güç dengeleme algoritmaları basit ve çoğu dağıtık olarak gerçekleştirilmektedir ancak yakınsama açısından oldukça yavaş olması dezavantajdır.

Son yıllarda, oyun teorisi alternatif bir yaklaşım olarak veri şebekelerinde güç kontrolü çalışmaları için kullanılmıştır. Bu tez çalışmasında, DS-CDMA sistemlerin yukarı yönde iletişimindeki güç kontrolü probleminin oyun teorisi yaklaşımıyla ele alınması incelenmiştir. Bu problem çok kullanıcılı ve kullanıcılar arasında herhangi bir işbirliğinin olmadığı ve her kullanıcının kendi kazancını maksimize etmeye çalıştığı *N*-oyunculu işbirliksiz bir oyun olarak modellenmiştir. Her kullanıcı için tanımlanan kazanç fonksiyonu, SIR ve iletim gücüne bağlı olarak kullanıcının tercihini gösterir. Her bir kullanıcı için enerji verimliliğine ve yüksek hizmet kalitesine teşvik edici kazanç fonksiyonları tanımlanmıştır. Kazanç fonksiyonuna bağlı olarak, belirtilen oyunda optimum çalışma noktası olarak ifade edilen bir adet "Nash dengesinin" var olduğu gösterilmiştir.

Bunun yanında, yukarı yöndeki güç kontrolü için güç dengeleme algoritması ve oyun kuramı yaklaşımı uygulanmış ve güce karşılık gelen iterasyon sayısı baz alınarak analiz edilmiştir. Benzetim sonuçları karşılaştırılmış ve oyun kuramı yaklaşımının, güç dengeleme algoritmasından daha iyi sonuçlar verdiği gösterilmiştir.

1. INTRODUCTION

In recent years, the cellular communications market has exploded and the demand for wireless services increases due to the requirements for higher data rates and QoS requirements. For this reason, a major challenge in the operation of wireless communications systems is the efficient use of radio resources, and this have necessitated careful management of common radio resources. Radio resource management (RRM) is the process of optimizing the transmit power, spectrum, and channel allocation to maximize the number of users provisioned a minimum QoS for a specific set of base stations and coverage area.

Spread spectrum multiple access (SSMA) communication, DS-CDMA, is the rapidly advancing methods in personal communications industry. Their greater bandwidth efficiency and multiple access capabilities put them on top of the technology. In CDMA systems, RRM is mainly a task of interference management. Interference management is accomplished through four basic functions: power control, base station assignment (hand-off), admission control, and load control [1].

Power control is one of the most important issues in a DS-CDMA system because it has a significant impact on both performance and capacity. For this reason, power control in wireless networks has been studied since 1970s. Over the last 15 years, enormous growth of cellular networks and considerable investigation for cellular network power control has produced many results in modeling, analysis and design techniques [2].

1.1 Review of the Literature on Power Control Techniques

One of the most common approaches to power control in wireless communication networks is power balancing, similarly called SIR balancing. Aein [3] originally derived the power balancing solution for satellite communications. He investigated power assignment to mitigate co-channel interference in both noiseless and noisy satellite systems to reach a common SIR for satellite systems. By using the Perron-Frobenius theorem [4] the existence and uniqueness of a feasible power vector associated with the eigenvalue of the link gain matrix is established. Based on Aein's work, Meyerhoff [5] proposed an iterative procedure for finding power levels and demonstrated that maximizing a common SIR is equivalent to maximizing minimum SIR for overall users. Nettleton and Alavi [6] extended the concept of SIR-balancing to Spread Spectrum (SS) systems without background noise. Hence, it has been adopted for wireless communication systems. The above concepts were further enhanced when applied to narrowband systems by Zander [7]. In his study, the optimum power assignment is proposed for minimizing the outage probability (the probability that a mobile has SIR of less than the minimum threshold) in terms of finding the maximum achievable SIR that all links can simultaneously reach. Furthermore, he refined his work by including nonzero background noise and showed that the same SIR can be achieved if there are no constraints on transmitter power [8-9]. Grandhi et al. [10] studied distributed power control for cellular radio systems by following the same approach as Zander [7,8]. Grandhi et al. [11] also developed centralized power control algorithm.

Foschini and Miljanic [12] proposed the first Distributed Power Control (DPC) algorithm. In this study, the aim was optimizing the power control by minimizing the total power. The only variable was transmit power constrained by fixed target SIR.

The DPC algorithm has been extensively studied, with results on existence of feasible solution and convergence to optimal solution characterized through several approaches [13-17].

SIR balancing algorithms are simple and most can be implemented distributively, but have the disadvantage that convergence can be slow and is guaranteed only if every mobile's target SIR is feasible. Convergence time is the key concern for distributed algorithms because if the situation is stationary then the convergence time does not matter. However if the average network condition is changing, then convergence time for the power control algorithm has to be faster than the rate of change. To address the convergence issue, a number of power control algorithms have been developed [15-17].

An asynchronous version of Foschini and Miljanic's algorithm [12] was proved to be geometrically convergent by Mitra [18]. An extension of the DPC algorithm to include background noise and maximum power constraints called Distributed Constrained Power Control (DCPC) was presented in [19].

The Minimum Power Assignment (MPA) problem, which includes base station selection for finding the lowest possible uplink vector, has independently been solved by Yates and Huang [20]. In [21], Yates gives a general framework with sufficient conditions for proving convergence of power control algorithms. An algorithm exhibiting such conditions is referred to as a standard power control algorithm.

The power control problems discussed above can also be reformulated and analyzed to propose an alternative framework via a game-theoretic approach. In [22], the authors provide some motivation for using game theory to study communication systems and in particular power control. With fixed SIR targets, the authors in [23] show that the classical power control algorithms can be modeled as non-cooperative games. On the other hand, when variable SIR are considered, individual utility functions can be assigned to Mobile Station's (MS) measuring transmission power they consume and the SIR that they attain. Each MS is then assumed to decide on his own transmission power level so as to maximize his utility.

There have been a variety of selfish utility functions which have been used in non-cooperative power control formulations. For example, in [24], utility is defined for single carrier systems such that each MS seeks to minimize the distance between its achieved SIR and its specified target. In [25], linear and exponential functions based on carrier SIR are proposed for multi-carrier systems. To take transmit power consumption also into account in [26], the authors introduce a utility function defined as the ratio of throughput to transmit power.

A pricing scheme is first studied in [27] using sub-modular games. It has been discussed in [26,28,29] that a non-cooperative power control game with a pricing scheme is superior to one without pricing, in terms of fairness and convergence. Similar approaches are taken in [30-32] for different utility functions. In [33,34] a cost function is introduced as the difference between the pricing of transmission power and utility functions.

1.2 Purpose of Thesis

There are several power control techniques and algorithms in both forward and reverse channels to adjust the power levels. On the other hand, the application of mathematical analysis for power control in distributed wireless networks have limited success because of the complexity of mobility and traffic models, dynamic topology. In recent years, an alternative approach based on game theory has been used to study power control in data networks. Game theory offers a substantial amount of tools that may be used effectively in modeling the interaction among individual nodes in wireless networks.

The main objective of this study is to compare game theoretical approaches of power control in DS-CDMA networks to the classical methods. Power control problem is modeled as an N-person non-cooperative game in which each mobile user tries to maximize its own utility without any deal among the users. A utility function is defined for each user which represents the user's choice with respect to SIR and the transmitter power. This thesis follows the work by Ji and Huang [25]. According to [25], it is shown that there exists an optimum operating point referred to as a "Nash equilibrium" that is unique.

Additionally, the convergence speed of power control is one of the most important criteria to determine whether the algorithm is better. To see the robustness of the proposed model, one of the most common approaches to power control in wireless communication networks which is power balancing, is considered. Power balancing algorithm and game theoretic approach to uplink power control algorithm were implemented and analyzed based on power versus number of iterations. Simulation results are compared.

The outline of the thesis is organized as follows. In Chapter 2, basic concepts of power control in wireless data communications systems and classification of power control methods are studied. Moreover, the power balancing algorithm which is proposed by Foschini and Miljanic [12] is described in detail. In Chapter 3, basic concepts of the game theory and game theoretic approaches to wireless communications and networking problems are discussed. In Chapter 4, non-cooperative uplink power control game are constructed based on Ji and Huang's work [25] for DS-CDMA systems. The equilibrium and its properties are presented. In Chapter 5, power balancing algorithm and non-cooperative game-theoretic approach to uplink power control algorithm for DS-CDMA systems are simulated and results are compared with different scenarios. Finally, in Chapter 6, conclusions and final recommendations are given.

2. BACKGROUND KNOWLEDGE AND RELATED WORKS

An effective implementation of different power control algorithms in cellular radio communication systems can offer a significant improvement in the QoS to all the users. Choice of an appropriate power control algorithm is quite important, as it should aim at increasing the overall efficiency of the system. In order to understand the basic concepts of uplink power control problem for CDMA systems, background knowledge of power control techniques must be known. For this reason, general information about power control in DS-CDMA systems, the types of uplink power control processes and the classification of power control techniques are given in this chapter.

Furthermore, one of the earliest works on decentralized power control algorithm for wireless data networks that was proposed by Foschini and Miljanic [12] will be considered in more detail. Finally, general information about the proposed system is given at the end of the chapter.

2.1 Power Control in DS-CDMA Systems

In wireless DS-CDMA systems, multiple users are allowed to use the same transmission frequencies at the same time with different codes. Hence, in these DS-CDMA systems, power control allows users to share resources of the system equally among the users. Number of users that can be supported in CDMA system is a measure of capacity of that system. The capacity enhancement can be achieved by properly managing the transmitters' power levels. A non-orthogonal CDMA scheme also requires power control in the uplink to compensate for the near-far effect [35]. For simplicity, the near-far problem is a condition in which a strong signal captures a receiver making it impossible for the receiver to detect a weaker signal. If power control is not used, all the mobile users transmit signals to the base station with the same power without considering the distance from the base station. However, mobile users that are close to base station cause to large interference to the others that are further located from the base station as shown in Figure 2.1. Hence, power control is used to equalize the received powers from all of the users.

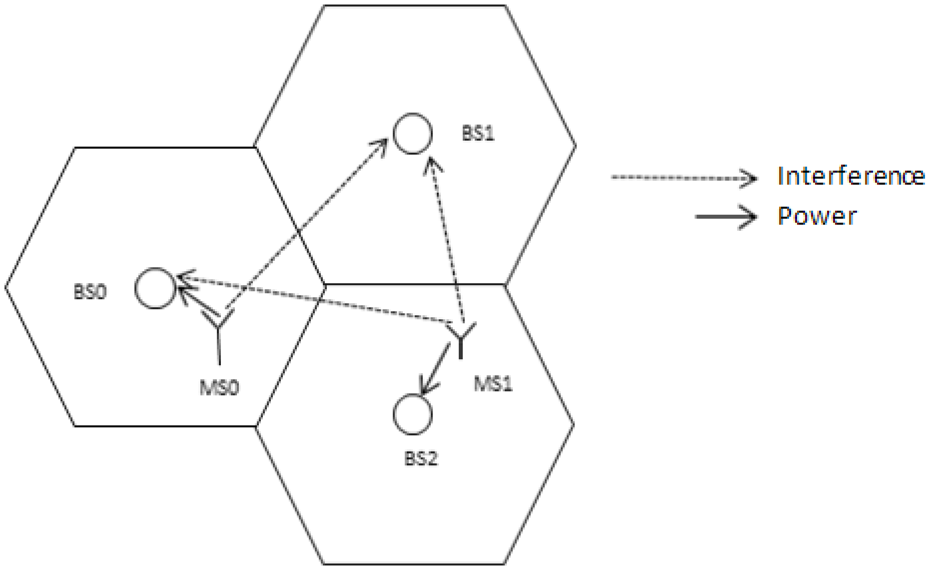

Figure 2.1 : An example of a multi-cellular network and uplink transmission

Therefore, transmission powers represent a significant role in the design of wireless networks. In cellular networks, power control can be used for three major purposes [2]:

- Interference management: Well-defined power control is essential for interference-limited systems like DS-CDMA. In DS-CDMA systems, it is not easy to find perfect orthogonality between code sequences so the signals starts interfere with each other. Power control helps to avoid these interference effects [2].
- Energy management: Mobile users access a wireless system through the air interface and they transmit information expending battery energy. Typically, a user desire to achieve a high quality of reception and expend a small amount of energy at the same time. For this reason, power control is used for energy conservation by minimizing overall energy consumption [2].
- Connectivity management: Even if there is not signal interference or energy limitation, the receiver still needs a minimum level of received signal because of uncertainty and time-variation of wireless channels. Power control helps maintain logical connectivity [2].

Power control techniques can be divided into two part that are;

- Power control for reverse (uplink) link from mobile station (MS) to base station (BS).
- Power control for forward (downlink) link from base BS to MS.

Many schemes are suggested for power control in uplink channel, which generally offer a strategy for transmit power of users to optimize interference and battery life while maintaining data rates required for QoS. In many formulations, uplink problems are more difficult to solve because of BS power consumption is less important in comparison to MS power consumption. Besides, downlink intra-cell interference is much smaller than uplink intra-cell interference.

Uplink power control achieves the above functions through the following mechanisms:

- Open-loop power control
- Closed-loop power control, which can be sub-divided into
    - Closed outer-loop power control
    - Closed inner-loop power control

2.1.1 Open-loop power control

The simplest form of power control is open-loop power control. In this process, the transceiver simply estimates the transmission signal strength by measuring the received power level of the pilot signal from the BS in the downlink and adjusts its transmission power level in a way that is inversely proportional to the pilot signal power level. Here, the received signal strength is an indicator of path loss. Such a scheme is fairly slow and can be inaccurate when multipath fading dominates performance. Furthermore, the losses on uplink and downlink are not symmetric because Rayleigh fading is frequency-selective so this method gives the power values only in average. However, if fast power control is unnecessary and multipath fading can be averaged out, the approach may provide sufficient performance.

2.1.2 Closed-loop power control

A more complicated form of power control is closed-loop power control. In this process, the quality measurements are done on the other end of the connection, at the base station, and results are then sent back to mobile’s transmitter so that it can adjust its transmitted power.

In closed-loop power control, the receiver feeds back either channel quality information or direct power control commands, depending on the amount of feedback that can be supported. Power control can be based on various channel quality indicators, but the most common is received signal strength. In IS-95, cdma2000, and Universal Mobile Telecommunications System (UMTS) which are used in commercial DS-CDMA systems, the base station receiver measures the received signal power, compares the value to a stored threshold, and sends back a single bit every T_{pc} seconds (T_{pc} = 1.25 ms in IS-95 and *cdma2000* and half that length in UMTS) to indicate whether the mobile should increase or decrease power by some fixed amount. This fixed amount of the transmission power adjusted by one power control message as the power control step size [46]. According to update strategies, power control algorithms can be classified as those where the transmit power step size is fixed (fixed step size algorithm) and those where the transmit power step size is made adaptive to the channel variation. Power control command in fixed step size algorithms is a simple 1-bit command and easier to implement. On the other hand, a specific example of the adaptive step size approach is the inverse update algorithm, which increases and decreases the mobile users' transmit power by the actual difference between the received signal power and desired received signal power. Thus, closed-loop power control rapidly adjusts the transmission power of the mobile user in order to make the received SIR of the user equal to the required amount of it [1].

As described, closed-loop power control attempts to adjust the transmit power to achieve a target received signal power threshold. However, the needed threshold is dependent on system loading, fading statistics, the number of resolvable multipath components, and other factors. For this reason, the form of power control that we just described is often divided into two loops. In this two-loop arrangement, the loop that adjusts transmit power is called *inner-loop power control* and a second loop that adjusts the received power threshold is called *outer-loop power control*.

The outer-loop power control sets the target SIR value used in the closed-loop power control, where the SIR value is also the value at the reception instance. Feedback information sent by the base station controller is used to adjust the target SIR value, where the feedback information is made based on the Frame Error Rate (FER).

The inner loop closed loop power control adjusts the transmitted power in order to keep the received SIR (SIRest) equal to given target (SIRtarget). The SIRtarget is fixed according to the received FER. If SIRest > SIRtarget then inner loop algorithm generates a Power Control Bit (PCB) command to transmit is “0”, requesting a transmit power decrease. Otherwise, PCB command to transmit is “1”, requesting a transmit power increase by a fixed step size algorithm.

Figure 2.2 depicts the practical model of inner-loop and outer-loop power controls.

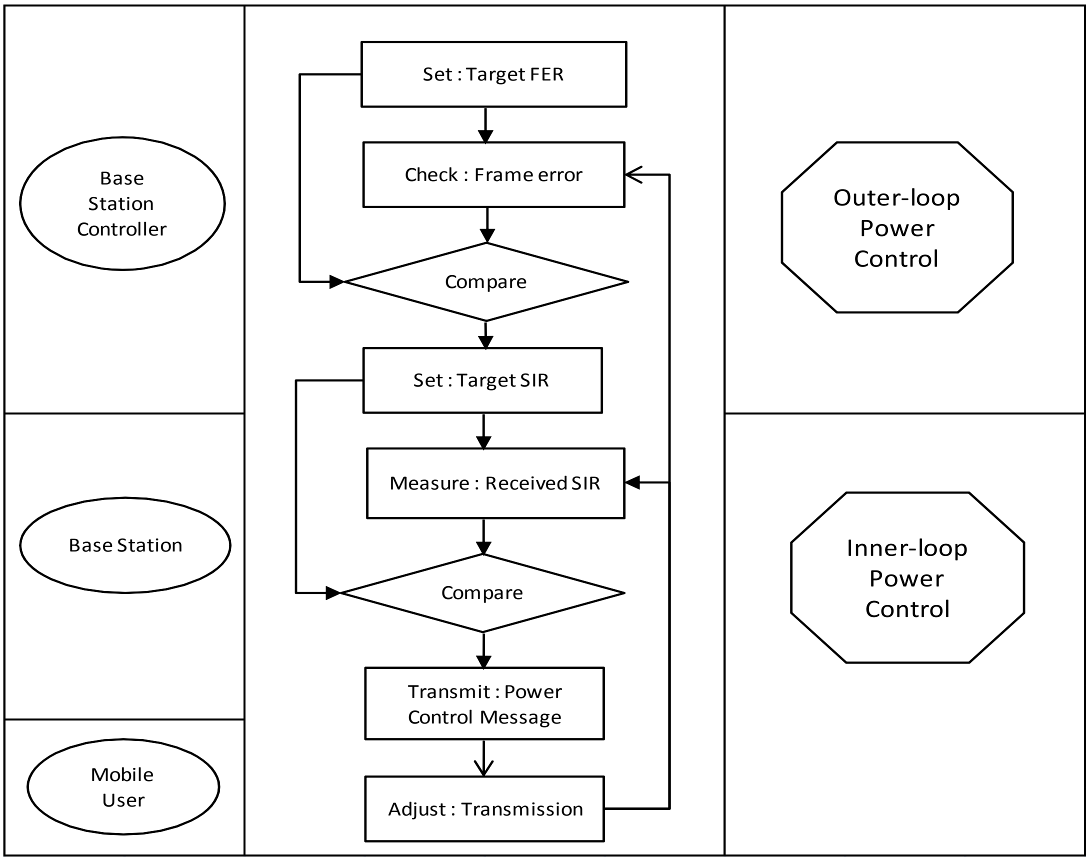

Figure 2.2 : Practical power control model

To understand the effect that power control has on system performance, let us consider three specific channel scenarios: an AWGN channel, a slow fading channel relative to the power control update rate, and a fast fading channel.

Figure 2.3 shows the plots of the channel, transmit power, and received power for an AWGN channel with 500-Hz power control feedback. We assume that the receiver simply transmits a single bit indicating that the transmitter should increase or decrease the transmit power by 0.5dB step size and ignore measurement or feedback errors. The receiver threshold is assumed to be unity. The top plot in Figure 2.3

shows the channel, which is assumed to be constant. The transmit power (and thus the received power) simply oscillates around the threshold value since the power control dictates that the power must increase or decrease every T_{pc} seconds. Fast power control is unnecessary in this case, but it does not deteriorate performance [1].

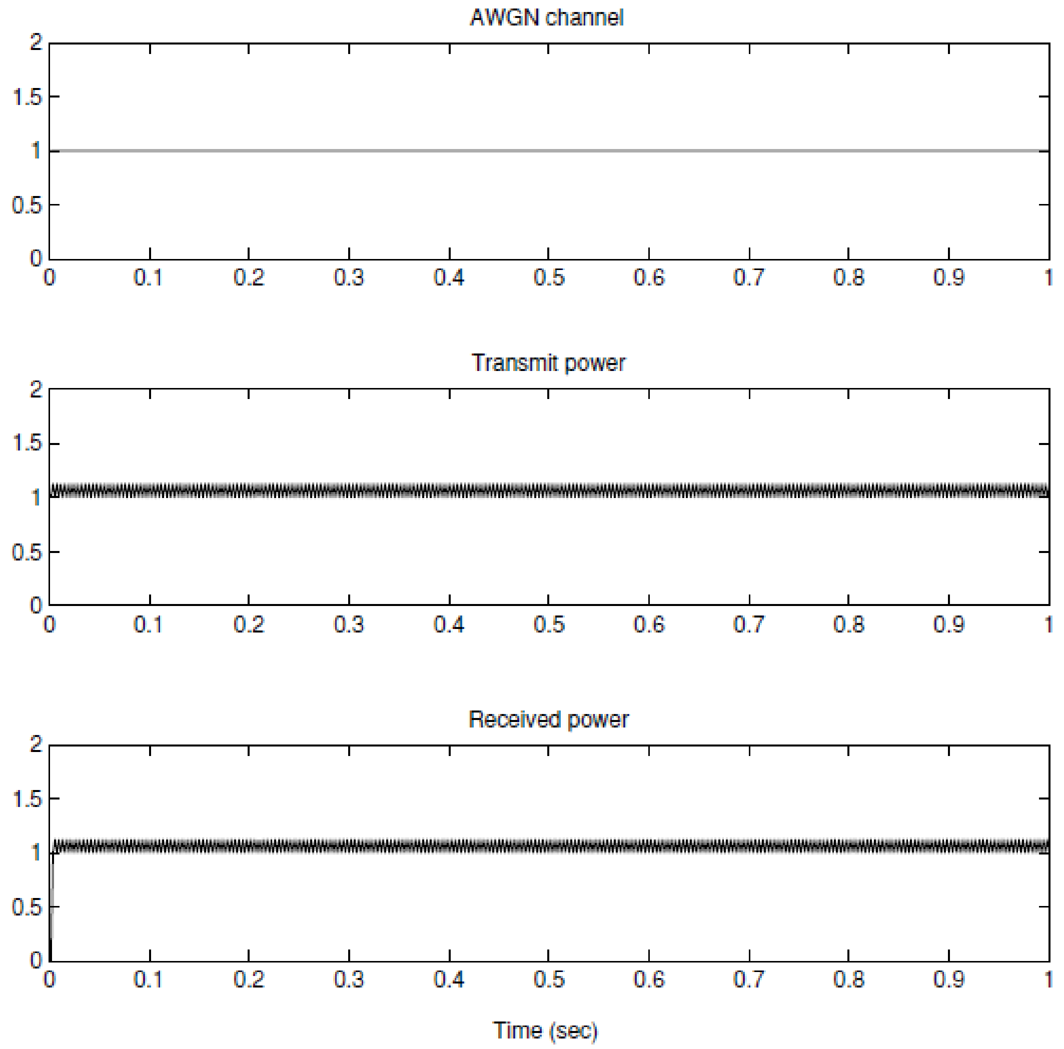

Figure 2.3 : Illustration of power control in an AWGN channel [1].

Now let us consider a slow fading channel (5Hz Rayleigh fading) as shown in Figure 2.4. The top plot shows the envelope of the channel, which demonstrates that the channel varies slowly with time. Due to the power control, the received power is nearly constant. This dramatically improves performance since it essentially converts a Rayleigh fading channel into an AWGN channel. The transmit power essentially inverts the fading channel. Because the transmitter must provide large increases in power to prevent deep fades, the average power is largely increased. This is illustrated in the middle plot of Figure 2.4 and is termed a power rise at the transmitter. This increase in the average transmit power consume at the overall system gain achieved by power control [1].

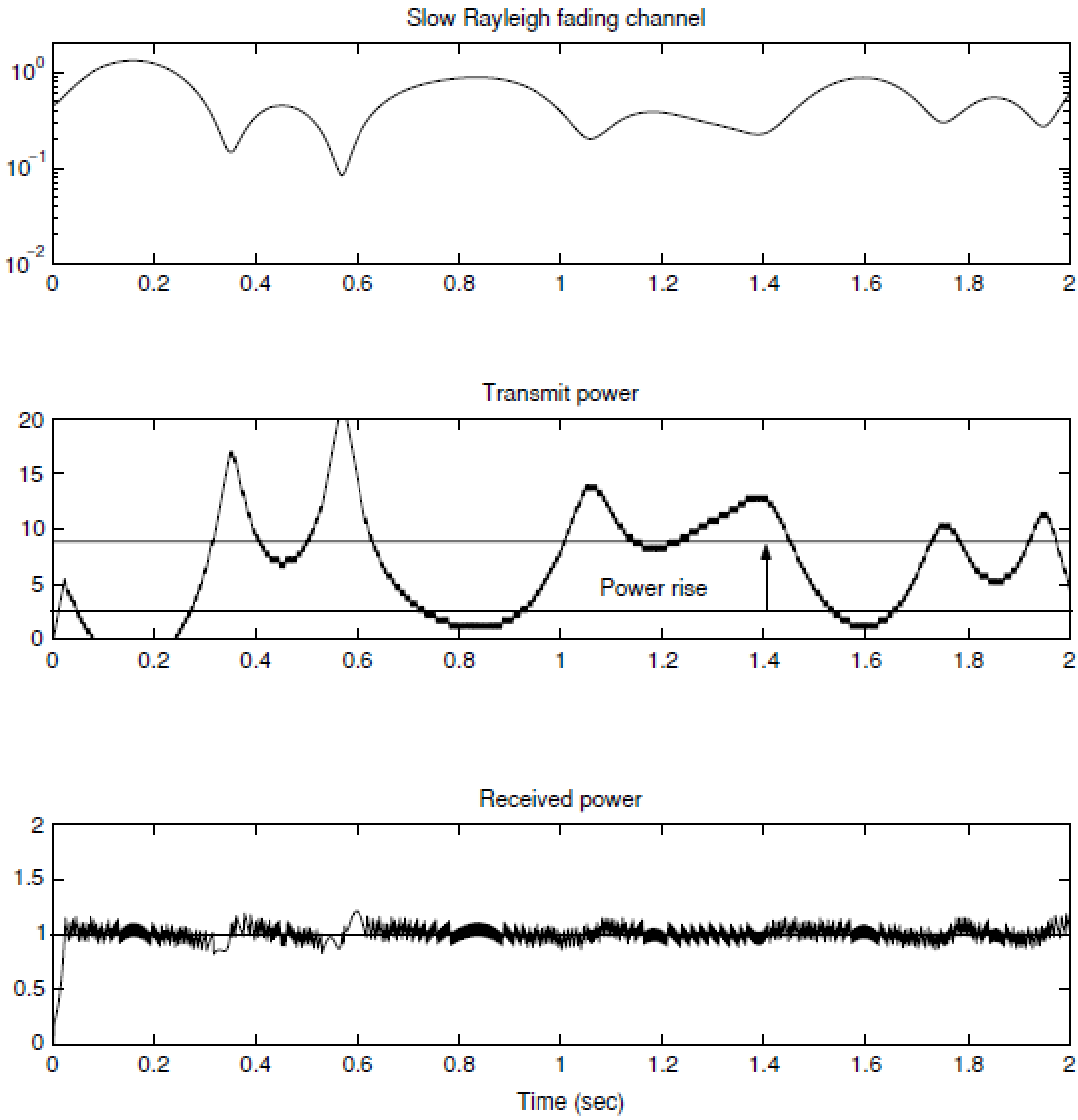

Figure 2.4 : Illustration of power control in slow fading channel [1].

The last example that is examined is a fast (150Hz) fading channel shown in Figure 2.5. The fading rate is significantly faster than what the power control can accommodate. Thus, the received signal varies wildly and power control is ineffective. In fact, it is worse than ineffective since, in addition to providing no benefit at the receiver, it also results in an increase in the average transmit power [1].

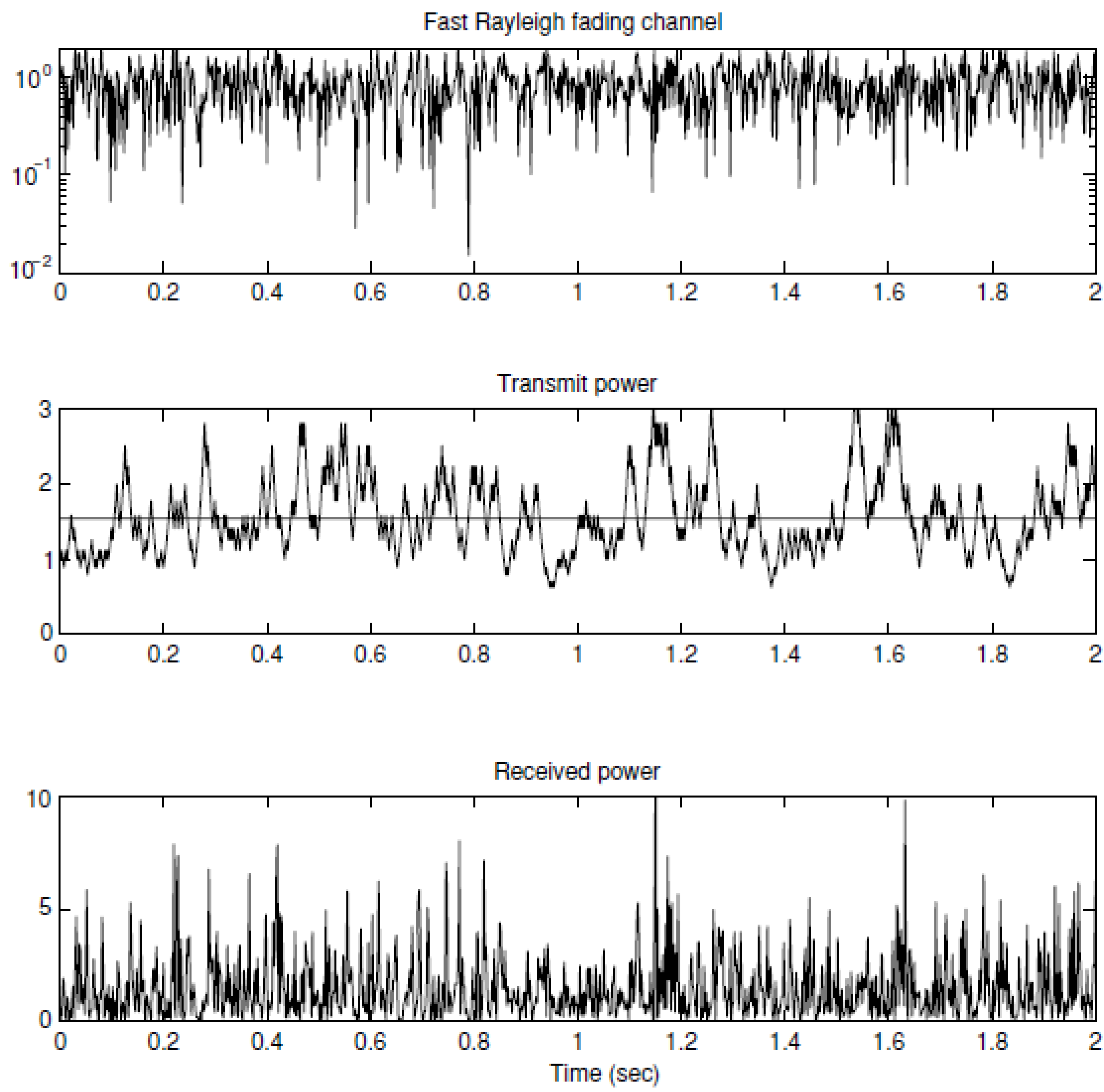

Figure 2.5 : Illustration of power control in fast fading [1].

2.2 Classification of Power Control Techniques

According to what is measured to determine power control command, power control techniques can be classified into three categories [35]:

- Strength-based
- SIR-based
- BER-based

<u>In strength based schemes</u>: the strength of a signal arriving at the base station from a mobile is measured to determine whether it is higher or lower than the desired strength. The command is sent to increase and decrease transmits power [35].

In SIR-based schemes: the measured quantity is the SIR where interference consists of channel noise and multi-user interference. Strength-based power control is easier to implement but SIR-based power control reflects better system performance such as QoS and capacity. A serious problem associated with SIR-based power control is the potential to get positive feedback to endanger the stability of the system. Positive feedback arises in a situation when one mobile under instructions from the base station has to raise its transmit power in order to deliver SIR to the base station but increase in its power also results in an increase in interference to other mobiles so that these other mobiles are then forced to also increase their power, etc. In the case of N mobiles in the system, this becomes a typical non-cooperative N-person game problem [25].

In BER-based schemes: BER is defined as an average number of erroneous bits compared to the original sequence of bits. If the signal and interference powers are constant, the BER will be a function of the SIR, and in this case the QoS equivalent. However, in reality SIR is time-variant and thus the average SIR will not correspond to the average BER. In this case the BER is a better quality measure. Since the channel coding is implemented in every practical system, power control can be based on the average number of erroneous frames as well [35].

2.3 Power Balancing (PB) Algorithm

Much of the study on cellular network power control started with a series of results that solve the basic problem formulation where transmit power is the only variable, constrained by fixed target SIR, and optimized to minimize the total power. Foschini and Miljanic [12] was the first who proposed distributed power balancing (PB) algorithm. Before explaining their PB algorithm let us consider basic system model.

2.3.1 Notation

The following notation are used throughout this thesis [2]. Vectors are denoted in bold small letter, e.g., $\mathbf{z}$, with their i^{th}component denoted by z_i. Matrices are denoted by bold capitalized letters, e.g., $\mathbf{Z}$, with Z_{ij} denoting the $\{i,j\}^{\text{th}}$ component. Vector division $\mathbf{x}/\mathbf{y}$ and multiplication $\mathbf{xy}$ are considered component-wise, and vector inequalities denoted by $\geq$ and $\leq$ are component-wise inequalities. We use $\mathbf{D}(\mathbf{x})$ to denote a diagonal matrix whose diagonal elements are the corresponding components from vector $\mathbf{x}$.

2.3.2 Basic system model

Assume that there are N MSs establish links to K BSs and a common radio channel. For simplicity, it could be considered fixed base station assignment which means each MS is served by one of the K BS, thereby establishing N logical links. Let a_i denote the receiving BS for link i.

Let C_i denote the set of links whose transmitted power appear as interference to link i. In a non-ortogonal uplink, such as CDMA, transmitted power from all links appear as interference so we set $C_i = \{j \mid j \neq i\}$. Let $h_{a_j,j}$ denote the path gain from MS on link j to its serving BS. Define $N \times N$ power-gain matrix **G** by

$$G_{ij} = \left|h_{a_j,j}\right|^2 \quad \textbf{(2.1)}$$

Which represents the power gain from MS on link j to the receiving BS on link i. Let define a normalized gain matrix **F** where

$$F_{ij} = \begin{cases} G_{ij}/G_{ii} & \text{if } j \in \mathrm{C}_i \\ 0 & \text{if } j \notin \mathrm{C}_i \end{cases} \quad \textbf{(2.2)}$$

Let $\boldsymbol{D_h} = diag(G_{11}, \dots, G_{NN})$ be the diagonal matrix representing direct link channel gains, which depend on **h**.

Let p_j be the transmit signal power on link j at its serving BS a_j. The receiver on link j receives the signal at the power of $\left|h_{a_j,j}\right|^2 p_j = G_{jj}p_j$. If $j \in C_i$, this transmission will appear as interference to link i with a power of $\left|h_{a_j,j}\right|^2 p_j = G_{ij}p_j$. The total interference and noise at the BS serving MS i is given by

$$q_i = \sum_{j \in C_i} G_{ij}p_j + n_i = \sum_{j=1}^{M} F_{ij}G_{jj}p_j + n_i, \quad \textbf{(2.3)}$$

where $n_i \geq 0$ is the power of noise other than interference from other links.

Let γ_i be the SIR achieved by link i. It is given by

$$SIR_i = \frac{G_{ii}p_i}{q_i} = \frac{G_{ii}p_i}{\sum_{j \in C_i} G_{ij}p_j + n_i} \quad \textbf{(2.4)}$$

According to their PB algorithm, each user proceeds iteratively to reset its power level to what it needs to be to have acceptable performance. Yet the other users are following the same algorithm and, therefore, are changing their power levels. Foschini and Miljanic have shown that this iterative approach results in exponentially fast convergence to a power vector $\mathbf{p}$, such a vector exists for the overall system. PB algorithm was used to satisfy fixed target SIR constraints γ and MS transmit power are varies to minimize the total power. The power control problem can be shown as follows [2]:

Minimize $\sum_i p_i$

Subject to $SIR_i(\mathbf{p}) \geq \gamma_i^{tar}$ $, \forall i,$ **(2.5)**

Variables $\mathbf{p}$

$SIR_i(\mathbf{p}) \geq \gamma_i^{tar}$, where γ_i^{tar} is the target SIR of i^{th} user. To select a power level for the MS i if all other powers are kept fixed is calculated as follows:

$$p_i \geq \gamma_i^{tar} \left(\sum_{j=1, j\neq i}^{N} \frac{G_{ij}}{G_{ii}} p_j + \frac{n_i}{G_{ii}}\right) \quad \textbf{(2.6)}$$

Each link is assumed to have a minimum SIR requirement $\gamma_i > 0$ that represents the i^{th} user's QoS requirements. This constraint can be represented in matrix form as:

$$(\mathbf{I} - \mathbf{D}(\boldsymbol{\gamma})\mathbf{F})\mathbf{p} \geq \mathbf{u} \text{ with } \mathbf{p} > 0 \quad \textbf{(2.7)}$$

where $\mathbf{p} = (p_1, p_2, \dots, p_n)^{\mathrm{T}}$ is the column vector of transmitter powers, $\mathbf{I}$ is identity matrix, $\mathbf{D}(\boldsymbol{\gamma})$ is diagonal matrix whose diagonal elements are corresponding components from vector $\boldsymbol{\gamma}$, and

$$\mathbf{u} = \left(\frac{\gamma_1 n_1}{G_{11}}, \frac{\gamma_2 n_2}{G_{22}}, \dots, \frac{\gamma_N n_N}{G_{NN}},\right)^{\mathrm{T}}, \quad \textbf{(2.8)}$$

is the column vector of noise powers scaled by the SIR constraints and channel gain, and $\mathbf{D}(\boldsymbol{\gamma})\mathbf{F}$ is a matrix has non-negative elements. Let $\rho(\mathbf{D}(\boldsymbol{\gamma})\mathbf{F})$ be the Perron-Frobenius eigenvalue of $\mathbf{D}(\boldsymbol{\gamma})\mathbf{F}$, then according to Perron-Frobenius theorem [4] we have the following equivalent statements

1. $\rho(\mathbf{D}(\boldsymbol{\gamma})\mathbf{F}) < 1$
2. There exists a vector $\mathbf{p} > 0$ such that $(\mathbf{I} - \mathbf{D}(\boldsymbol{\gamma})\mathbf{F})\mathbf{p} \geq \mathrm{u}$
3. $(\mathbf{I} - \mathbf{D}(\boldsymbol{\gamma})\mathbf{F})^{-1}$ exists and is positive componentwise.

If the above conditions hold we have that $\mathbf{p}^* = (\mathbf{I} - \mathbf{D}(\boldsymbol{\gamma})\mathbf{F})^{-1}$ is the Pareto optimal [39] (this phrase will be explained in Chapter 3) solution to (2.7). Hence, if the SIR requirements for all users can be met simultaneously the best power allocation is $\mathbf{p}^*$, and iterative PB algorithm converges to a power-minimum solution.

$$\mathbf{p}[\mathrm{t}+1] = \mathbf{D}(\gamma)\mathbf{F}\mathbf{p}[\mathrm{t}] + \mathbf{u} \quad \textbf{(2.9)}$$

Furthermore, the above iterative algorithm is simplified into the following distributed version by [12].

Algorithm 2.1 (Power Balancing Algorithm [12])

$$p_i[t+1] = \frac{\gamma_i^{tar}}{SIR_i[t]} p_i[t], \ \forall i \quad \textbf{(2.10)}$$

where $t = 1, 2, \ldots$, and $SIR_i[t]$ is the received SIR at the t^{th} iteration. The update in (2.10) is distributed as each user only needs to monitor its individual received *SIR* and can update by (2.10) independently. Each user i increases its power when its $SIR_i[t]$ is below γ_i and decreases otherwise. Assuming the fixed SIR targets γ is feasible, the PB algorithm converges to a power-minimum solution.

2.4 Non-Cooperative Game-Theoretic Power Control (NGPC) Algorithm

The power control problem with fixed SIRs discussed in PB conventional approach can be reformulated and analyzed within the game-theoretic framework, where each MS decide dynamically on his own transmission power level so as to minimize it.

The power control problem in PB algorithm can be shown as equation (2.5). First it is observed that although power control decisions are coupled due to the SIR constraints, total power can be computed so as to minimize the power of each MS separately while satisfying the SIR constraints. Therefore, problem (2.14) can be viewed as a non-cooperative game: the utilities are each assigned to one MS, and maximization subject to SIR constraints is performed by each MS.

In this thesis, we follow up on uplink power control game, based on Ji and Huang's work [25], in DS-CDMA systems, which is an application of Direct Sequence Spread Spectrum (DSSS) communication systems [43]. For this reason, before constructing of the game model, basic concepts of game theory will be reviewed in the following chapter.

3. GAME THEORY FOR WIRELESS SYSTEMS

There are many sources books and papers about game theory. Many of them adopt economic perspective or a mathematical perspective. Game theory has been used in economics, in order to model competition between companies. In the last three decades, game theory has not been applied to only economics but also have found application in sociology, psychology, political science, law and biology as shown in Figure 3.1. Moreover, it has drawn the attention of computer scientist recently because of its use in artificial intelligence and networks [36]. During last years, game theory has also been applied to some communications and networking problems such as power control, spectrum allocation, call admission control, medium access control and routing in a competitive environment [37].

Game theory is the study of the interaction of autonomous agents with conflicting interests. In the context of wireless networks, it should be clarified how game theory could be helpful. In a modern wireless network, each node running a distributed protocol has to make its own decisions instead of being controlled by a central authority. They are the setting parameters relying on information from other nodes. Therefore, these nodes are autonomous agents, making decisions about transmit power, packet forwarding, and so on [38]. In making these decisions, nodes may behave selfishly, looking out for only their own user's interests. In a final analysis, nodes may harm the overall network performance for other users. For this reason, the application of game theory could be useful, if it is a tool for analyzing the interaction of decision makers with conflicting objectives. Therefore, game formulations are used, and a stable solution for the players is obtained through the concept of equilibrium [39].

Having shown that game theory may be an appropriate model to analyze uplink power control problem, a brief overview of some of the most important concepts of game theory will be reviewed in this chapter. For further details, the reader is prompted at [38,40].

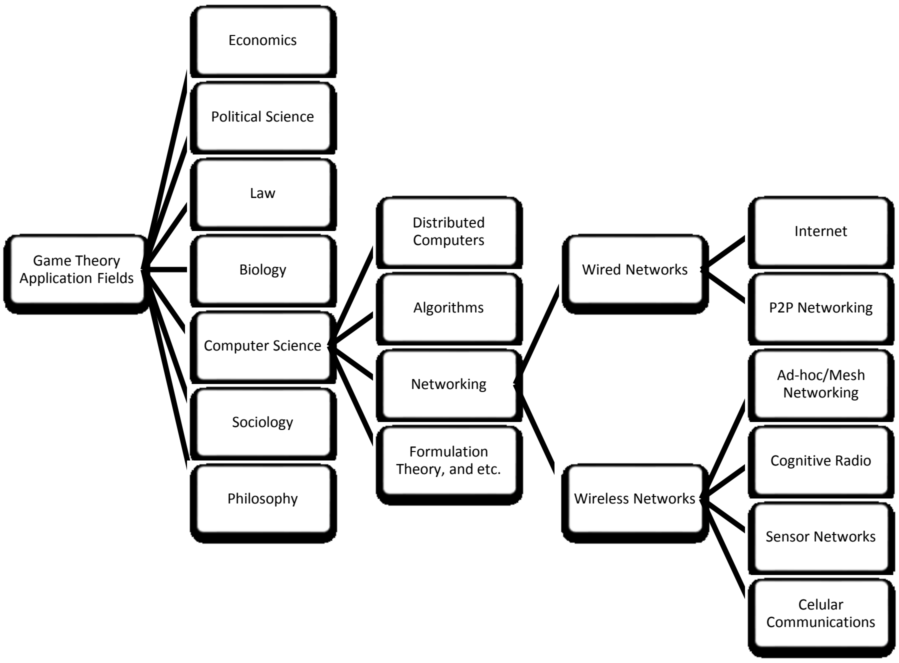

Figure 3.1 : Game Theory Application Fields

3.1 Game Theory Concepts

3.1.1 What is game theory

Game theory is a mathematical formalism for understanding, designing and predicting the outcomes of games, where a game is characterized by the number of intelligent players interacting with each other [40]. Before we start, we should define a "game" clearly. A game is characterized by a number of players (at least 2 or more). It is assumed to be intelligent and rational. In a game each player interacts with the other players by selecting various actions, based on their assigned preferences. The games we are going to study in this thesis have the following crucial elements: a set of players, a set of actions, a set of preferences and payoff functions;

- Players: there is a finite set of players who are the decision makers (who may be people, groups of people, or in a wireless system the players are most often the nodes of the network).
- Actions: The actions are the alternatives available to each player. This set of actions is finite. In a wireless system, actions may include the choice of coding rate, protocol, flow control parameter, transmit power level, etc.
- Preferences and payoff functions: at the end of each game stage, each player receives a numerical payoff, which is decided by the all players' actions. A

preference relationship for each player represents that player's evaluation of all possible outcomes. We can represent the preferences by a payoff function or equivalently, utility function, which assigns a number to each possible outcome. This means that higher utilities representing more desirable outcomes. We are trying to maximize the utility function u_i for the i^{th} of player. In the wireless scenario, a player might prefer outcomes that yield higher signal-to-noise ratios (SNRs), lower BERs, more robust network connectivity, and lower power expenditure, although in many practical situations these goals will be in conflict.

3.1.2 Nash equilibrium

Nash equilibrium is one of the most basic concepts in game theory. It is named after John Nash, a mathematician born in the early part of this century. Nash equilibrium occurs when the strategies of the various players are best responses to each other. Equivalently, Nash equilibrium is a joint strategy where no player can increase her utility by unilaterally deviating.

Formally, according to strategies of players, the action profile a^* is a Nash equilibrium if, for every player i and every action a_i of player i, a^* is at least as good according to player i's preferences as the action profile (a_i, a^*_{-i}) in which player i chooses a_i while every other player j chooses a_j^* (a_{-i} be a strategy profile of all players except for player i). Equivalently, for every player i,

$$u_i(a_i^*, a^*_{-i}) \geq u_i(a_i, a^*_{-i}) \quad \textbf{(3.1)}$$

for every action a_i of player i, where u_i is payoff function that represents player i's preferences.

3.1.3 Pareto efficiency

According to player's strategies, an action profile is Pareto optimal if some players must be hurt in order to improve the payoff of other players.

Formally, an action profile a^* is said to be Pareto optimal if and only if there exists no other action profile $\acute{a}$, such that if for some i,

$$u_i(\acute{a}_\iota, a^*_{-i}) \geq u_i(a_i^*, a^*_{-i}) \quad \textbf{(3.2)}$$

3.1.4 Game types

In game theory, games are classified into two categories: non-cooperative and cooperative games. In non-cooperative games, the players are autonomous that making their decisions independently and compete with each other. On the other hand, players can negotiate with others and form joint strategies in cooperative games [40]. Often it is assumed that communication among players is allowed in cooperative games, but not in non-cooperative ones. In this thesis, we will focus on non-cooperative games.

3.2 Game Theory in Wireless Networks via a Layered Perspective

We can solve a variety of communications and networking problems by considering a game theoretic approach. It is presented in a layered perspective in Table 3.1, emphasizing on which game theory could be effectively applied.

Table 3.1 : Layered presentation of game theory applications [39].

OSI Layer	Application Field	Specific Application
Physical	Power control	Power control for CDMA Power control for Orthogonal Frequency-Division Multiple Access (OFDMA)
	Spectrum allocation	Spectrum Sharing
	MIMO systems	Power management in Multiple-Input and Multiple-Output (MIMO)
Data link	Medium access control	Access to slotted Aloha
Network	Routing	Routing and forwarding
Transport	Call admission control	Request distribution among providers
		Call acceptance based on provider and customer context
	Load control	Termination of sessions based on provider and customer context
	Cell selection	Inter-cell and intra-cell games
	Flow Control	Managing the rate of data transmission between nodes

So as to make a game-theoretic approach to a certain problem about communications and networking, the key points of the game must be defined well such as the players of the game, available actions to them, their objectives, whether there exists an equilibrium point, and the following set of questions would be considered: Who are the players of the game? What actions are available to the players? What are the players' objectives? Does equilibrium exist for the given game? Is it unique? Is there a dynamic process by which players update their strategies? If so, what is it and is it guaranteed to converge?

To be brief, Table 3.2 summarizes the key elements of the games which are used to solve communications and networking problems.

Table 3.2 : Collective information on game theory applications [39].

Specific application	Objective	Game type	Players
Power control for CDMA	Set transmission power in order to maximize SIR with minimum interference	Non-Cooperative/ Repeated games	Users/Terminals
Power control for OFDMA	Minimize the overall transmitted power under rate and power constraints	Non-Cooperative	Users/Terminals
Spectrum sharing	Distribute spectrum to maximize utilization and fairness	Cooperative/ Non-Cooperative	Users/Terminals, Service providers
Power management in MIMO	Power allocation in links to minimize interference	Non-Cooperative	Links
Access to slotted Aloha	Model random access to slotted Aloha to minimize collisions.	Non-Cooperative	Users/Terminals
Routing and forwarding	Decide if a packet from another node should be forwarded or not. Choose the optimal path.	Non-Cooperative	Users/Terminals
Call acceptance admission	Decide if acceptance of a service request would be useful for players-Selection of optimal service provider	Non-Cooperative	Service provider-User/ terminal
Inter-cell and intra-cell games	Decide which cell can best fulfill service requirements	Non-Cooperative	Service provider-User/ terminal, service provider
Termination of sessions	Decide if termination of an ongoing session would be beneficial for players	Non-Cooperative	Service provider-User/ terminal
Managing the rate of data transmission	Maximizes average throughput by minimizing the average delay	Markov/Repeated	Users/Terminals

4. NON-COOPERATIVE UPLINK POWER CONTROL GAMES IN DS-CDMA SYSTEMS

In wireless communication systems, power and bandwidth (spectrum) are two fundamental and conflicting resources. Efficient use of these resources in the operation of wireless communication systems is challenging. For this reason, power control is an essential requirement for radio resource management in the design of DS-CDMA systems. Since the DS-CDMA system is interference-limited, when a user acts selfishly to improve its QoS requirements by increasing its individual transmit power at the uplink, unnecessary interference to other users in the cell is generated. QoS depends on SIR, and achieving a high SIR requires a high transmit power, resulting in a lower BER and thus higher throughput. However, increasing the transmit power of a user expedites the battery drain which effectively reduces the satisfaction of the mobile user. Hence, SIR and transmit power become valuable commodities. A wireless user prefers to obtain high SIR and to consume low energy. Finding a good balance between two conflicting objectives is the primary focus of the power control component of radio resource management in DS-CDMA networks. Power control has mainly used to reduce co-channel interference and to guarantee SIR, resulting better QoS.

The application of mathematical analysis to wireless networks has limited success because of the complexity of mobility and traffic models, dynamic topology. In recent years, an alternative approach that is game theory has been used to implement power control in data networks. The objective of uplink power control studied in this thesis is to provide each user adequate signal quality without causing unnecessary interference to other users by a game–theoretic approach. Game theory is a branch of mathematics and is a powerful tool for analyzing resource conflicts, or more generally, optimization problems with multiple conflicting objective functions, comes up at this point [41].

Power control can be centralized or distributed. In this thesis, distributed power control is considered in which individual users, who are selfish, make their decisions independently instead of being controlled by a central authority.

Furthermore, the application of game theory for studying uplink power control in DS-CDMA networks is proposed. Power control problem is modeled as an *N*-person non-cooperative game in which each mobile user tries to maximize its own utility without any deal among the users. Service preferences for each user are represented by a utility function. A utility function is defined for each user, which represents the user's choice with respect to SIR and the transmitter power. It indicates the level of users' satisfaction. For this reason, we first identify the preference relations that are specific to our problem and then describe a utility function that satisfies this structure. Determination of utility functions will be considered further based on [25]. Before this, the following properties, which make this problem appropriate for a game model should be considered [38].

- Each player's utility is a function of its own transmits power level and its SIR. Additionally, each player's SIR is a function of its own transmit power and the transmit powers of the other players in the cell.
- If a player increases its power level, this will increase its own SIR, but will decrease the SIRs of all other players.
- For a fixed SIR, the players would prefer to low power levels rather than higher ones. This will help players to conserve power and extend their battery life when possible.
- For a fixed power level, players will prefer higher SIR values to lower SIR values. In this way, players want the best possible channel conditions for a given expenditure of power.

According to these properties, the uplink power control problem in a single-cell CDMA wireless data system with *N* users in which each user maximizing its own utility by adjusting its transmit power is considered. In this chapter, two main assumptions will be made about the utility function based on [25]. Under the two assumptions, it is shown that there exists an optimum operating point referred to as a "Nash equilibrium" that is unique.

4.1 System Model

In our game model, $G = \left(\{\mathcal{N}, \{\mathbf{P_j}\}, \{u_j(.)\}\}\right)$ denote the non-cooperative power control game. Players, $\mathcal{N} = \{1, \dots, N\}$, are mobile users in the cell. $\mathbf{P_j}$ is the strategy set which represents actions that can be taken by player j with the objective of maximizing its utility $u_j(.)$. Each player chooses a power level $p_j \in \mathbf{P_j}$. Preferences of each user are represented by a utility function. Utility is defined as a measure of satisfaction experienced by a user using a service. For this reason, we first identify the preference relations that are specific to our problem and then describe a utility function that satisfies this structure.

It is necessary to find a power vector, $\mathbf{p} = (p_1, \dots, p_N)$ which is a Nash equilibrium of the non-cooperative power control game. The Nash equilibrium is a joint strategy where no player can increase her utility by unilaterally deviating [40]. Mathematically we can represent a Nash equilibrium as a power vector $\mathbf{p}$ such that $u_i(\mathbf{p}) \geq u_i(\acute{\mathbf{p}}_i, \mathbf{p}_{-i}), \ \forall \acute{p}_i \in S_i, \ i \in 1,2, \dots, K,$ where $\mathbf{p}_{-i}$ is a power vector that contains the powers of all the users except the i^{th} user.

Theorem 4.1: There exists a unique Nash equilibrium to the non-cooperative power games [26].

The proof of the above theorem follows from the fact that the utility function is quasi-concave and the use of Debreu's theorem [42].

Another underlying definition is Pareto efficiency. A strategy profile is called Pareto efficient if it is not possible to make an improvement in the utility of any player without harming another user. Nash equilibrium point might be more than one in some game examples but Pareto efficient point is the only one if exists [5, 26].

In this thesis, the simple *N*-user DS-CDMA model is used as shown Figure 4.1. To generate Pseudo Noise (PN)-sequences [43], linear feedback shift register method is chosen because of its simplicity. It is assumed that there are *N* co-channel users and *M* fixed base stations and a common radio channel. For simplicity, it is considered that interference source for the user is only the users in the same cell not the other base stations' users.

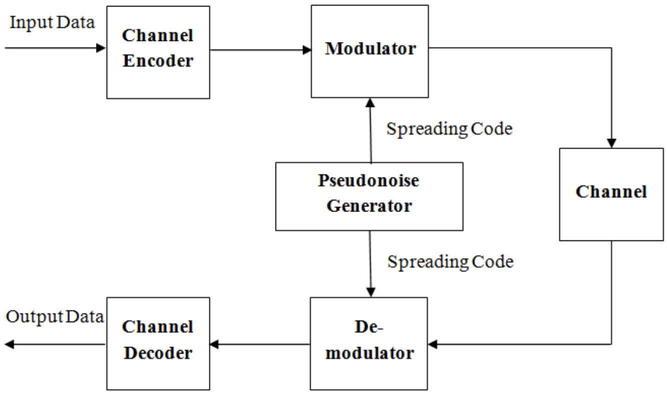

Figure 4.1 : DS-CDMA system model [43].

Let p_j denotes transmit power level of mobile j. In general, we have the notation $h_{a_j,j}$ for the path gain of terminal j to base station a_j. However, in this work, we assume that there is only one base station. Therefore, the notation to a use single subscript so that h_i is the path gain from terminal i to the system base station is simplified. At the base station the received signal power of mobile j is $g_{jj}p_j$ and the interference received from all other mobiles is given by $\sum_{i\neq j} g_{ij}p_j + n_j$, where n_j denotes receiver noise power at base station. Power vector is defined with $N \times 1$ dimension, $\mathbf{p}$. Similarly, $\overline{\mathbf{p}_\mathrm{j}}$ denotes the vector obtained by deleting the j^{th} element from $\mathbf{p}$. In this problem formulation, the SIR of the j^{th} user at the base station, denoted by γ_j, where

$$\gamma_j = \frac{g_{jj}p_j}{\sum_{i\neq j} g_{ij}p_j + n_j} \qquad \textbf{(4.1)}$$

Considering the uplink power control for a single-cell CDMA system

$$g_{ij} := \begin{cases} h_j & j = i \\ h_i c_{ij}, & otherwise \end{cases} \qquad \textbf{(4.2)}$$

where c_{ij} is the code correlation coefficient for CDMA systems. Hence, the SIR of the j^{th} mobile at the base station is

$$\gamma_j = \frac{h_j p_j}{\sum_{i\neq j} h_i p_i c_{ij} + n_j} \qquad \textbf{(4.3)}$$

Define the SIR factor, denoted by $\mu_j(\overline{\mathbf{p}_{\mathrm{j}}})$, of the j^{th} user at the base station as [21]

$$\mu_j(\overline{\mathbf{p}_{\mathrm{j}}}) \triangleq \frac{h_j}{\sum_{i \neq j} h_j p_j c_{ij} + n_j}. \tag{4.4}$$

It can be obtained from (4.3) and (4.4) that

$$\gamma_j = \mu_j(\overline{\mathbf{p}_{\mathrm{j}}}) p_j \tag{4.5}$$

From the equation (4.5) we can easily see that there is linear relation between the SIR and SIR factor if all other users have fixed transmit power.

4.2 Non-Cooperative Uplink Power Control

In cellular radio networks, a user adjusts its transmitter power to obtain satisfactory QoS that depends on the SIR. When a user acts selfishly to improve its QoS requirements by increasing its individual transmit power, that causes unnecessary interference to other users in the cell. Additionally, increasing the transmit power of a user expedites the battery drain, which effectively reduces the satisfaction of the mobile user. Furthermore, a mobile user prefers to transmit less power for a given SIR, since power is a valuable commodity. On the other hand, for a fixed transmitter power, a user gives preference to increased SIR. This type of preference is represented by utility function $u_j(p_j,\gamma_j)$ for j^{th} user, is dependent on both its own transmit power and SIR. Based on these observations, the following assumptions can be made about utility function:

Assumption 1: For the j^{th} user, if the SIR were to be fixed, the utility function is a monotonically decreasing concave function of its transmitter power [25].

Assumption 2: For the j^{th} user, if the transmitter power were to be fixed, the utility function is monotonically increasing concave function of the SIR [25].

These assumptions are shown in the Figure 4.2.

Figure 4.2 : Utility function as functions of transmitter power and SIR.

The reason of the concavity in the first assumption is that the user needs to transmit more power in order to achieve its target SIR, though, after obtaining target SIR, transmitting more power will be unfavorable. Hence, perpendicular decrease occurs in the utility function of a user since less power consumption becomes valuable. The reason of second assumption concavity, when a user obtains its target SIR value, user becomes indifferent to further QoS improvement.

When taking first order partial derivate of utility function with respect to p_j, the new terms, named the shadow prices [44], are appeared as given in (4.6b) [25].

$$\left(\frac{\partial u_j}{\partial p_j}\right) = \frac{\partial u_j(p_j,\gamma_j)}{\partial p_j} + \frac{\partial u_j(p_j,\gamma_j)}{\partial \gamma_j}\frac{d\gamma_j}{dp_j}. \quad \textbf{(4.6a)}$$

$\frac{d\gamma_j}{dp_j} = \frac{\gamma_j}{p_j}$ and from the equation (4.5) $\frac{\gamma_j}{p_j} = \mu_j(\overline{\mathbf{p}_\mathrm{j}})$, so

$$\left(\frac{\partial u_j}{\partial p_j}\right) = \frac{\partial u_j(p_j,\gamma_j)}{\partial p_j} + \frac{\partial u_j(p_j,\gamma_j)}{\partial \gamma_j}\mu_j(\overline{\mathbf{p}_\mathrm{j}}). \quad \textbf{(4.6b)}$$

The terms appearing on the right hand side of (4.6b) are the users' marginal utility of transmit power, $\zeta_j(\mathbf{p})$ and marginal utility of transmit power SIR, $\xi_j(\mathbf{p})$, respectively.

$$\zeta_j(\mathbf{p}) \triangleq \frac{\partial u_j}{\partial p_j}, \quad \xi_j(\mathbf{p}) \triangleq \frac{\partial u_j}{\partial \gamma_j} \quad \textbf{(4.7)}$$

It is seen in the Figure 4.2, $\zeta_j(\mathbf{p})$ is always negative valued and $\xi_j(\mathbf{p})$ is always positive valued. The change of the marginal terms with respect to p_j is shown in Figure 4.3 [45].

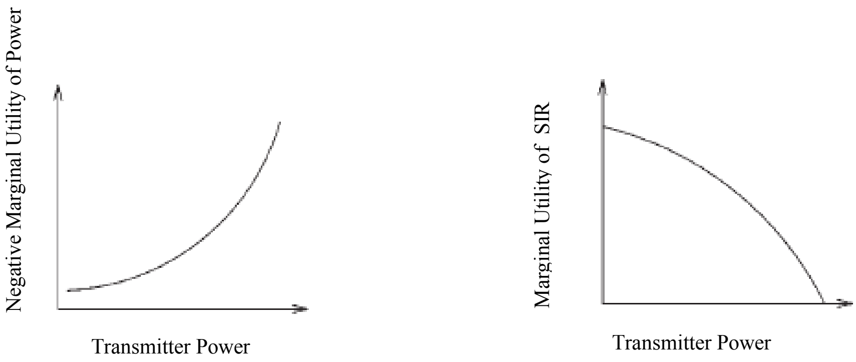

Figure 4.3 : Negative marginal utility of transmitter power -$\zeta_j(\mathbf{p})$ and marginal utility of SIR $\xi_j(\mathbf{p})$ with respect to p_j.

The main objective of the game theoretic approach to uplink power control is to find the point, the Nash equilibrium point, where all users' utility function maximizes with respect to transmitter power under the stated two assumptions. We can rewrite the equation (4.6b) in terms of shadow prices, to obtain [25]:

$$\left(\frac{\partial u_j}{\partial p_j}\right) = \zeta_j(\mathbf{p}) + \xi_j(\mathbf{p})\mu_j(\overline{\mathbf{p}}_j). \quad \textbf{(4.8)}$$

The non-cooperative equilibrium problem that we posed is reduced to a problem of finding a power vector. Let us define, the power vector with *N x 1* dimension $\mathbf{p}^*$, such that

$$\mathbf{p}^* \triangleq [p_1^*, p_2^*, \dots, p_N^*]^T, \quad \textbf{(4.9)}$$

where p_j^* is the optimal transmitter power for j^{th} user, $j = 1, 2, \dots N$, and vector $\overline{\mathbf{p}}_j^{\,*}$ with $(N-1)\ x\ 1$ dimension denote the vector obtained by deleting the j^{th} element.

When the derivative of the utility function with respect to transmitter power in equation (4.8) equals zero, the non-cooperative equilibrium satisfies following equation [25]:

$$\xi_j(\mathbf{p}^*)\mu_j(\overline{\mathbf{p}}_j^{\,*}) = -\zeta_j(\mathbf{p}^*) \quad \textbf{(4.10)}$$

The right hand side of (4.10) is monotonically increasing function of the transmitter power and the left hand side of (4.10) is monotonically decreasing function of the transmitter power. This can be easily seen in the Figure 4.3. Hence, there is a unique intersection point which is Nash equilibrium.

5. SIMULATION RESULTS

There are many aspects of measuring performance of a cellular system, especially with diverse QoS objectives. Moreover, network operators and subscribers may have different perspectives on which is the primary performance measure. Users would typically be interested of the availability of the service along with its quality (data rates, BERs etc.). Network operators seek to maximize revenue, considering network costs and performance of the system as a whole. In this thesis, we shall not consider economical aspects but focus on end-user performance measures.

For some SIR-target $\gamma^{tar} > 0$, if the obtained SIR_i is greater than γ^{tar}, the connection i is said to be supported, otherwise non-supported. In this thesis, we compare the performance analysis of uplink power control in DS-CDMA systems via Power Balancing (PB) and Non-cooperative Game-Theoretic Power Control (NGPC) algorithms. In this chapter, these two iterative power control algorithms are compared through different simulation scenarios on the basis of performance metric related to the rate of convergence.

To illustrate the advantages of the proposed NGPC algorithm based on [25], it is compared with the PB algorithm results. The performance analysis and comparison of the power control algorithm was carried out by using MATLAB as the simulation tool.

5.1 Power Balancing (PB) Algorithm

In simulation scenarios, a special case in which each base station will control the transmitter power of its carried users without taking into account interferences to those users who are assigned to its neighbor base stations is considered. This may correspond to the indoor wireless communication.

The PB algorithm iteratively updates power levels according to [12]

$$p_i[t+1] = \frac{\gamma_i^{tar}}{\gamma_i[t]} p_i[t]. \tag{5.1}$$

A 2-km-square cell with the base station centered at the origin and mobile locations were chosen randomly from a uniform distribution is considered. A typical cell is shown in Figure 5.1.

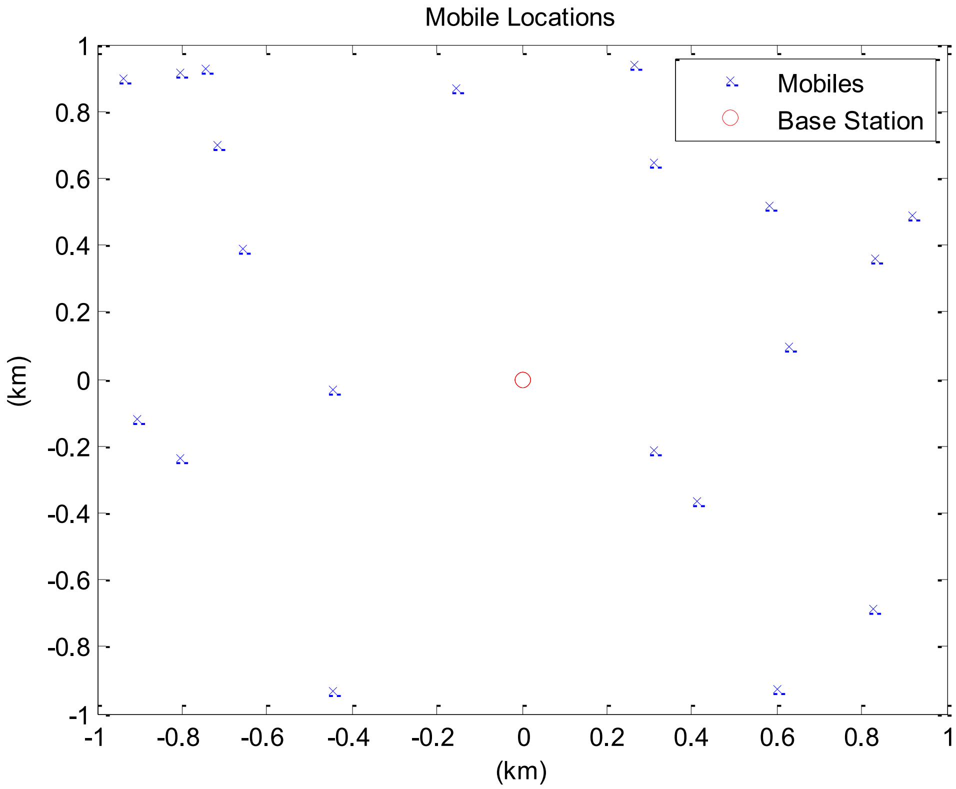

Figure 5.1 : Typical random distribution of 20 mobiles.

Mathematically, the transmitter powers depend on path gain, h_i, between transmitter and receiver. To calculate path gains, a simple propagation model is chosen in which all the path gains are deterministic functions of the distance between a terminal and base station,

$$h_i = \frac{A}{d_i^{\alpha}} \tag{5.2}$$

where d_i(km) is the distance between terminal i and its assigned base station. α is the propagation exponent could take numerical values between 3-5. α is assumed to be 4 in our simulations. A, is the proportionality constant and is taken as 10^{-11}, corresponding to a path loss of 110 dB at a distance of 1 km. Fast fading, shadow fading, and interference from adjacent cells is ignored.

In the first scenario, we considered 10 mobiles whose locations were chosen uniformly at random within the cell. Our initial power for all mobiles was assumed to be $p_i^0 = 2.22 \times 10^{-12}$ for the PB algorithm. The goal in the power control of wireless systems is to ensure that no mobile's SIR, γ_i, falls below its threshold γ_i^{tar} chosen to ensure adequate QoS, in other words to maintain $\gamma_i \geq \gamma_i^{tar}$. Morover, it is assumed that we want to achieve $\gamma_i^{tar} = 0.111$ via PB algorithm. Furthermore, power was limited to 600 mW, $0 \leq p_i \leq p_i^{max} = 600$ mW. Background receiver noise power within the user's bandwidth of $n_i = 10^{-25}$ mW is assumed in the simulations.

The pseudo-code for the simulation is as follows.

Pseudo-code

1. Initialize number of iterations.
2. Initialize number of mobiles.
3. Generate uniformly distributed vector of mobile-to-base station distance.
4. Generate vector of link gains from each mobile to the base station based on equation (5.2).
5. Allocate initial power for each mobile at the base station.
6. Initialize SIRtarget.
7. for $i = 1$ to iterations
    for $j = 1$ to mobiles
      • Calculate SIRobserved at each mobile
      • Compare SIRobserved with SIRtarget
      • if (SIRobserved < SIRtarget
          o Adjust (increase) power.
      • Else
          o Adjust (decrease) power.
    end
end
8. Plot power (mW) versus number of iterations.

5.1.1 Scenario I

In the first scenario, PB algorithm for DS-CDMA systems is analysed based on transmitter powers versus number of iterations. The corresponding equilibrium powers are also displayed in Figure 5.2. The mobiles those are closer to the base station expending smaller power as compared to mobiles further away from the base station. It is found that the PB algorithm converges to steady state values in about 70 iterations for 10 mobiles.

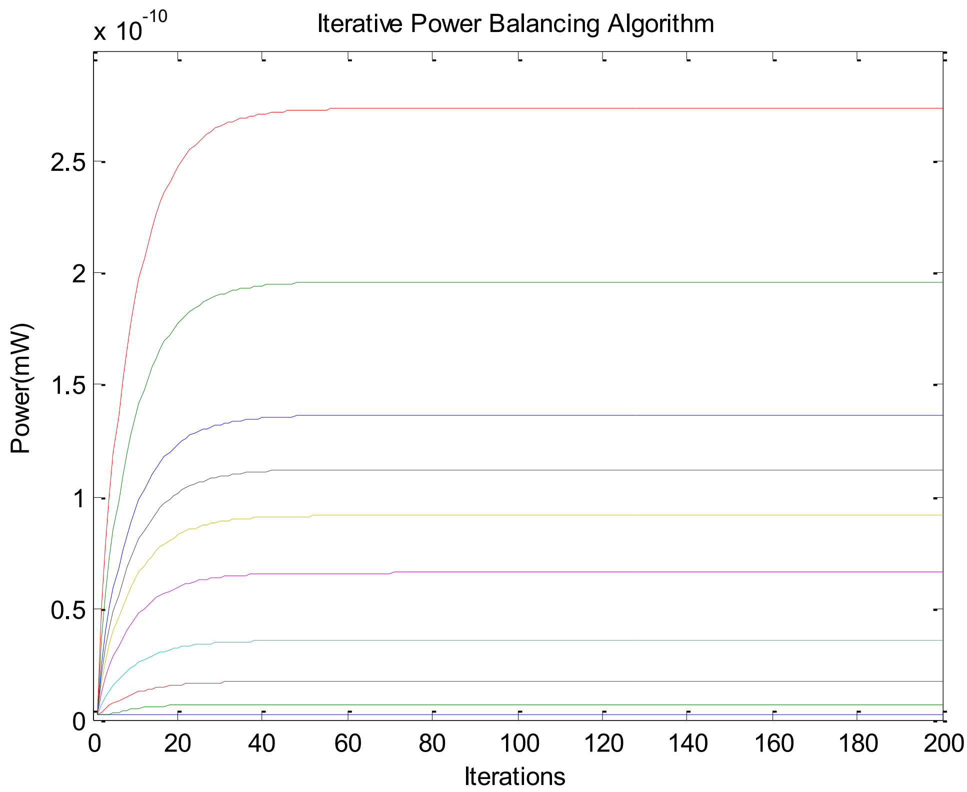

Figure 5.2 : PB algorithm for 10 users with $\gamma_i = 0.111$ for all mobiles.

The convergence of PB algorithm to the target SIR is depicted in Figure 5.3 for 10 users.

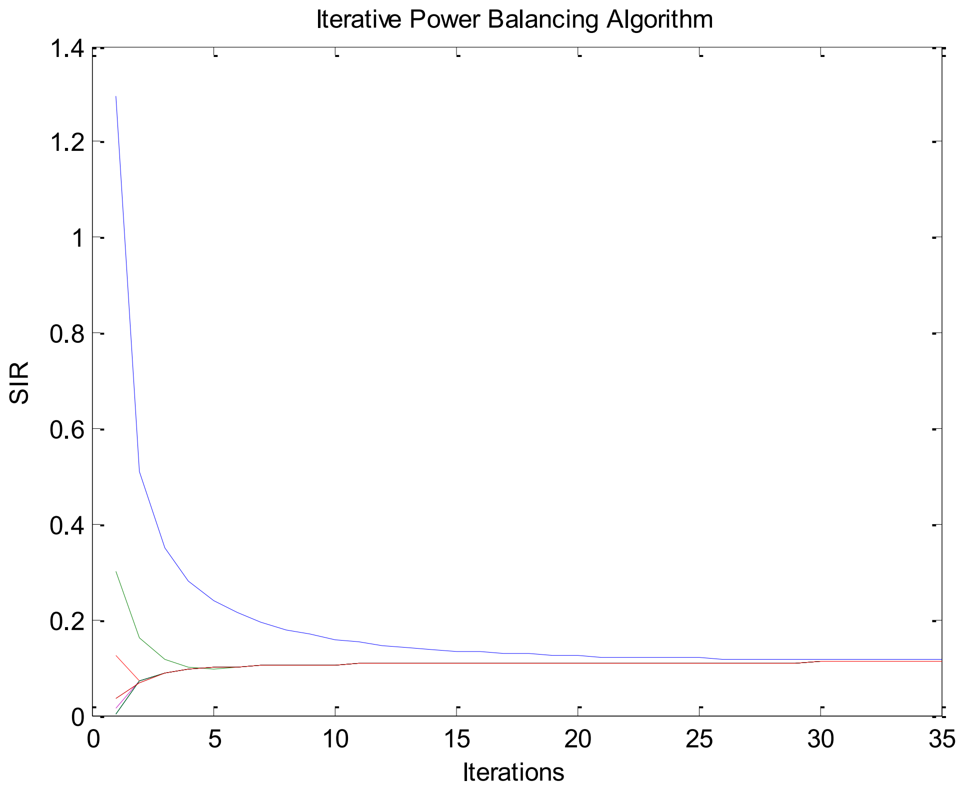

Figure 5.3 : The convergence to the target SIR for 10 users.

5.1.2 Scenario II

In the second scenario, the aim is to see the effect of increasing number of users in the cell. Figure 5.4 and Figure 5.5 show the transmitter power levels and the number of iterations when the number of mobiles are increased to 20, and 40. As the number of users increases, the number of iterations to reach steady state power levels also increases. It can be observed that the mobiles are reaching the steady state power levels in about 120 and 280 iterations, respectively. Besides, with a large number of users, the average power is also increased and the achievable SIRs are decreased to ~0.055, and ~0.0028, respectively as shown in Figure 5.6 and Figure 5.7.

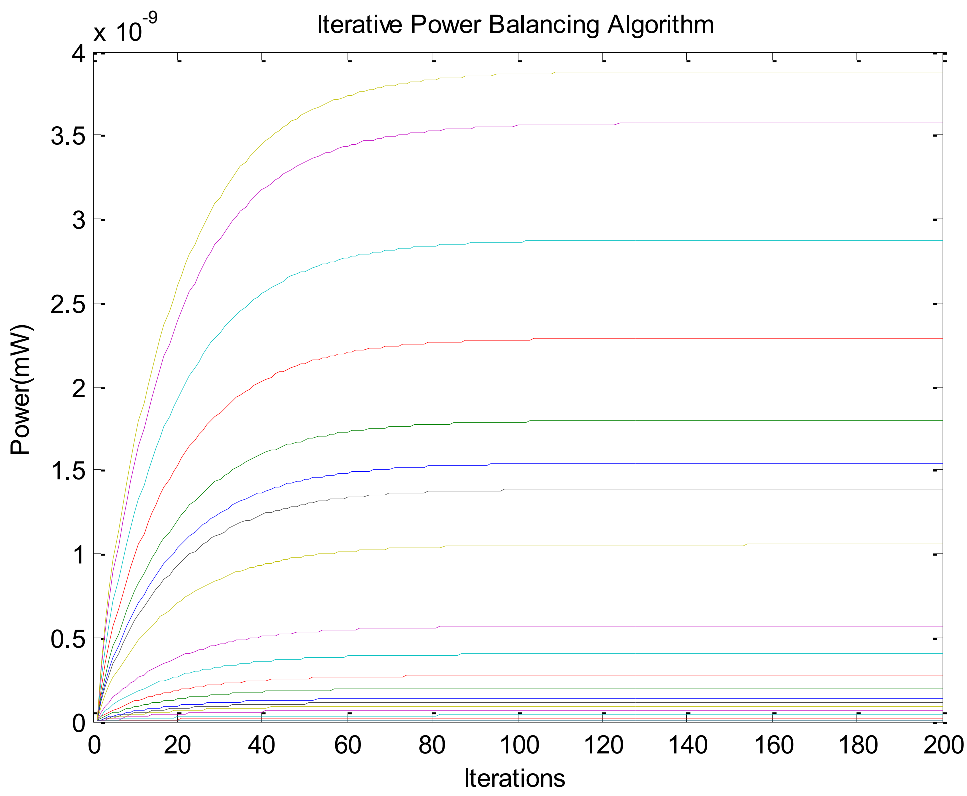

Figure 5.4 : Power Balancing algorithm for 20 users.

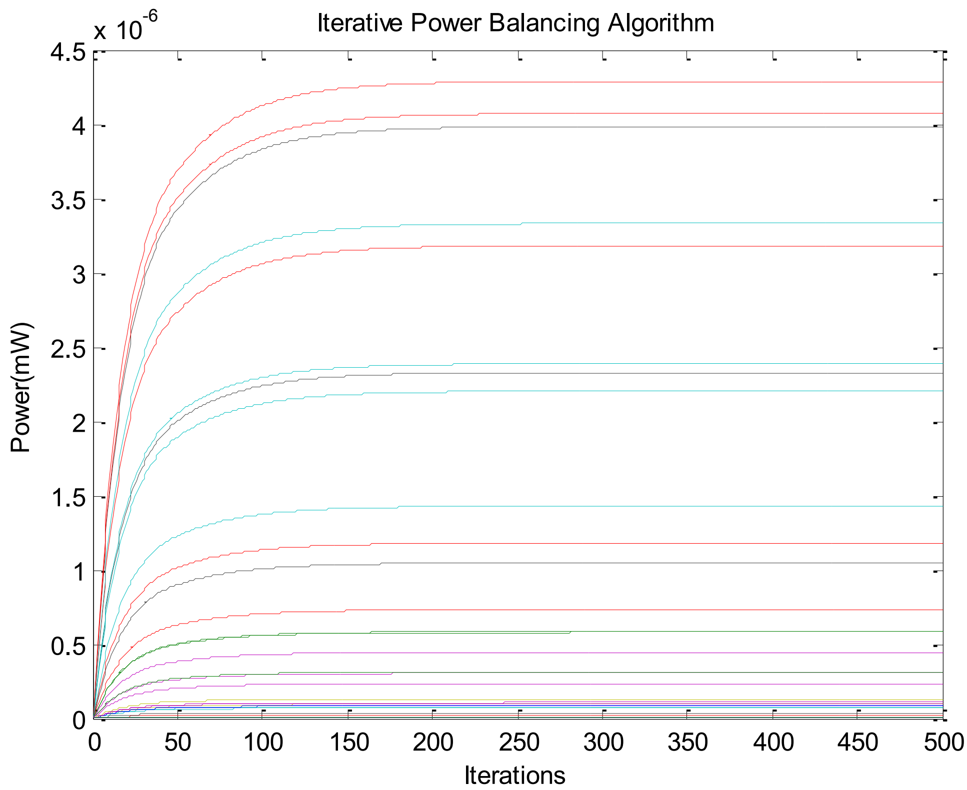

Figure 5.5 : Power Balancing algorithm for 40 users.

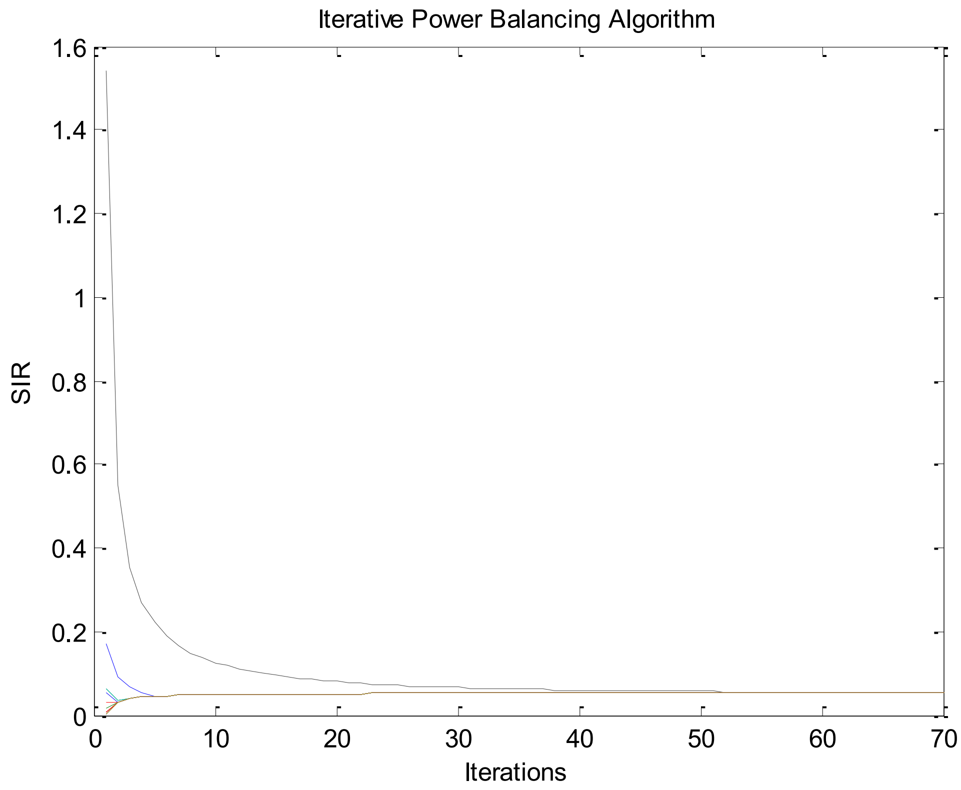

Figure 5.6 : The convergence to the target SIR for 20 users.

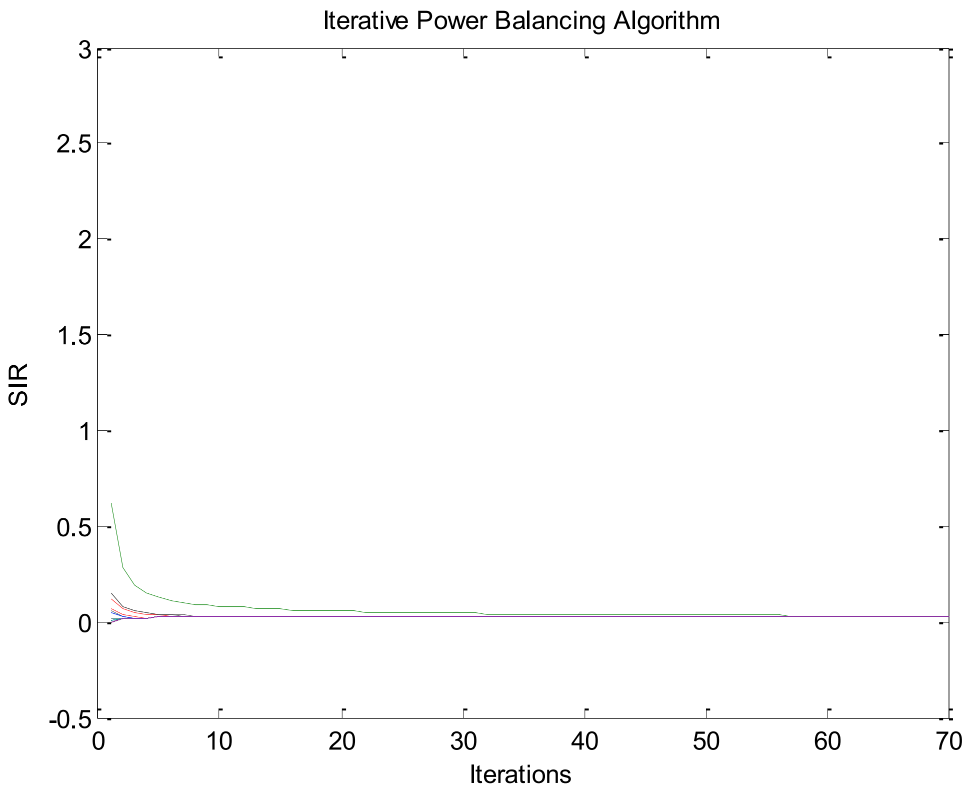

Figure 5.7 : The convergence to the target SIR for 40 users.

5.1.3 Scenario III

Background receiver noise power within the user's bandwidth of $n_i = 10^{-25}$ mW is assumed in the previous scenarios. To observe the impact of noise, the PB algorithm is tested for different range of noise power values. The results are shown from Figure 5.8 to Figure 5.10. In these tests, when the noise power level is increased, the power levels of mobiles are also increased.

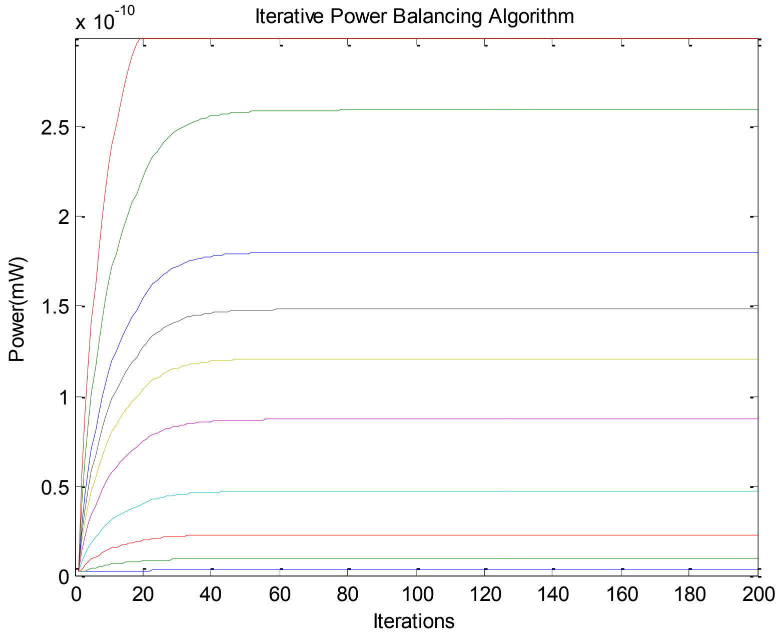

Figure 5.8 : Power Balancing algorithm for 10 users with $n_i = 10^{-22}$ mW.

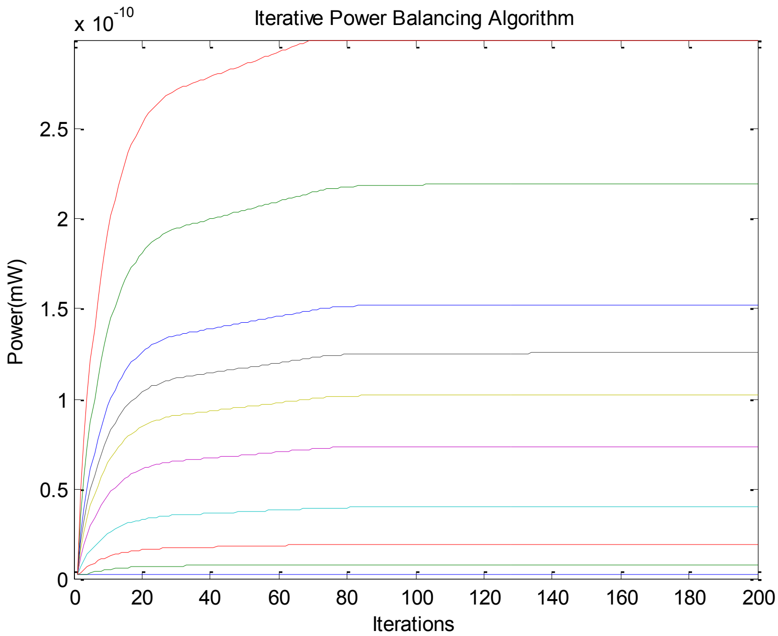

Figure 5.9 : Power Balancing algorithm for 10 users with $n_i = 10^{-21}$ mW.

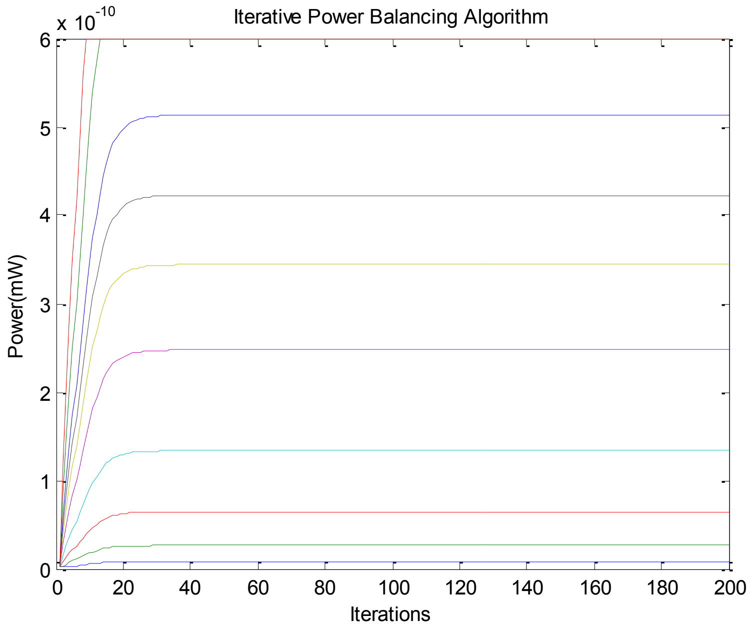

Figure 5.10 : Power Balancing algorithm for 10 users with $n_i = 10^{-19}$ mW.

5.2 Non-cooperative Game-Theoretic Power Control (NGPC) Algorithm

In the second part, the NGPC algorithm, which is based on Ji and Huang's work [25], is implemented and analyzed based on transmitter powers versus number of iterations. According to [25], utility function is considered as a linear function for simplicity, given as

$$u_j(p_j,\gamma_j) \triangleq (p_j^{max} - p_j) + \lambda_j(\gamma_j - \gamma_j^{min}), \tag{5.3}$$

where λ_j stands for user's relative preference of good SIR over saving power. Moreover, p_j^{max} denotes the j^{th} user's maximum power level and γ_j^{min} denotes the threshold which is the minimum SIR for an acceptable QoS. $\mathbf{P_j} = [0, p_j^{max}]$ is the strategy space of user j.

The aim is to maximize the linear utility function under the following constraints:

$$\gamma_j \geq \gamma_j^{min}\ , \tag{5.4}$$

$$0 \leq p_j \leq p_j^{max}. \tag{5.5}$$

By taking into account those constraints, the non the non-cooperative power control becomes

$$\max_{p_j} \lambda_j \gamma_j - p_j = \max_{p_j} \left[-1 + \lambda_j \frac{h_j}{\sum_{i \neq j} h_i p_i c_{ij} + n_j} \right] p_j \tag{5.6}$$

According to equation (5.6), if λ_j is chosen relatively small, which implies that the users are more concerned with saving transmitter power, then the non-cooperative power control is equivalent to minimizing transmitter power. Furthermore, code correlation coefficient, c_{ij}, is assumed to be 1. Then, the optimal solution will occur at the boundary of (5.4) if there is feasible solution,

$$\mu_j(\overline{\mathbf{p}_j^*}) p_j^* = \gamma_j^{min} \tag{5.7}$$

On the other hand, if λ_j is chosen relatively large, which means that the users are more concerned with obtaining better QoS, then the users will keep on increasing their transmitter power. In this case, the optimal solution will occur at the upper boundary of (5.5)

$$p_j^* = p_j^{max} \tag{5.8}$$

In simulation scenarios, a special case in which each base station will control the transmitter power of its carried users without taking into account the interferences to those users who are assigned to its neighbor base stations as in PB algorithm is considered.

A 2-km-square cell with the base station centered at the origin and mobile locations were chosen randomly from a uniform distribution which is shown in Figure 5.1 is considered. Moreover, path gains were calculated by using equation (5.2).

For searching the equilibrium point, the same iterative algorithm is used which is proposed in [25]. Algorithm used in [25] consists of three steps:

Step 1: Set the initial power $\mathbf{p}^o$, initial step size $\Delta_j^o > 0$, $j = 1, 2, \ldots, N$, iteration number $t = 0$.

Step 2: For each user, iterate

$$p_j^{t+1} = p_j^t + \Delta_j^t \left[\mu_j(\overline{\mathbf{p}_j^t}) \zeta_j(\mathbf{p}^t) + \xi_j(\mathbf{p}^t) \right] \tag{5.9}$$

If $\mu_j(\overline{\mathbf{p}_j^{t+1}}) \zeta_j(\mathbf{p}^{t+1}) + \xi_j(\mathbf{p}^{t+1})$ has the same sign as $\mu_j(\overline{\mathbf{p}_j^t}) \zeta_j(\mathbf{p}^t) + \xi_j(\mathbf{p}^t)$, increase the step size by a factor of 2, $\Delta_j^{t+1} = 2\Delta_j^t$.Otherwise, $\Delta_j^{t+1} = \Delta_j^t/2$.

Step 3: If $|\mathbf{p}^{t+1} - \mathbf{p}^{t}| > \varepsilon$, let $t = t + 1$ and go to step 2. Otherwise, stop.

ε is defined as $N \times 1$ vector that represent the requirement of convergence precision.

5.2.1 Scenario I

In the first scenario, we used 5 mobiles whose locations were chosen uniformly at random within the cell. Our initial power for all mobiles was assumed to be $p_i^0 = 2.22 \times 10^{-12}$ for the NGPC algorithm. Working with above iterative algorithm, it is important to choose initial step size appropriately so that the algorithm converges efficiently. According to [3], the power control step size of about 1.096 (0.4dB) which is an optimum selection in the sense of both system performance improvement and fast power control convergence under the simulated environment. $\mathbf{P_j} = [0, p_j^{max}]$ is the strategy space of user j and p_j^{max} is assumed to be 1 W. To see the effect of λ_j, it is chosen relatively large that is $\lambda_j = 10^4$.

Figure 5.11 shows that if λ_j is chosen relatively large, the optimal solution occurs at the boundary (5.5), $p_j^* = p_j^{max}$.

The first user reached at the 18th iteration, the second user reaches at the 19th iteration, the third user reached at the 23th, fourth and fifth users reach at the 16th iteration to the p_j^{max}.

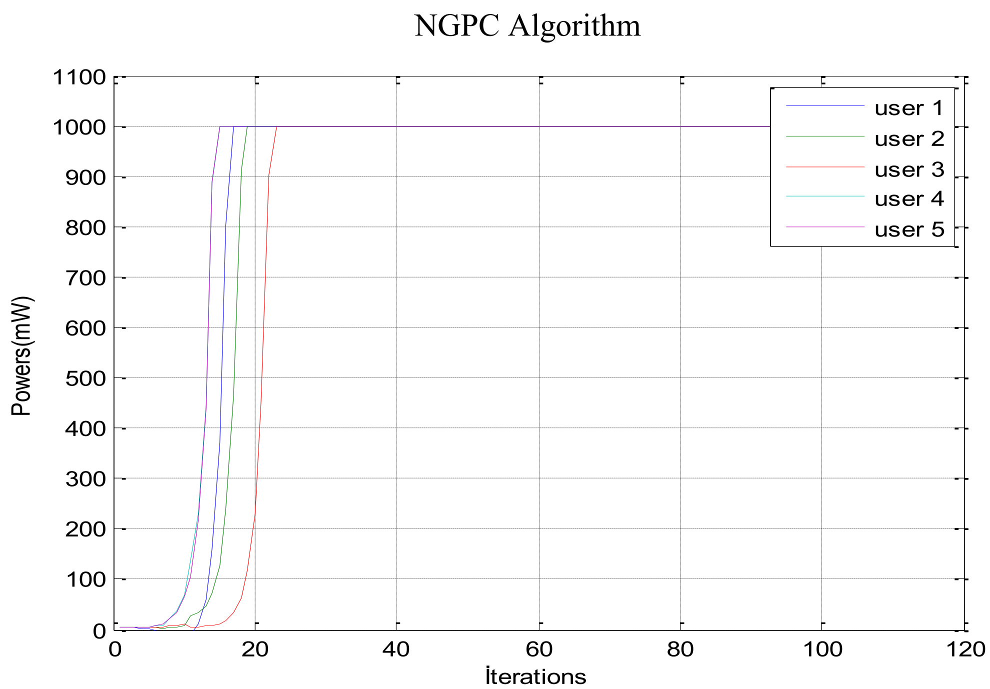

Figure 5.11 : NGPC algorithm for 5 users with $\lambda_j = 10^4$ and $\Delta_j^o = 1.096$.

When the initial step size is taken as $\Delta_j^o = 10^{-4}$, the NGPC algorithm converges inefficiently and slow as shown in Figure 5.12.

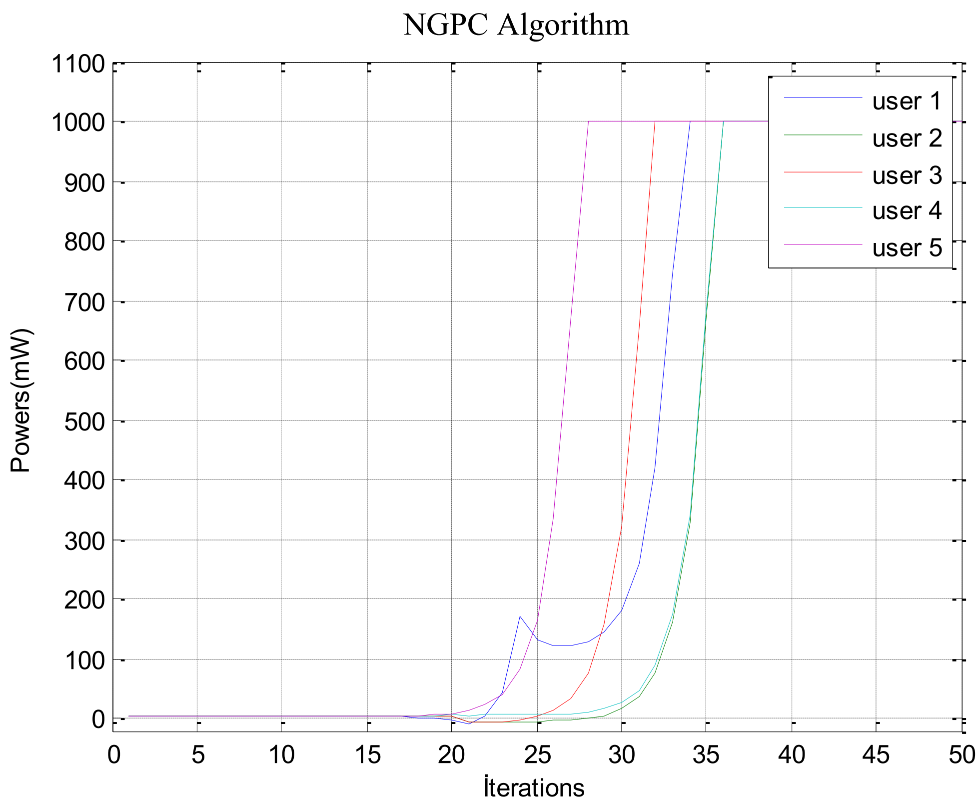

Figure 5.12 : NGPC algorithm for 5 users with $\lambda_j = 10^4$ and $\Delta_j^o = 10^{-4}$.

5.2.2 Scenario II

In the second scenario, we used 5 mobiles whose locations were chosen uniformly at random within the cell. Our initial power for all mobiles was assumed to be $p_i^0 = 2.22 \times 10^{-12}$ for the NGPC algorithm. λ_j is assumed to be relatively small that is $\lambda_j = 10^{-11}$.

Figure 5.13 shows that if λ_j is chosen relatively small, the optimal solution occurs at the lower boundary (5.5), $0 \leq p_j \leq p_j^{max}$. All the mobiles reach the lower boundary in about 20th iterations.

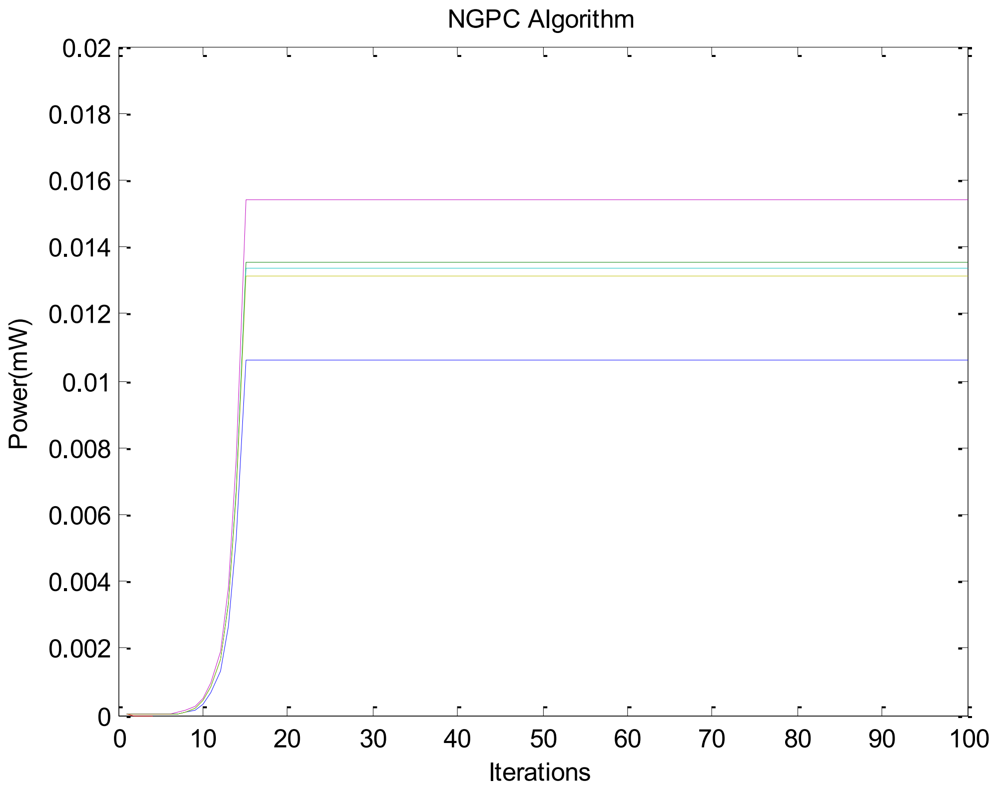

Figure 5.13: NGPC algorithm for 5 users with $\lambda_j = 10^{-11}$.

5.2.3 Scenario III

In this scenario, NGPC algorithm is implemented and compared to PB algorithm. The system performance is evaluated in terms of the number of iterations to examine power control convergence speed. In order to analyze the performance of NGPC algorithm, the same system model and parameters were used as in the PB algorithm. we used 10 mobiles whose locations were chosen uniformly at random within the cell. Our initial power for all mobiles was assumed to be $p_i^0 = 2.22 \times 10^{-12}$ for the NGPC algorithm. In this simulation, it is assumed that we want to achieve $\gamma_i^{tar} = 0.111$ via NGPC algorithm. Furthermore, power was limited to 600 mW, $0 \leq p_i \leq p_i^{max} = 600$ mW. λ_j is assumed to be relatively small, $\lambda_j = 1$.

It is observed that the PB algorithm converges to steady state values in about 70 iterations for 10 mobiles. On the other hand, it is found that the NGPC algorithm converged in fewer iterations than the PB algorithm, in about 30 iterations.

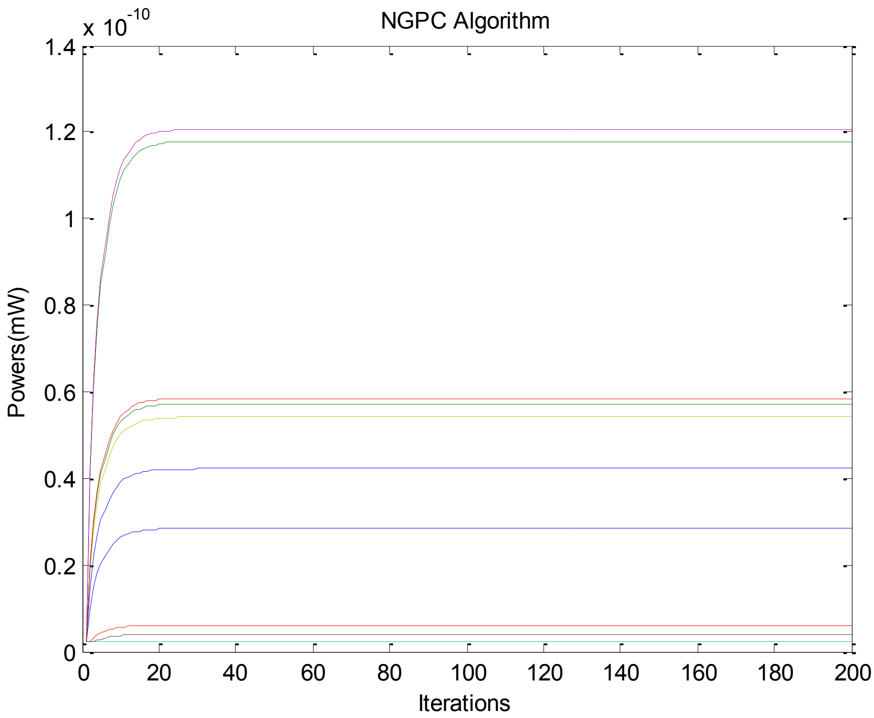

Figure 5.14 : NGPC algorithm for 10 users.

5.2.4 Scenario IV

Examining the performance of NGPC algorithm in Figure 5.15, one sees that NGPC algorithm also give better results compared to PB algorithm for 20 mobiles (80 iterations vs. 120 iterations).

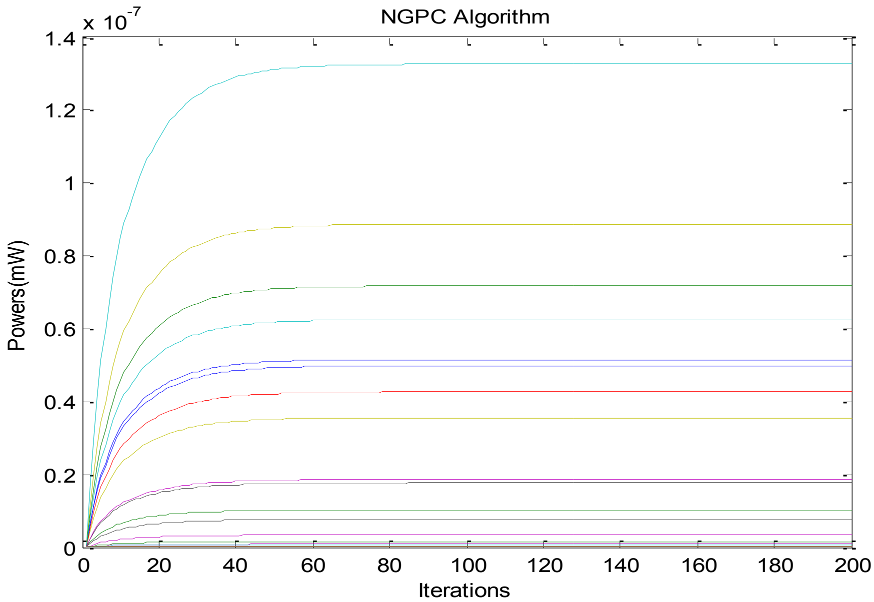

Figure 5.15 : NGPC algorithm for 20 users.

An efficient power control algorithm converges to the threshold SIR fast. Figure 5.16 shows that NGPC algorithm have a faster rate of convergence when it is compared to PB algorithm.

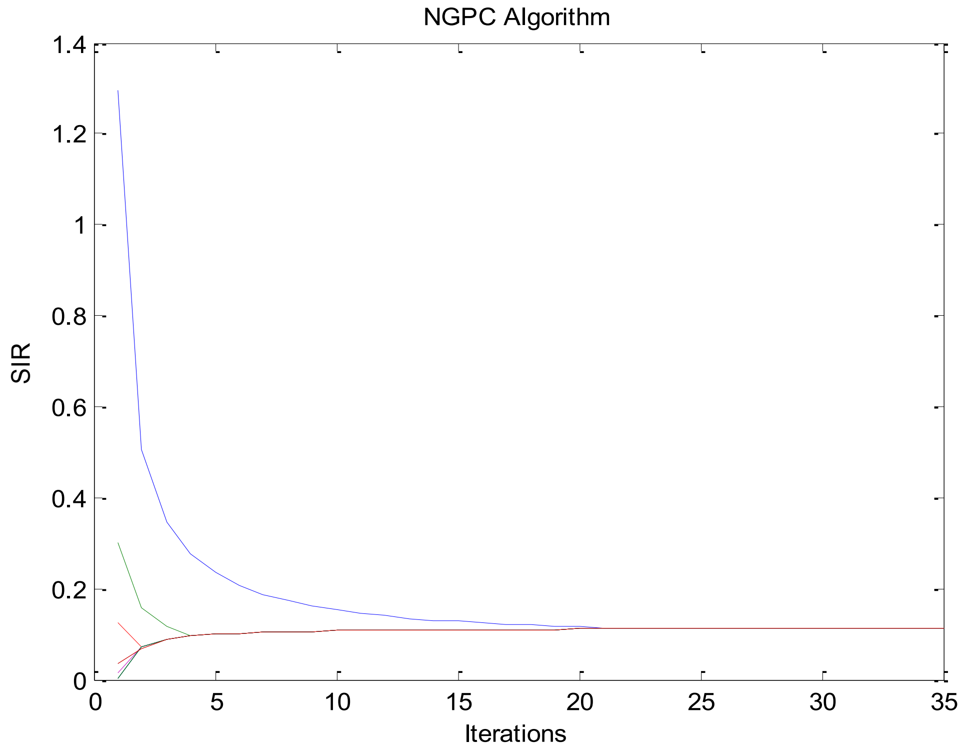

Figure 5.16 : The convergence to the target SIR for 10 users.

5.2.5 Scenario V

To observe the impact of noise, NGPC algorithm is tested for different range of noise power values. The results are shown from Figure 5.17 to Figure 5.19. In these tests, when the noise power level is increased, the power levels of mobiles are also increased.

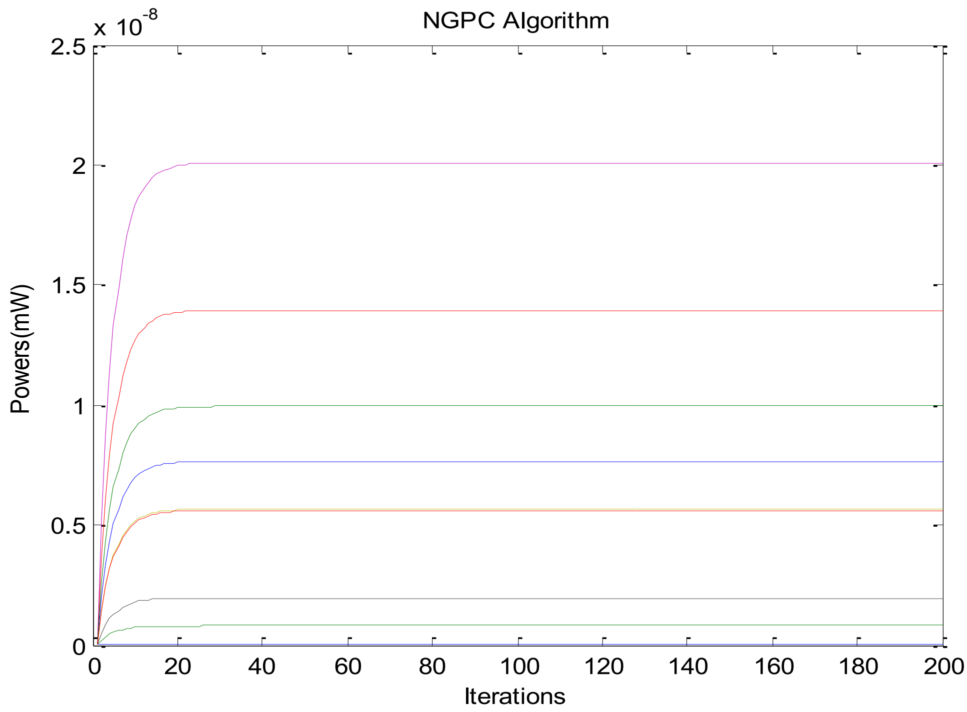

Figure 5.17 : NGPC algorithm for 10 users with $n_i = 10^{-19}$ mW.

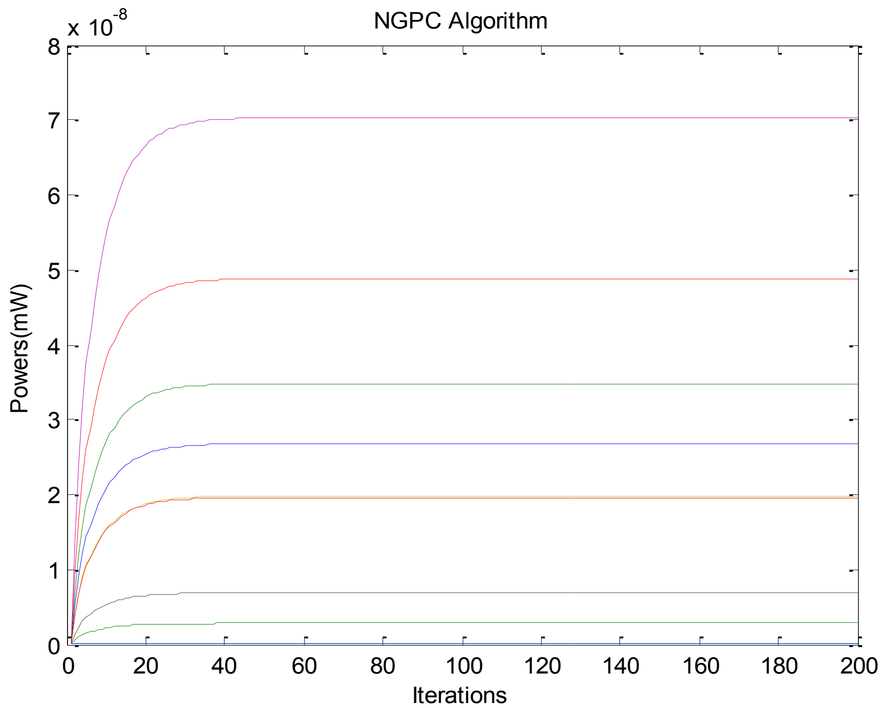

Figure 5.18 : NGPC algorithm for 10 users with $n_i = 10^{-18}$ mW.

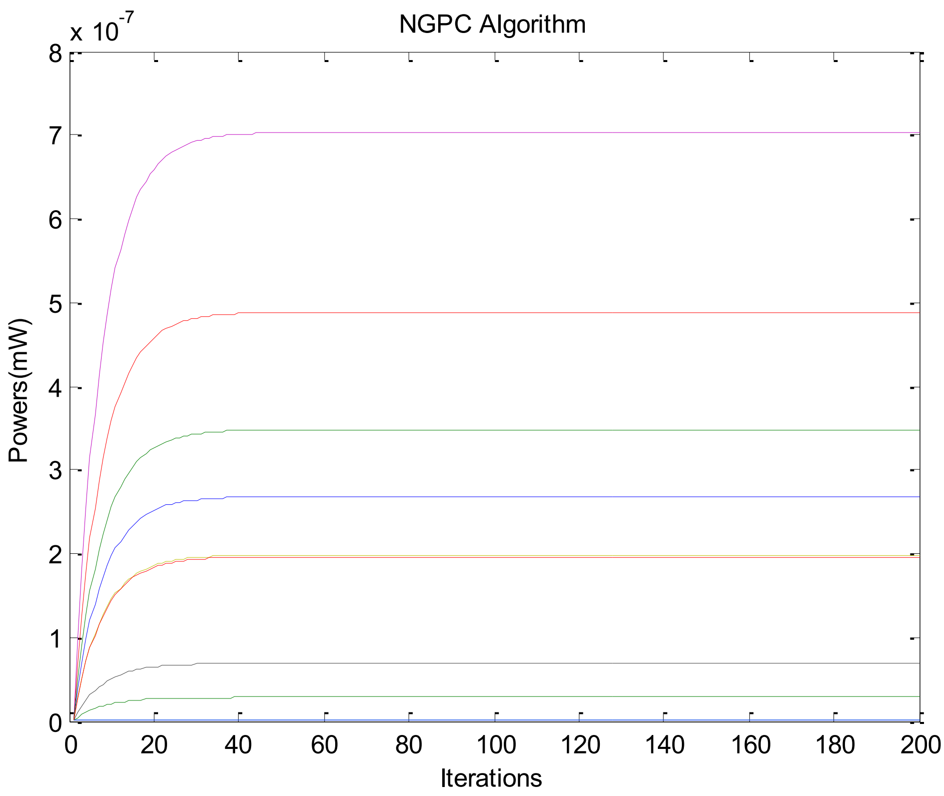

Figure 5.19 : NGPC algorithm for 10 users with $n_i = 10^{-17}$mW.

5.3 Discussion

In this chapter, performance analysis of uplink power control in DS-CDMA systems via Power Balancing (PB) and Non-cooperative Game-Theoretic Power Control (NGPC) algorithms are investigated, implemented and compared.

Firstly, PB algorithm is considered. In the first scenario, 10 mobiles whose locations were chosen uniformly at random within a cell were used. PB algorithm for DS-CDMA systems is analysed based on transmitter powers versus number of iterations. PB algorithm converges to steady state values in about 70 iterations for 10 mobiles. It is shown that the mobiles those are closer to the base station expending smaller power as compared to mobiles further away from the base station. The convergence of PB algorithm to the target SIR is also presented. In the second scenario, the effect of increasing number of users is discussed. As the number of users increase to 20, and 40, the number of iterations to reach steady state power levels also increases to 120, and 280 iterations, respectively. Besides, with a large number of users, the average power is also increased and the achievable SIRs decrease to ~0.055, and ~0.0028, respectively. In the last scenario, to observe the impact of noise, PB algorithm is tested for different range of noise power values. In these tests, when the noise power level is increased, the power levels of mobiles increase.

On the other hand, the NGPC algorithm, which is based on Ji and Huang's work [25], is implemented and analyzed based on transmitter powers versus number of iterations. The utility function is taken as a linear function for simplicity. In the first scenario, 5 mobiles are considered whose locations were chosen uniformly at random within the cell. For searching the equilibrium point, the same iterative algorithm is used which is proposed in [25]. Then, the effect of λ_j is tested, it is chosen relatively large that is $\lambda_j = 10^4$. It is shown that if λ_j is chosen relatively large, the optimal solution occurs at the upper bound, $p_j^* = p_j^{max}$. Moreover, according to [3], it is discussed that the power control step size of about 1.096 (0.4dB) is an optimum selection in the sense of both system performance improvement and fast power control convergence under the simulated environment. When a small initial step size is taken as $\Delta_j^o = 10^{-4}$, it is noticed that the NGPC algorithm converges inefficiently and slowly. In the second scenario, λ_j it is assumed to be relatively small that is $\lambda_j = 10^{-11}$. Then, it is observed that when λ_j is chosen relatively small, the optimal solution approaches at lower bound, $0 \leq p_j \leq p_j^{max}$. In the third scenario, NGPC algorithm is compared to PB algorithm. The system performance is evaluated in terms of the number of iterations to examine power control convergence speed. In order to analyze the performance of NGPC algorithm, the same system model and parameters were used as in the PB algorithm.

λ_j is assumed to have an average value, namely, $\lambda_j = 1$. We found that the NGPC algorithm converged in fewer iterations than the PB algorithm, in about 30 iterations (30 vs. 70 iterations). In the fourth scenario, the performance of NGPC algorithm is examined, when the number of mobiles increased to 20 in the cell, it is shown that NGPC algorithm also give better results compared to PB algorithm for 20 mobiles (80 iterations vs. 120 iterations). Meanwhile, it is also presented that NGPC algorithm has a faster rate of convergence to the target SIR when it is compared to PB algorithm. In the last scenario, NGPC algorithm is tested for different range of noise power values. In these tests, when the noise power level is increased, the power levels of mobiles are also increased.

To summarize, these two iterative power control algorithms are compared through different simulation scenarios on the basis of performance metric that is rate of convergence. The results show that the convergence speed of the proposed NGPC algorithm faster than the PB algorithm.

6. CONCLUSION AND FUTURE WORK

With an increased request for wireless data services, methods for managing the scarce radio resources become needful. Due to the necessity of sharing the radio spectrum, mutual interference will limit system capacity. To allocate resources for maximizing system capacity is an important but enormous task. Power control is one essential issue in this problem, in particular for DS-CDMA.

The work presented in this thesis has aimed to provide insight on how to improve system performance by means of suitable power control algorithms. Accordingly, the choice of an appropriate power control algorithm is very important as it should aim at increasing the overall efficiency of the system. Specifically, two distributed power control algorithms that are PB and NGPC algorithm have been studied and evaluated in this thesis.

Firstly, one of the most common approaches to power control in wireless communication networks is PB algorithm, also called SIR balancing algorithm is considered. The PB algorithm proposed by Foschini and Miljanic [12] is reviewed then, it is tested with different simulation scenarios.

Besides, we outlined fundamental concepts of game theory and developed a game theoretic power control game for wireless data in single cell DS-CDMA communication systems. The problem of uplink power control is formulated. A distributed solution to the power control problem is proposed by posing it as an *N*-person non-cooperative game based on [25]. Each user adjusts its transmitter power to maximize its utility. We also run simulations for different scenarios in which utility is defined as a linear function. We have shown that there is a unique operating point, Nash equilibrium point, for the proposed game. It is shown that it converges to theoretical value given in the reference articles.

Furthermore, we carried out the performance analysis and comparison of these two power control algorithms. Using the PB algorithm and the NGPC algorithm, the uplink power control was implemented and analyzed based on power versus number of iterations. Simulation results are compared. The results show that the convergence speed of the proposed NGPC algorithm faster than that of the algorithm.

On the other hand, it is observed that, taken as a simple game, the power control situation described here usually leads to inefficient outcomes. What typically occurs is that each player increases her power to increase her SIR. This power increase, decreases the SIRs of other users, who then increase their power levels to compensate. By the time an equilibrium is reached, all users will be at much higher power levels than necessary, however they could all reduce their powers and everyone would be better off. For future work, an interesting topic is the development of a pricing function. Because it is shown that, the equilibrium solution is Pareto inefficient. A pricing function can be developed to charge users for using the network and achieve Pareto improvements. The effect of pricing applied to the non-cooperative power control game for wireless data networks is to yield favorable utility solutions at reduced transmitter powers.

In this thesis, one special case by defining utility as a linear function for simplicity is studied. For future work, a more general case can be studied by defining utility as an nonlinear function.

To conclude, game theory is a fascinating field of study. In spite of the recent popularity of game theory in communications and networking research, the potential for further improvements are quite vast. The outlined uplink power control in CDMA networks is believed to be wide open for further exploration. This thesis aims to be the groundwork for further game theoretic power control problems.

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