JOINT POWER CONTROL AND CODEWORD ADAPTATION FOR MULTICELL CDMA SYSTEMS

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

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By

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CANDIDATE'S DECLARATION

I hereby declare that the work, which is presented in this dissertation report entitled, " **JOINT POWER CONTROL AND CODEWORD ADAPTATION FOR MULTICELL CDMA SYSTEMS"** towards the partial fulfillment of the requirements for the award of the degree of **Master of Technology** with specialization in **Communication Systems**, submitted in the Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee, Roorkee (India) is an authentic record of my own work carried out during the period from July 2007 to June 2009, under the guidance of **Mr. S. CHAKRAVORTY, Assistant Professor, Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee.**

I have not submitted the matter embodied in this dissertation for the award of any other Degree or Diploma.

Date: 30-06-09

Place: Roorkee

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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge and belief.

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ABSTRACT

With increase in demand for wireless data services, it becomes very essential to manage scarce radio resources. Especially in CDMA systems, where all the users share the same radio spectrum, mutual interference plays a crucial role in determining system capacity. Good codewords with small cross-correlation help in reducing mutual interference and power control mitigates near-far effect bringing energy efficiency. Joint codeword adaptation and power control can help users to achieve their desired Quality of Service (QoS) as well as in increasing the system capacity. The QoS can be defined in terms of target Signal to Interference plus Noise Ratio (SINR), acceptable bit error rate.

In this dissertation work non co-operative game theoretic approach has been used to deal with joint power control and codeword adaptation in wireless synchronous CDMA system. In CDMA system, every user tries to achieve its desired QoS with least possible transmitting power and best codeword sequence. Thus, all the users have conflicting interests and with their actions being interrelated. Non co-operative game theory can be used to model this scenario. In this dissertation, Non co-operative Joint power control and codeword adaptation game (NPCG) is considered where each user adjusts its codeword and power to minimize its cost while achieving its desired QoS. The NPCG is formulated as separable game with respect to codeword and power.

Simulations have been carried out for continuous and quantized codeword and power profiles for single cell and multi-cell systems. Incremental update strategy has been used for power and codeword update so that receiver can follow changes in transmitter. The performance for dynamic wireless systems under varying QoS and varying number of users has been evaluated. The algorithm effectively tracks variable target SINR and variable number of users. In multi-cell systems, the algorithm reaches equilibrium with increase in signal dimension. For quantized codewords, different signal space dimensions with different quantization level have been used. Coarser quantization has been used for larger signal dimension to compensate for the bandwidth increment. Its effect on various performance parameters at equilibrium has been studied.

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CHAPTER 1

INTRODUCTION

Radio resource management is one of the most challenging and important aspects of wireless communications. Radio resource management basically deals with the allocation of limited resources such as power, bandwidth, channels etc to satisfy the desires of users, service providers. The efficient use of radio resources can be ensured in many ways such as power control, frequency reuse, adaptive modulation etc. In CDMA/OFDM systems, a lot of effort has been dedicated to provide more efficient use of available radio resources. At physical layer, the research is focused on spectrum allocation through signal design for more efficient multiple access and transmitter's power control. The capacity of the system is maximized if the transceivers are able to change their modulation schemes according to varying interference conditions. These adaptive transmitters may increase the user capacity by controlling the transmitter power combined with allocating nonorthogonal and real codewords.

1.1 POWER CONTROL

The primary objective of power control is to regulate the transmit power level of the mobile user so as to maintain certain quality of service for as many users as possible. It is a major problem in CDMA. Since, in CDMA, all users transmit in the same frequency band, signals from different users act as interference for each other. As a result of which, the base station receiver might not recognize a distant mobile user due to strong interference from the nearby mobile users. This is known as near-far effect [1]. Power control mitigates the near-far effect and also helps in extending the battery life of mobiles. Power control techniques must be designed in order to achieve certain Quality of Service (QOS) requirement regardless of the channel conditions by minimizing the interference and hence improving the overall system performance [1]. Power control schemes must operate very fast to track the changes in the path gains which arise due to mobility of the users. Another factor which affects the signal is multi path fading which is caused due to mobile movement and reflections from terrestrial objects. So power control must also track multi path fading [1].

1.1.1 CLASSIFICATION OF POWER CONTROL

Power control can be classified as :

(a) *Open Loop and Closed Loop Power Control* : In open loop power control, the transmitter tries to estimate the channel interference based on the measurements of received signal and then change its power level accordingly. This method gives good results when uplink and downlink channels are strongly correlated such as in Time Division Duplex (TDD) mode [1].

In closed loop power control, the mobile transmitted power is controlled by a signal from the base station. According to power level assigned by the system controller, each base station maintains the desired power level for each mobile that is active within that cell. To maintain independence of fading on forward and reverse link, the mobile will be controlled by power adjustment commands from the base station. So generally a combination of both open and closed loop is normally used [1].

(b) *Centralized and Distributed Power Control* : In a centralized system, there is a centralized controller that has all the information about established connections and channel gains and controls all the power levels in the network or that part of the network. Centralized power control is generally not used at it requires extensive control signaling. In distributed power control, each mobile station has its own controller and it controls the power of one single transmitter and the algorithm depends only on local information such as measured Signal to Interference plus Noise Ratio (SINR) and the channel gain of the specific user [2],[3].

1.2 CODEWORD ADAPTATION

In CDMA systems, users are differentiated by their choice of codeword used for spreading their signal. Since all the users in a CDMA system utilize common frequency band for communication and signals from other users work as interference, it becomes very important for every user to choose its codeword in such a way that the cross correlation between codewords of different users remains as small as possible while keeping autocorrelation high [4]. A careful selection of codewords reduces the multiple-access interference (MAI) which, in turn, results in capacity maximization for the system [4]. The amount of interference seen by a user changes with the change in number of users in the system. Therefore, the codeword adaptation schemes employed in the system must be able to adapt to the change in system. The codeword adaptation technique must be designed to reduce MAI and hence improve the system capacity. The codeword adaptation schemes must be fast so that users quickly adapt to the changed environment.

1.2.1 PERFORMANCE METRIC FOR CODEWORD ADAPTAION

The performance of any codeword adaption technique can be measured based on following criteria:

(a) User Capacity

(b) Sum Capacity

(c) Total Squared Correlation (TSC)

(d) Generalized Total Squared Correlation (GTSC)

(e) Total Weighted Squared Correlation (TWSC)

Out of various measures mentioned above, TSC is of the most importance because GTSC and TWSC are variation of TSC and User capacity and Sum capacity are related to TSC. To understand the how these two distinctly different measures of system capacity relate to TSC, we must first understand the meaning of these terms.

Consider a system with codeword dimension of N and K number of users. The SINR for user k is given by [4],

$$\gamma_k = \frac{p_k \boldsymbol{s}_k^T \boldsymbol{s}_k}{\sum_i p_i (\boldsymbol{s}_i^T \boldsymbol{s}_k)^2 - p_k + w_k}$$

where, $\boldsymbol{s}_k$ is the codeword vector for user k, p_k is the received power of user k and w_k is the energy in the projection of the additive noise onto $\boldsymbol{s}_k$. Assuming equal powers and uninorm codewords

$$\gamma_k = \frac{1}{\mathrm{Trace}[(\boldsymbol{S}\boldsymbol{S}^T)^2] - 1 + w_k}$$

where $\boldsymbol{S} = [\boldsymbol{s}_1\ \boldsymbol{s}_2 \dots \boldsymbol{s}_K]_{N\times K}$

This leads to a compact figure of merit for codeword ensemble called Total Squared Correlation (TSC).

$$\mathrm{TSC} = \sum_i (\boldsymbol{s}_i^T \boldsymbol{s}_k)^2 = \mathrm{Trace}[(\boldsymbol{S}\boldsymbol{S}^T)^2]$$

It is clear that smaller TSC results in higher value of SINR. It can be shown that TSC is lower bounded by K^2/N when $K \geq N$ and by K when $K < N$ [5]. These bounds are known as Welch Bound and the sequence sets which satisfy these bounds are called as Welch Bound Equality (WBE) Sequences.

<u>*User Capacity*</u> : User capacity of a system is defined as the maximum number of users admissible at a given target SINR value. K users are said to be admissible in the system if

there exist a codeword and power allocation for each user such that the SINR achieved by the user is greater than its target SINR value. It has been shown in *ref.* [6] that user capacity is maximized if coderwords satisfy

$$\boldsymbol{SS}^T = \boldsymbol{I}_K , \qquad \text{if } K \leq N \tag{1.1}$$

$$\boldsymbol{SS}^T = \frac{K}{N}\boldsymbol{I}_K, \qquad \text{if } K > N \tag{1.2}$$

and received powers for all users are chosen to be equal. It is clear that these results agree with the Welch Bound. So, the codeword ensembles which satisfy eq. (1.1) or (1.2) (depending upon condition applied) also result in minimization of TSC.

Sum capacity : User capacity is somewhat subjective as it depends on a performance criteria i.e. target SINR. Therefore, it is reasonable to examine codeword ensembles in the context of more objective measures like information theoretic capacity. In a white noise background with equal received powers over all users we define the sum capacity as the maximum sum of reliable (error-free) rates over all users given by [4]

$$C_S = \frac{1}{2}\log\left[\det\left(\boldsymbol{I}_N + \frac{p}{\sigma}\boldsymbol{SS}^T\right)\right] = \frac{1}{2}\log\left[\det\left(\boldsymbol{I}_K + \frac{p}{\sigma}\boldsymbol{S}^T\boldsymbol{S}\right)\right]$$

This sum capacity is achieved when codeword ensemble is chosen such that it satisfies Welch Bound with equality.

Thus, it can be seen that TSC can be used as a measure of both user capacity and sum capacity and minimization of TSC results in maximization of both user capacity and sum capacity [7].

1.3 MOTIVATION FOR GAME THEORY

Game theory is a tool for analyzing the interaction of decision makers with conflicting interests. As in modern communication and networking systems, users try to maximize their QoS while using limited resources, often their interests result in conflicting behavior. Therefore, game theory has generated a lot of interest among wireless and networking engineers to find stable solution for such problems. It has been used to model several communication and networking issues such as power control, medium access control, cognitive radio, routing etc [8][9][10][11]. Most of the work done so far focuses on application of noncooperative game theory because of its distributive nature which is easier to realize than the cooperative game which requires additional signaling or agreements between the decision makers.

1.4 STATEMENT OF PROBLEM

The main objective of any resource management scheme in cellular CDMA system is to utilize available resources to maximize system capacity. Power control and codeword adaptation are some of the ways to achieve this objective. Power control and Codeword adaptation can be modeled as noncooperative game, separately or jointly. When it is modeled as separate games, two situations may occur:

(i) Optimal powers are obtained through a power control game (PCG) and then a codeword adaptation game (CAG) is performed for this power profile. However, in this case, a still better power profile may exist corresponding to the codewords obtained through CAG.

(ii) Optimal codewords are obtained through CAG first and then a PCG provides optimal powers. In this case, still better codewords may exist for the power profile obtained from PCG.

In joint power control and codeword adaptation, users update their transmit powers to achieve higher QoS with lower power levels and simultaneously update their codewords to reduce the cross-correlation between codewords of different users. This results in jointly optimized power and codeword profile unlike separate optimization. The joint optimization is the task undertaken in the present work.

The major objectives of this dissertation are:

(a) To study and review Power Control, Codeword Adaptation and, Joint Power Control and Codeword Adaptation from game theoretic perspective.

(b) Simulation of Joint Power Control and Codeword Adaptation Game for Single Cell CDMA System.

(c) Simulation of Joint Power Control and Codeword Adaptation Game for Multi-Cell CDMA System for both continuous and quantized codewords.

1.5 ORGANIZATION OF THE DISSERTATION

Including this introductory chapter, the dissertation is organized in six chapters. Chapter 2 introduces the basics of game theory and its applications to power control and codeword adaptation. Different utility functions and pricing functions that have been used for power control game are presented. Further, this chapter includes discussion on different game theoretic approaches towards codeword adaptation. In chapter 3, joint power control and codeword adaptation using game theoretic formulation is studied for both single cell and multi-cell scenarios and the problem is modeled as a separable game.

Chapter 4 contains system model and simulation parameters for the joint power control and codeword adaptation game for single cell and multi-cell systems. Results and their discussion are presented in chapter 5. Conclusion and scope of future work are included in chapter 6.

CHAPTER 2

GAME THEROY AND ITS APPLICATION TO POWER CONTROL AND CODEWORD ADAPTATION

Game theory is often described as a branch of applied mathematics and economics that studies situations where multiple players make decisions in an attempt to maximize their returns. Game theory is used in many diverse fields such as Political Science, Biology, Business, Economics and Mathematics. In recent years, game theory has found its application in fields of computer science and wireless engineering to solve problems such as flow control and spectrum sharing. In other words, game theory studies choice of optimal behavior when costs and benefits of each option depend upon the choices of other individuals.

2.1 GAME THEORY

Game theory is a collection of mathematical models formulated to study situations of conflict and cooperation. It is concerned with finding the best actions for individual decision makers in these situations and recognizing stable outcomes. This theory is not useful when decisions are made ignoring the reaction of others. The essential elements of a game are players, actions, payoffs and information. These are collectively known as the rules of the game [12].

Some of the important definitions in Game theory are:

(i) Player: These are the individuals who make decisions. Each player's aim is to maximize its utility by proper choice of actions.

Sometimes it is useful to explicitly include individuals in the model called pseudo-players whose actions are taken in purely mechanical way.

Nature : it is a pseudo-player who takes random action at specified points in the game with specified probabilities.

(ii) Actions: An action by player *i*, denoted by a_i, is the choice it can make. Player *i*'s action set, $A_i = \{a_i\}$, is the entire set of action available to it. An action combination is an ordered set $\boldsymbol{a} = \{a_1, a_2, \ldots a_n\}$ of one action for each of the n players in the game.

(iii) Utility: It is a function that maps action profiles into real numbers. It quantifies the quality level i.e. the level of satisfaction of the player.

(iv) Payoff: Player *i*'s payoff $\pi_i\,(s_1, s_2, \ldots s_n)$ means that the utility player *i* receives after all players and nature have picked their strategies and the game has been played out.

(v) Outcome: The outcome of the game is a set of the elements that the modeller picks from the values of actions, payoffs and other variables after the game is played out.

(vi) Strategy: Player *i*'s strategy is a rule that tells him which actions to choose at each instant of the game, given his information set. Player *i*'s strategy set, $S_i = \{s_i\}$, is the set of strategies available to him. A strategy combination $\boldsymbol{s} = (s_1, s_2, \dots . s_n)$ is an ordered set consisting of one strategy for each of the n players in the game. Information set includes the knowledge of player about values of different variables and also about the previous actions of other players. The strategy tells him how to react to their actions.

(vii) Equilibrium: An equilibrium $\boldsymbol{S}^* = (s_1^*, s_2^*, \dots . s_n^*)$ is a strategy combination consisting of best strategy for each of the *n* players in the game, which is picked by them in trying to maximize their individual payoffs.

(viii) Dominant strategy: The strategy s_i^* is a dominant strategy if it is a player's strictly best response to any strategies the other players might pick, in the sense that whatever strategies they pick, his payoff is highest with s_i^* . Mathematically

$$\pi(s_i^*, \boldsymbol{s}_{-i}) \geq \pi(s_i^{'}, \boldsymbol{s}_{-i}) \qquad \forall \boldsymbol{s}_{-i}\ ,\ \forall s_i^{'} \neq s_i^*$$

where $\boldsymbol{s}_{-i}$ is the strategy combination of all the players except player *i*.

The strategies that yield the worst payoff regardless of others' strategies are known as dominated strategies.

A dominant strategy equilibrium is the strategy combination consisting of each player's dominant strategy.

(ix) Nash Equilibrium: The strategy combination $\boldsymbol{S}^*$ is Nash equilibrium (NE) if no player has incentive to deviate from its strategy given that the other players do not deviate. In other words, a player cannot increase its utility function by changing its strategy whereas other players are not changing their strategies.

$$\forall i, \qquad \pi(s_i^*, \boldsymbol{s}_{-i}^*) \geq \pi(s_i^{'}, \boldsymbol{s}_{-i}^*), \qquad \forall s_i^{'},$$

(x) Pareto Efficiency: A strategy combination is said to be Pareto efficient if it is impossible for any player to increase its payoff without harming any other player's payoff.

Game theory may generally be categorized as:

- Noncooperative Game
- Cooperative Game

A noncooperative game is a game in which each player tries to selfishly maximize its own utility. In this game, players do not interact with each other. A cooperative game (also called coalitional game) is a game in which the players can make binding commitments, as is not the case in the noncooperative game. Analysis in cooperative game theory is centered on coalition formation and distribution of wealth gained through cooperation.

Nash Equilibrium is a very important concept of Noncooperative game. It signifies a situation in the game where unilateral deviation does not result in any advantage for any player which forces players to stick to their current actions. Thus, it is very necessary to examine the existence of Nash equilibrium in any noncooperative game formulation. Nash equilibrium for a game exists if action set of each user is convex and compact, and utility function is continuous and quasi-concave in users' strategy space [13].

Though game theory is very useful tool for modeling problem having interacting users, there are some pitfalls in the application of game theory [14]. One of these pitfalls is to mistake a simple optimization problem as a game. Some other common mistakes are confusing between theories of noncooperative and cooperative games and in defining the game and the settings in which it is to be played. Therefore, one must be very careful while applying game theory.

2.2 GAME THEORY AND POWER CONTROL

In CDMA, all the users share the same frequency spectrum. The transmitted signal of each user works as interference of every other user. If one user increases it's transmit power to obtain higher SINR, it increases interference for all the other users in the system and, in turn, reduces their respective SINR values. Since every user wants to obtain higher SINR to get better Quality of Service (QoS), transmit power increment from one user prompts other users to increase their transmit power. But the main objective of every user is to maximize its SINR and at the same time transmit at low power. Thus, the problem of power control in a cellular CDMA system shows a conflict of interests between all the users in the system. This situation makes power control an ideal candidate for application of game theory [15].

The power control problem is modeled as a noncooperative game because, in a cellular CDMA scenario, it is very difficult for users to cooperate and communicate with each other. Every user tries to acts selfishly and maximizes its own utility without considering the effect of its actions on other users. As every user takes actions to increase its own utility, an equilibrium point is reached when no user can increase its utility unilaterally. This point is the Nash Equilibrium of the power control game.

Let $G = [\boldsymbol{K}, \{P_i\}, \{u_i(.)\}]$ denotes the non-cooperative power control game (NPG) where $\boldsymbol{K} = \{1,2,\ldots,K\}$ is the set of users currently in the system, P_i is the strategy set and u_i (.) is the utility of user i. Each user selects a power level such that $p_i \in P_i$. The power vector $\boldsymbol{p} = (p_1, p_2, \ldots, p_K)$ denotes the outcome of the game in terms of selected power level of all users. The resulting utility function for the i^{th} user is given by $u_i(\boldsymbol{p})$. This can also be written as $u_i(p_i, \boldsymbol{p}_{-i})$ where $\boldsymbol{p}_{-i}$ denotes the vector consisting of powers of all users other than user i.

2.2.1 UTILITY FUNCTIONS

In game theory, Utility is defined as level of satisfaction that a user derives from undertaking an activity. In cellular systems, Utility is defined as the measure of satisfaction or quality of service (QOS) that a user derives from accessing the wireless data network. For voice communications, the utility function is zero below the minimum SINR and one above the value of minimum SINR [16]. For data communications probability of error is directly related to SINR. High SINR value implies low probability of error, low delay and higher throughput. This implies that utility is generally a increasing concave function of SINR.

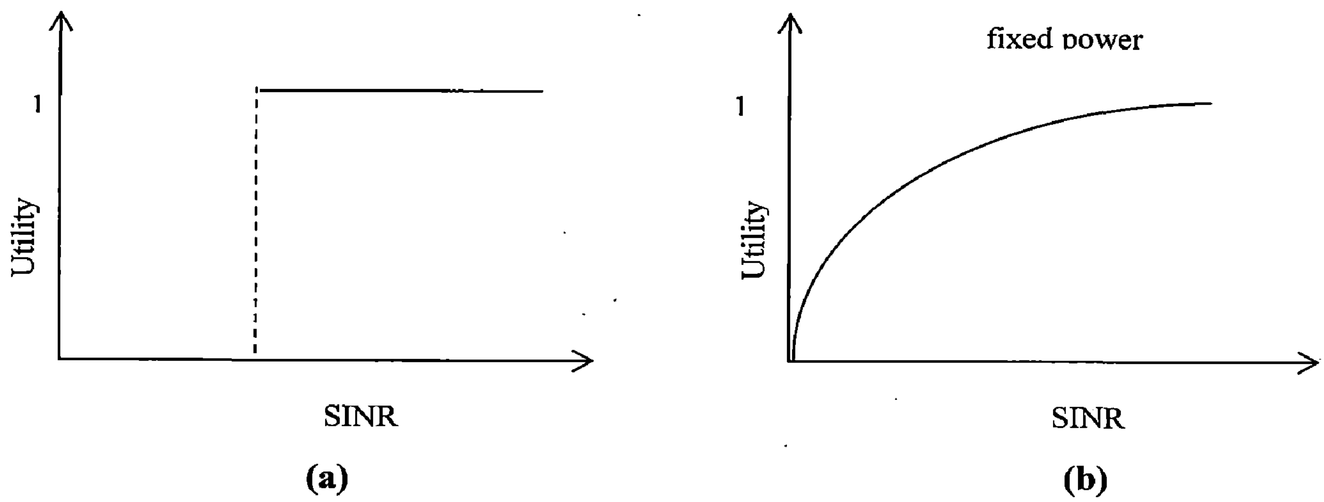


Figure 2.1 (a) Utility for voice is a step function of SINR **(b)** Utility for data is continuous function of SINR .

In Fig. 2.1, it can be seen that utility is a step Function for voice [16] whereas for data, Utility is an increasing concave function of SINR, when power is fixed, for a throughput based utility function [17].

The way in which user satisfaction can be defined, differs depending upon the system model and user requirements. This leads to a change in definition of utility function. Different authors have defined utility function in different ways. Some of the important utility functions that exist in literature are as follows:

(a) $u = \frac{L * R * f(\gamma)}{M * p}$ [16]

L : Number of information bits

M : Length of frame

p : Power of a given user

$f(\gamma)$: Efficiency function = $(1-2P_e)^M$

R : Rate in bits/sec

This utility function value depends on the details of data transmission, modulation, coding, radio propagation and receiver structure. The properties of this utility function are

$u_i \to 0$ as $p_i \to 0$: zero utility when no usage

$u_i \to 0$ as $p_i \to \infty$: zero utility when power consumption is excessive

u_i is quasi-concave in p_i when BER (γ) decays exponentially in γ.

(b) $u = R * \log_2(1+\gamma)$ [18]

R : Data rate (bits/sec)

γ : SINR

This utility function uses channel capacity as a figure of merit for the purpose of power control and leaves the decision as to whether the capacity will be fully exploited by coding/modulation.

(c) $u = U_i * \log(prob(\gamma_i \geq \gamma_i^*))$ [19]

$= U_i * \log(1 - O_i(\gamma_i^*))$

U_i : User specific utility parameter

$prob(\gamma_i \geq \gamma_i^*)$: Probability that SINR of a particular user is greater than threshold

$O_i(\gamma_i^*)$: Outage probability defined as the proportion of time that some SINR threshold γ_k^* is not met for sufficient reception at receiver.

This utility function makes sure that SINR of user does not go below a threshold value which is carefully chosen to establish a satisfactory QoS.

2.2.2 NASH EQUILIBRIUM AND PARETO EFFICIENCY

Nash equilibrium for the non cooperative power control game is defined as the power vector p^* such that no single user can improve its utility by a unilateral change in its power. Mathematically Nash equilibrium is defined as power vector $\boldsymbol{p}^*$ such that

$$u_i(p_i^*, \boldsymbol{p}_{-i}) \geq u_i(p_i', \boldsymbol{p}_{-i}) \quad \forall p_i' \in P_i \qquad \text{for all } i \in \boldsymbol{K} \qquad \text{........(2.1)}$$

where $\boldsymbol{p}_{-i}$ is a power vector which contains the powers of all users except the i^{th} user, P_i is the strategy space for user i and $\boldsymbol{K} = \{1,2,\ldots,K\}$ is the set of users in cellular system.

A classical measure of the efficiency of an equilibrium solution is the Pareto efficiency. A power vector $\boldsymbol{p}^*$ is said to be Pareto efficient if and only if there exists no such vector $\boldsymbol{p}'$ such that at least one user achieves higher utility, while other user's utilities remains constant. In other words there exists no power vector $\boldsymbol{p}'$ such that

$$u_i(p_i^*, \boldsymbol{p}_{-i}) < u_i(p_i', \boldsymbol{p}_{-i}) \quad \forall p_i' \in P_i; \qquad \text{for all } i \in \boldsymbol{K} \qquad \text{........(2.2)}$$

The equilibrium analysis of the non cooperative power control game involving utility function is Pareto inefficient [16][18][19]. In order to improve the inefficient equilibrium, the behavior of users is influenced by a pricing mechanism which will lead to a better equilibrium point.

2.2.3 PRICING FUNCTION

In the Non Cooperative Game (NPG), the primary objective of each terminal is to attain maximum utility by adjusting its transmit power but, while doing so, it overlooks the cost (harm) to other users caused by its selfish behavior. This self-optimizing behavior of an individual terminal creates an externality by degrading the quality of service for every other terminal in the system [17]. Among many ways to deal with externalities, pricing (or taxation) has been used effectively. Typically, pricing is motivated by two different objectives:

1) It generates revenue for the system,

2) It encourages players to use system resources more efficiently.

Pricing does not imply a monetary incentive rather it refers to control signals that motivate a user to exhibit social behavior. A pricing policy is said to be incentive compatible if it results in a Nash equilibrium which improves social welfare where social welfare can be defined as the sum of utilities [17]. There are various pricing strategies that can be applied, such as flat rate, access-based, usage-based, priority-based, etc. The choice of pricing policy depends upon the services offered by the system and the demand for those services. Pricing helps in improving the utilities at equilibrium in the Pareto sense. Pricing improves system performance by inherently bringing cooperation in users' actions while maintaining the noncooperative nature of the game.

The pricing function can be defined in many ways. Usage-based pricing is the most common approach. Some of the pricing functions that have been used are as follows:

(a) *Pricing proportional to power* :

Pricing Factor = C*p;

C : Cost per unit power

p : Power of user

In this method of usage based pricing, pricing is proportional to power transmitted by user. Therefore, net utility obtained by above method is larger in value compared to utility obtained by NPG. Similarly Nash equilibrium power vector of users is less in value compared to power vector obtained by NPG [17].

(b) Pricing proportional to Throughput :

Pricing Factor = C*T

C : Cost per unit throughput

T : Throughput of user

In this method of usage based pricing, pricing is proportional to throughput of user. Revenue is the product of price/unit service and amount of service provided. The amount of service provided by the network to any user is the amount of useful data bits that user sends to network over fixed time frame. This pricing factor is considered more natural when we are dealing with network centric situation [20].

2.3 GAME THEORY AND CODEWORD ADAPTATION

Codeword adaptation in a CDMA system involves the selection of a codeword by a node such that the interference at the receiver in minimized. In an ideal scenario, each user is assigned mutually orthogonal codewords so that their signals do not interfere with each other. However, in practical scenario, it becomes difficult to keep the codewords mutually orthogonal because of the changes in channel conditions and change in the number of users in the system. Since, interference at the receiver is a function of the correlation of a user's codeword with the codewords of other users in the system, it becomes essential for every user in the system to change its codeword to effectively deal with the varying interference environment [7]. But the change in codeword by one user changes the interference to the received signal of other users prompting then to change their codeword as well. Thus, it can be seen that actions of one user have its effect on the action taken by all other users. This scenario makes this problem suitable for game theoretic formulation. Also, in general, individual users have no or very little information about interference environment at the receiver. Hence, distributive algorithms that require minimum amount of feedback between receiver and the transmitter needs to be developed. Game theory can prove to give some insight into this scenario as well [21]. To understand application of game theory to this problem in a better way, some more concepts of game theory are explained below:

<u>Convex Game</u>: A game is said to be convex for a closed, convex and bounded joint strategy space, if the cost function of users is a convex in their strategy space [24].

<u>Best Response Function</u>: For any strategy space vector $\mathbf{s}_{-k} \in S_{-k}$, the best response function for user k is the set of best actions of user i. So a function $B_k(\mathbf{s}_{-k})$ is user k's best response if [13],

$$B_k(\mathbf{s}_{-k}) = \{s_k \in S_k : u_k(s_k, \mathbf{s}_{-k}) \geq u_k(s'_k, \mathbf{s}_{-k}) \quad \forall s_k' \in S_k\}$$

The Nash equilibrium for the game is a profile $\boldsymbol{s}^*$ for which

$$s_k^* \in B_k(\boldsymbol{s}_{-k}^*) \qquad \text{for all } k$$

<u>*Potential Game*</u>: It is a special class of games. A potential game is a normal form game such that any changes in the utility function of any player in the game due to a unilateral deviation by the player is reflected in a global function referred to as the potential function [14][21]. Depending upon the relation between utility function of individual users and the potential function, potential game can be classified into different categories. A function f: $\boldsymbol{A} \rightarrow \mathbb{R}$ is called:

(a) an exact potential function if

$$u_k(\boldsymbol{a}) - u_k(b_k, \boldsymbol{a}_{-k}) = f(\boldsymbol{a}) - f(b_k, \boldsymbol{a}_{-k}), \qquad \forall\, k \in \boldsymbol{K}, \boldsymbol{a} \in \boldsymbol{A}, b_k \in \boldsymbol{A}_k$$

(b) an *ordinal potential function* if

$$u_k(\boldsymbol{a}) \geq u_k(b_k, \boldsymbol{a}_{-k}) \Leftrightarrow f(\boldsymbol{a}) \geq f(b_k, \boldsymbol{a}_{-k}), \qquad \forall\, k \in \boldsymbol{K}, \boldsymbol{a} \in \boldsymbol{A}, b_k \in \boldsymbol{A}_k.$$

(c) a *best response potential* function if

$$\underbrace{\arg max}_{b_k \in A_k} u_k(b_k, \boldsymbol{a}_{-k}) = \underbrace{\arg max}_{b_k \in A_k} f(b_k, \boldsymbol{a}_{-k}), \qquad \forall\, k \in \boldsymbol{K}, \boldsymbol{a} \in \boldsymbol{A}, b_k \in \boldsymbol{A}_k.$$

where, $\boldsymbol{K}$ is set of players in the game, $\boldsymbol{A}_k$ is set of actions available for player *k*, $\boldsymbol{A}$ is the set of all available actions for all players and u_k is the utility function for user *k*.

A game is an exact, ordinal or best response game if there exists an exact, ordinal or best response potential function respectively for the game [21][22].

These games are easier to analyze because any change in utility of any user is reflected as corresponding change in the value of global potential function. Moreover, if utility and potential functions are chosen such that potential function becomes a measure of global network performance, then these games give a framework where users can maximize a global utility by only trying to maximize their own utilities [21]. Thus, the selfish behavior of individual users results in improvement in system performance. It should also be noted that the maximizers (local and global) of the potential function result in NE for the potential game but that not all NE are maximizers of the potential function because some NE, referred to as suboptimal NE, could result from saddle points of potential function [21].

Some of the approaches used towards game theoretic formulation of codeword adaptation problem are discussed below:

(a) <u>*Noncooperative Game Formulation*</u>: The distributed codeword adaptation problem in DS-CDMA has been in formulated as a noncooperative game in *ref.* [23] for single cell systems. The utility function for user *i* is defined as

$$u_k = \boldsymbol{s}_k^T \boldsymbol{R}_{ii} \boldsymbol{s}_k$$

where, $\boldsymbol{s}_k$ = codeword vector for user *k*.

q_k = received power of user *k*.

$\boldsymbol{R}_{ii} = \sum_{j \neq k} q_j \boldsymbol{s}_j \boldsymbol{s}_j^T$ is the correlation matrix of the interference for user *k*'s signal.

To understand the results at Nash equilibrium, the notion of oversized users for this problem needs to be explained. Let there are *K* users in the system and each user chooses unit-norm signature sequence (codeword) from an *N*-dimensional signal space. It can be assumed, without loss of generality, that $q_1 > q_2 > q_3 > \ldots\ldots > q_K$. A users *k* is said to be oversized if

$$q_k > \frac{\sum_{j=k+1}^{K} q_j}{N-k}$$

The codeword distribution at Nash equilibrium is as follows [23] :

(1) Oversized users are allocated orthonormal sequences. That is, if there are *L* oversized users, then codeword vector e_k is allocated to k^{th} oversized user for $k = 1, 2, \ldots, L$, where e_k is a vector with a '1' at the k^{th} position.

(2) Non-oversized users are allocated Generalized Welch Bound Equality (GWBE) sequences from the codeword subspace spanned by $\{e_{L+1}, e_{L+2}, \ldots, e_K\}$.

It is seen that there are multiple Nash Equilibria in this game but none of them is pareto dominant. On the other hand, one of them is optimal in that the sum capacity is maximized.

(b) <u>*Potential Game Formulation*</u>: The codeword adaptation problem is interpreted as a potential game in *ref.* [21]. The negated generalized total squared correlation function

$$V(s) = -||\boldsymbol{SPS}^T + \boldsymbol{W}||_F^2$$

is defined as potential function. where,

$\boldsymbol{S} = [\boldsymbol{s}_1, \boldsymbol{s}_2, \dots \dots \colon\dots, \boldsymbol{s}_K]$ is $N \times K$ coderword matrix with columns as codeword vector of individual user,

$\boldsymbol{P}$ is a diagonal matrix with k^{th} diagonal entry being the received power of k^{th} user.

$\boldsymbol{W}$ is covariance matrix of AWGN,

$\|\boldsymbol{A}\|_F$ is the Frobenius Matrix Norm of matrix $\boldsymbol{A}$.

The utility function is defined as

$$u_k(\boldsymbol{s}_{k,}\boldsymbol{s}_{-k}) = -2p_k \boldsymbol{s}_k^T \boldsymbol{R}_{ii}(k)\boldsymbol{s}_k$$

where, $\boldsymbol{s}_k$ = codeword vector for user k,

$\boldsymbol{S}_{-k}$= matrix $\boldsymbol{S}$ excluding k^{th} column,

$\boldsymbol{R}_{ii}(k)$ = interference plus noise cross correlation matrix at receiver for user k.

Some other utility functions which allow a potential game formulation with $V(s)$ as the potential function have also been described in *ref.* [21]. The nature of these utility functions depends upon two factors: receiver type and the user's end performance metric. Some of these utility functions are :

(1) SINR/Correlator Game: The utility function is chosen as the SINR at the output of the correlator receiver given by

$$u_k = SINR_k = \frac{p_k}{\boldsymbol{s}_k^T \boldsymbol{R}_{ii}(k)\boldsymbol{s}_k}$$

(2) MSE/Correlator Game:.

$$u_k = -MMSE = -\frac{\boldsymbol{s}_k^T \boldsymbol{R}_{ii}(k)\boldsymbol{s}_k}{\boldsymbol{s}_k^T \boldsymbol{R}\boldsymbol{s}_k}$$

where, $\boldsymbol{R} = \boldsymbol{SPS}^T + \boldsymbol{W}$ = received cross correlation matrix.

CHAPTER 3

JOINT POWER CONTROL AND CODEWORD ADAPTATION IN CDMA SYSTEMS

Wireless systems have always had to deal with interference from both natural sources and other users of the medium. Wireless engineers have always had a quest for techniques to mitigate the effect of interference and to reliably reconstruct the transmitted signal at the receiver. In CDMA systems, multiuser interference is the main limiting factor for system capacity and QoS achieved by users. Therefore, it becomes necessary to design codewords and regulate transmit powers to limit the interference. It is also important to design adaptive algorithm for codeword adaptation and power control so that the users can be able to achieve desired QoS in changing interference patterns. Earlier works on interference mitigation in CDMA systems were focused on separate algorithms for power control and codeword adaptation [16][17][21][23]. In this chapter, a joint power control and codeword adaptation algorithm is presented where users simultaneously change their codeword and transmit power to achieve their desired QoS. The algorithm is derived using game-theoretic approach and the user's desired SINR value is taken as its QoS [24].

3.1 NONCOOPERATIVE GAME-THEORETIC FORMULATION

The problem of joint power control and codeword adaptation is modeled as noncooperative game because individual users are only interested in minimizing their own cost function, without paying attention to how their actions affect other users. The objective of each user is to minimize the cost rather than maximizing the utility. The user cost function is associated with the use of system resources and the satisfaction experienced by users as a result of their actions. In general, it is desired that user cost functions satisfy the following properties:

(a) The user cost function increases with increasing user power.

(b) The cost function decreases with decreasing interference for fixed transmit power.

The user cost function, satisfying above condition, is defined as the product of its power and its corresponding interference [24]

$$u_k = p_k i_k \qquad \forall k = 1,2,\ldots K \qquad \text{......(3.1)}$$

Considering that matched filters are used at the receiver, the actual expression of the cost function becomes

$$u_k = p_k i_k^{MF} = p_k \boldsymbol{s}_k^T \boldsymbol{R}_k \boldsymbol{s}_k \qquad \forall k = 1,2,\ldots K \qquad \ldots\ldots(3.2)$$

where, K is the number of users in system,

$\boldsymbol{s}_k$ is user codeword vector such that $\|\boldsymbol{s}_k\| = 1$,

p_k is user received power such that $p_k \in (0, \mathrm{P_{max}}]$,

$\boldsymbol{R}_k$ is the correlation matrix of the interference + noise seen by user k.

The cost function in eq. (3.2) is separable with respect to the two parameters that define the user strategy, codeword and power. Using this separable property, noncooperative game is formulated as a separable game, with two corresponding subgames: the power control game and the codeword (sequence) control game [25]. The results of these subgames are used to study the joint power control and codeword adaptation.

The main aim of this problem is to derive a distributed algorithm in which users individually adjust codewords and powers to meet a set of specified target SINRs $(\gamma_1^*, \gamma_2^*, \ldots \gamma_K^*)$. It should be noted that K users with specified SINR requirements are admissible in the uplink of a CDMA system with signal space dimension N if and only if the sum of their effective bandwidths

$$e(\gamma_k^*) = \frac{\gamma_k^*}{1+\gamma_k^*} \qquad \forall k = 1,2,\ldots K$$

is less than the dimension of the signal space [6], i.e.

$$\sum_{k=1}^{K} e(\gamma_k^*) < N \qquad \ldots\ldots(3.3)$$

In the case of an underloaded system, with $K \leq N$, the desired stopping point for the algorithm is a set of orthogonal codewords. In the case of an overloaded system, with $K > N$, the desired stopping point for the algorithm is a set of GWBE user codewords and powers, with eventual oversized users as defined in section 2.3(a), for which the sum of allocated powers among all valid power allocations for the given target SINRs is minimum. The optimal codewords and power, with specified target SINRs, satisfy following properties:

(a) If there are l oversized users, then all oversized users have orthogonal codewords and the optimal powers for oversized users with target SINR γ_k^* is $p_k = \sigma^2\gamma_k^*$.

(b) The K-l nonoversized users will share a subspace of dimension N-l that is not occupied by oversized users and will use GWBE sequences.

3.2 NONCOOPERATIVE CODEWORD ADAPTATION GAME (NCG)

In this game, user powers are fixed, and individual users adjust only their codewords in order to minimize their corresponding cost function. The NCG is formally defined as

$$\text{NCG} = [\boldsymbol{K}, \{S_k\}_{k\in \boldsymbol{K}}, \{u_k(.)\}_{k\in \boldsymbol{K}}]$$

where, $\boldsymbol{K} = \{1,2,\ldots\ldots K\}$ is the set of players which are the active users in the system.

S_k is the strategy set for player k such that

$$S_k = \{\boldsymbol{s}_k | \boldsymbol{s}_{k,} \in \mathbb{R}^N, \|\boldsymbol{s}_k\| = 1\} \quad \forall k = 1,2, \ldots . K$$

$u_k : S \rightarrow (0,\infty)$ is the k^{th} user cost function which maps the joint strategy space S=$S_1 \times S_2 \ldots \ldots \times S_k$ to the set of positive real numbers.

Individual users select their strategies to minimize their corresponding cost functions for a given set of powers, that is

$$\min_{s_k} u_k \,|_{\mathrm{P}=fixed} \qquad \forall k = 1,2, \ldots . K$$

The user cost function in eq. (3.2) is a quadratic form in user codeword $\boldsymbol{s}_k$, which implies that it is twice differentiable, and differentiating it twice with respect to $\boldsymbol{s}_k$ we get

$$\frac{\partial^2 u_k}{\partial \boldsymbol{s}_k^2} = 2p_k\boldsymbol{R}_k$$

Since $\boldsymbol{R}_k$ is a symmetric positive definite matrix, the user cost function is convex, which further implies NCG is a convex game. The result for concave games can be extended to prove existence of Nash equilibrium point for convex games [24] and as a consequence, a Nash equilibrium point for NCG also exists. The Nash equilibrium for the game is a set of codewords $\boldsymbol{S}^*$ such that

$$\boldsymbol{s}_k^* \in B_k(\boldsymbol{S}_{-k}^*) \quad \forall k = 1,2, \ldots . K \qquad \ldots\ldots(3.4)$$

So to prove the existence of Nash equilibrium for NCG, it must be proved that there exists a codeword matrix $\boldsymbol{S}^*$. Let us define a set valued function $B: S \rightarrow S$ by

$$B(\boldsymbol{S}) = \times_{k\in \boldsymbol{K}} B_k(\boldsymbol{S}^*_{-k})$$

The eq. (3.4) can now be written as

$$\boldsymbol{S}^* \in B(\boldsymbol{S}^*) \qquad \text{......(3.4)}$$

Thus $\boldsymbol{S}^*$ is fixed point for function B. Fixed point theorems give conditions on B which make sure that there exists a strategy combination $\boldsymbol{S}^*$ such that eq. (3.4) is satisfied. According to Kakutani's fixed point theorem, there exists a point satisfying eq.(3.4) for function B if [13],

(a) The strategy space S is a convex and compact set.

(b) For every $\boldsymbol{S}\in S$, the set $B(\boldsymbol{S})$ is nonempty and convex.

(c) The graph of B is closed.

Since, the cost function defined in eq.(3.2) satisfies all the above properties, it is evident that Nash equilibrium exists for NCG. In order to find the Nash Equilibrium, the best response function for each user needs to be identified. The best response in terms of codeword updates can be found by solving the constrained optimization problem of minimizing the user cost function subject to unit norm constraints on the user codewords

$$\min_{\boldsymbol{s}_k} u_k \qquad \text{subject to} \qquad \boldsymbol{s}_k^T\boldsymbol{s}_k = 1$$

A Lagrangian function is defined to solve this constrained minimization problem

$$L_k^S(\boldsymbol{s}_k, \lambda_k) = u_k + \lambda_k(\boldsymbol{s}_k^T\boldsymbol{s}_k - 1) = p_k\boldsymbol{s}_k^T\boldsymbol{R}_k\boldsymbol{s}_k + \lambda_k(\boldsymbol{s}_k^T\boldsymbol{s}_k - 1) \qquad \text{......(3.4)}$$

where, λ_k is Lagrange multiplier.

Differentiating Lagrangian in eq. (3.3) w.r.t. $\boldsymbol{s}_k$ and equating it to zero leads to eigenvalue/ eigenvector equation

$$\boldsymbol{R}_k\boldsymbol{s}_k = \nu_k\boldsymbol{s}_k$$

where, $\nu_k = -\lambda_k/p_k$.

Thus, the best response for user k is the eigenvector corresponding to minimum eigenvalue of $\boldsymbol{R}_k$, since this choice minimizes the effective interference corrupting user k's signal at the receiver. Thus, at Nash equilibrium all user codewords will be the minimum eigenvectors of their corresponding interference-plus-noise correlation matrices.

It should be noted that a given Nash equilibrium point for the NCG does not correspond to a single codeword matrix, but rather to an entire class of matrices that can be related by unitary transformations which preserve the spectrum of the cross-correlation matrix [24].

3.3 NONCOOPERATIVE POWER CONTROL GAME (NPG)

In this game, user codewords are fixed, and individual users adjust only their powers in their corresponding strategy spaces, as defined in section 3.1, in order to minimize their corresponding cost function. The NPG is formally defined as [24]

$$\text{NPG} = [\boldsymbol{K}, \{P_k\}_{k\in K}, \{u_k(.)\}_{k\in K}]$$

where, $\boldsymbol{K} = \{1,2,\ldots\ldots K\}$ is the set of players which are the active users in the system.

P_k is the strategy set for player k such that

$$P_k = \{p_k | 0 < p_k \leq \mathrm{P_{max}}\} \quad \forall k = 1,2,\ldots.K$$

$u_k : P \rightarrow (0,\infty)$ is the k^{th} user cost function that maps the joint strategy space $P=P_1 \times P_2 \ldots\ldots \times P_k$ to the set of positive real numbers.

Individual users select their strategies to minimize their corresponding cost functions for a given set of user codewords, that is

$$\min_{p_k} u_k \,|_{S=fixed} \qquad \forall k = 1,2,\ldots.K$$

Similar to NCG, this game is also a convex game, since the user cost function is linear in p_k [24]. This property guarantees the existence of Nash equilibrium in NPG. Similar to NCG, the best response in terms of power can be obtained by solving the constrained optimization problem of minimizing the user cost function subject to constraints on the user SINR

$$\min_{p_k} u_k \qquad \text{subject to} \quad p_k = \gamma_k^* \boldsymbol{s}_k^T \boldsymbol{R}_k \boldsymbol{s}_k$$

where, γ_k^* is the specified target SINR value for user k.

User k's Lagrangian function is defined as

$$L_k^p(\boldsymbol{s}_k, \eta_k) = u_k + \eta_k(p_k - \gamma_k^* \boldsymbol{s}_k^T \boldsymbol{R}_k \boldsymbol{s}_k)$$

where, η_k is Lagrange multiplier.

The best response power in this game is $p_k = i_k\gamma_k^*$, with $\eta_k = i_k$. Thus, at Nash equilibrium, each user's received power is such that the user achieves it desired SINR.

3.4 NONCOOPERATIVE POWER CONTROL AND CODEWORD ADAPTATION GAME (NPCG)

The game of joint noncooperative codeword adaptation and power control consists of the two separable subgames NCG and NPG as explained earlier. Formally the NCPG is defined as

$$\text{NCPG} = [\boldsymbol{K}, \{ S_k \times P_k \}_{k\in \boldsymbol{K}}, \{u_k(.)\}_{k\in \boldsymbol{K}}]$$

where, all the components of the game are as defined in previous sections. Having defined the subgames for NCPG, the game can now be studied for single cell and multi-cell CDMA systems.

3.4.1 SINGLE CELL CDMA SYSTEM

Consider a single cell synchronous CDMA system with K active users and signal space dimension as N. Other system variables are same as defined in section 3.1. The existence of Nash equilibrium in this scenario can be proved using result from [24]. It states that Nash equilibrium solution for NCPG exists and is defined by codeword matrix **S** and power matrix **P** if and only if **S** represents a Nash equilibrium for NCG and **P** represents a Nash equilibrium for NPG. Since existence of NE for both NPG and NCG has been proved, it can be concluded that NCPG also has NE.

At the optimal Nash equilibrium point of the game, each user's strategy is a best response function to the other users' strategies, and all user codewords are minimum eigenvectors of their corresponding interference plus noise correlation matrices, that is

$$\boldsymbol{R}_k \boldsymbol{s}_k^* = \nu_k \boldsymbol{s}_k^* \quad \forall k = 1,2, \dots K$$

where, ν_k is the minimum eigenvalue of $\boldsymbol{R}_k$ and $\boldsymbol{s}_k^*$ is the corresponding minimum eigenvector.

The equilibrium power for a user is given by

$$p_k = i_k \gamma_k^* \qquad \forall k = 1,2, \dots . K$$

3.4.2 MULTI-CELL CDMA SYSTEM

In a multi-cell scenario, there is a set of users and base stations that are distributed over a given geographical area, such that subsets of users communicate directly with a given base, while creating interference to the other bases for which their transmission is not intended. There can be different ways of modeling a NPCG in multi-cell scenario.

One approach is to consider the intercell interference coming from other cells in the system as a colored Gaussian noise process. In this case, the covariance matrix of the intercell interference-plus-noise seen by the cell's base station receiver is considered as a general symmetric and positive definite matrix $\overline{\mathbf{W}}$, as opposed to the scaled identity matrix $\mathbf{W}$ that corresponds to the additive white Gaussian noise used in the single cell case. For any symmetric and positive definite matrix, the convexity of user cost function, u_k, is preserved in both p_k and $\boldsymbol{s}_k$. This implies that for convex and bounded joint codeword and power strategy spaces, S and P, the NCG and NPG will be convex games for which a Nash equilibrium exists. Furthermore, according to the discussion in section 3.4.1, the NCPG will also have a Nash equilibrium for which the optimal codewords and powers are according to *ref.* [26].

Another approach is where intercell interference is considered as it is and users in each cell try to achieve their desired QoS using NCPG. In this approach, the link gains from every user to base stations must be explicitly considered. As discussed earlier, Nash equilibrium for NPCG can only exist if NCG has a Nash equilibrium for some power matrix $\mathbf{P}$. As explained in *ref.* [27], there may exist some link gain matrix, for which, there is no NE for NCG regardless of $\mathbf{P}$. But the possibility of existence of NE cannot be ruled out if the link gain matrices are of special structure or if interference function is defined in a different manner [28].

CHAPTER 4

SYSTEM MODEL AND SIMULATION PARAMETERS

The joint power control and codeword adaptation game has been performed for single cell and multi-cell synchronous CDMA systems in this dissertation. The system model and simulation prameters for single cell CDMA system and multi-cell CDMA system are presented here. The power and codeword update algorithm used for simulation has been introduced later in the chapter. All the simulations have been performed in MATLAB 7.6.

4.1 SINGLE CELL CDMA SYSTEM

A single cell uplink synchronous CDMA system has been considered. The aim of each user is to achieve its desired QoS. The QoS is determined by the SINR obtained after chip level filtering. The utility function has been taken as the product of power and interference at the receiver. The simulation is performed for three different situations:

(a) *Variable QoS with fixed number of users*: This situation illustrates the tracking ability of the update algorithm for fixed users and variable target SINRs. Single cell system with 5 users is considered with their initial target SINRs as {5, 4, 3, 2.5, 1.5}. After reaching equilibrium with these target SINRs, last user changes it target SINR to 2 and a new set of equilibrium codeword and power is obtained. Then, the user again returns to its initial SINR of 1.5.

(b) *Variable number of users*: In this scenario, the ability of algorithm to track variable number of users is illustrated. Initially, 6 active users are taken having target SINRs as {1.6, 1.5, 1.4, 1.3, 1.2, 1}. After reaching equilibrium, last user becomes inactive and is dropped from the system. Remaining users keep their target SINRs unchanged and system again reaches to an equilibrium state. Another user with target SINR as 1.1 is added to the system and a new equilibrium state is obtained with this new configuration.

(c) *Quantized codewords and powers*: The power and codeword update algorithm yields real valued codewords and powers that can take any value in S and P. However, practical implementation of the algorithm in hardware employing digital signal processors usually uses a finite number of values corresponding to scalar quantization of user codewords and powers. Simulation is performed to analyze the effect of quantization on NE and it is found that if quantization levels are small enough to ensure the convex perception of strategy space, then NE can be achieved. The quantization level for codeword is taken as 1/32 and for power, it is taken 0.01.

User codeword matrix is initialized randomly and initial user power is set to 0.1. Other parameter values are listed in table 4.1. The simulation is performed with these parameters and user powers, SINRs and costs are plotted against number of iteration of algorithm.

Table 4.1 Simulation Parameters

Signal space dimension	N	4
AWGN variance	σ^2	0.1
Power update parameter	μ	0.2
Codeword update parameter	β	0.2

4.2 MULTI-CELL CDMA SYSTEM

4.2.1 CONTINUOUS CODEWORD AND POWER PROFILE

In this setup, user codeword and power take values from a continuous profile. Two different system scenarios have been considered under this setup.

(a) *Adaptation for intercell interference as colored noise* : A system with K = 5 users and signal space of dimension N = 4 is taken. The initial target SINRs are taken as {5, 4, 3, 2.5, 1.5}.

Table 4.2 Simulation Parameters

Signal space dimension	N	4
Power update parameter	μ	0.2
Codeword update parameter	β	0.2

System is initialized with random codewords for each user and initial powers equal to 0.1. The covariance matrix of the intercell interference plus noise seen by the cell base station receiver is taken

$$\bar{\mathbf{W}} = diag\{0.8501, 0.5167, 0.3471, 0.1467\}$$

(b) *Adaptation for intercell interference with path gain model*: In this setup, we consider a 4 cell system with 4 user per cell and the equilibrium is analyzed for two different dimensions of signal space N = 4 and N = 6. The cell dimensions are taken as 100m×100m. A simple path gain model with propagation exponent of 3.6 is used to calculate the intercell interference. The target SINRs for users in each cell have been chosen as {2.5, 2, 1.5, 1.2}.

Table 4.3 Simulation Parameters

Noise variance	σ^2	10^-9
Power update parameter	μ	0.1
Codeword update parameter	β	0.2

4.2.2 QUANTIZED CODEWORD PROFILE

In this setup, user codewords are taken from a quantized strategy space. The simulations are performed for static and dynamic system. Dynamics is introduced by varying the number of users in the system.

(a) *Adaptation for static CDMA system*: A 4 cell cellular system is considered with 5 users per cell. Different quantization levels are considered for different signal space dimensions. Signal space of dimension N=4 is simulated with quantization level q=1/32 whereas N=6 is simulated with q=1/16. Other simulation parameters are as shown in the table 4.4. The target SINRs for users in each cell have been chosen as {3, 2.5, 2, 1.5, 1.2}.

(b) *Adaptation for dynamic CDMA system*: A 4 cell cellular CDMA system is taken with N = 6 and quantization level q=1/16. After equilibrium is reached with initial setup, a user with target SINR equal to 2 from cell 4 becomes inactive and is dropped. A new set of equilibrium is reached before the user again becomes active. Once again the system updates itself to new system configuration and achieves a new equilibrium state. All the other system parameters are same as in table 4.4.

Table 4.4 Simulation Parameters

Noise variance	σ^2	10^-9
Power update parameter	μ	0.1
Codeword update parameter	β	0.2

4.3 POWER CONTROL AND CODEWORD ADAPTATION ALGORITHM

The algorithm for power control and codeword adaptation in a multicell CDMA system is presented here. Users update their codewords and power to arrive at a equilibrium point. The best response strategies for power and codeword update for NPG and NCG respectively (presented in chapter 3) may lead to abrupt power changes and/or new user codewords which are distant in signal space from current user codewords. As such behavior is not desirable in practical operation of a system, it is more appropriate to change user codewords and powers in small increments, with corresponding incremental changes of the receiver filter that follow the transmitter codeword changes. This will allow the receiver to continue detecting transmitted symbols with higher accuracy. At a given instance n of NPCG, codeword and power adaptation for user k is defined as

$$s_k(n+1) = \frac{s_k(n)+m\beta x_k(n)}{\|s_k(n)+m\beta x_k(n)\|} \qquad \text{...... (4.1)}$$

$$p_k(n+1) = p_k(n) - \mu[p_k(n) - i_k(n)\gamma_k^*] \qquad \text{....... (4.2)}$$

where, $x_k(n)$ is the best response strategy for NCG,

$m = \text{sign}(s_k^T x_k)$

β and μ determine how far the updated codeword and power can be from the old codeword and power respectively.

γ_k^* = target SINR of user k,

$i_k(n)$ = interference for user k at instant n.

The steps of adaptation algorithm for multicell CDMA system are presented below:

1. *Initialization*: Intialize the system with user codewords **S**, powers **P** and target SINR values. Also define noise covariance matrix and update parameters μ and β.

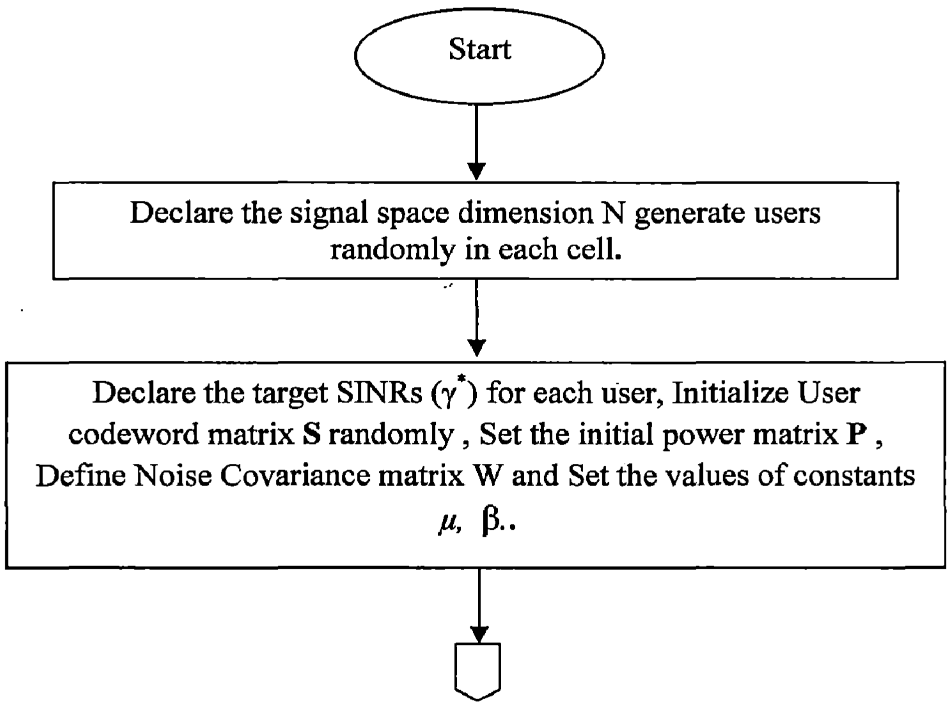
2. *Triggering Events*:
   (a) If user SINR with specified **S** and **P** is less than target SINR.
   (b) Any of the active users changes its target SINR.
   (c) Number of active users in the system changes.

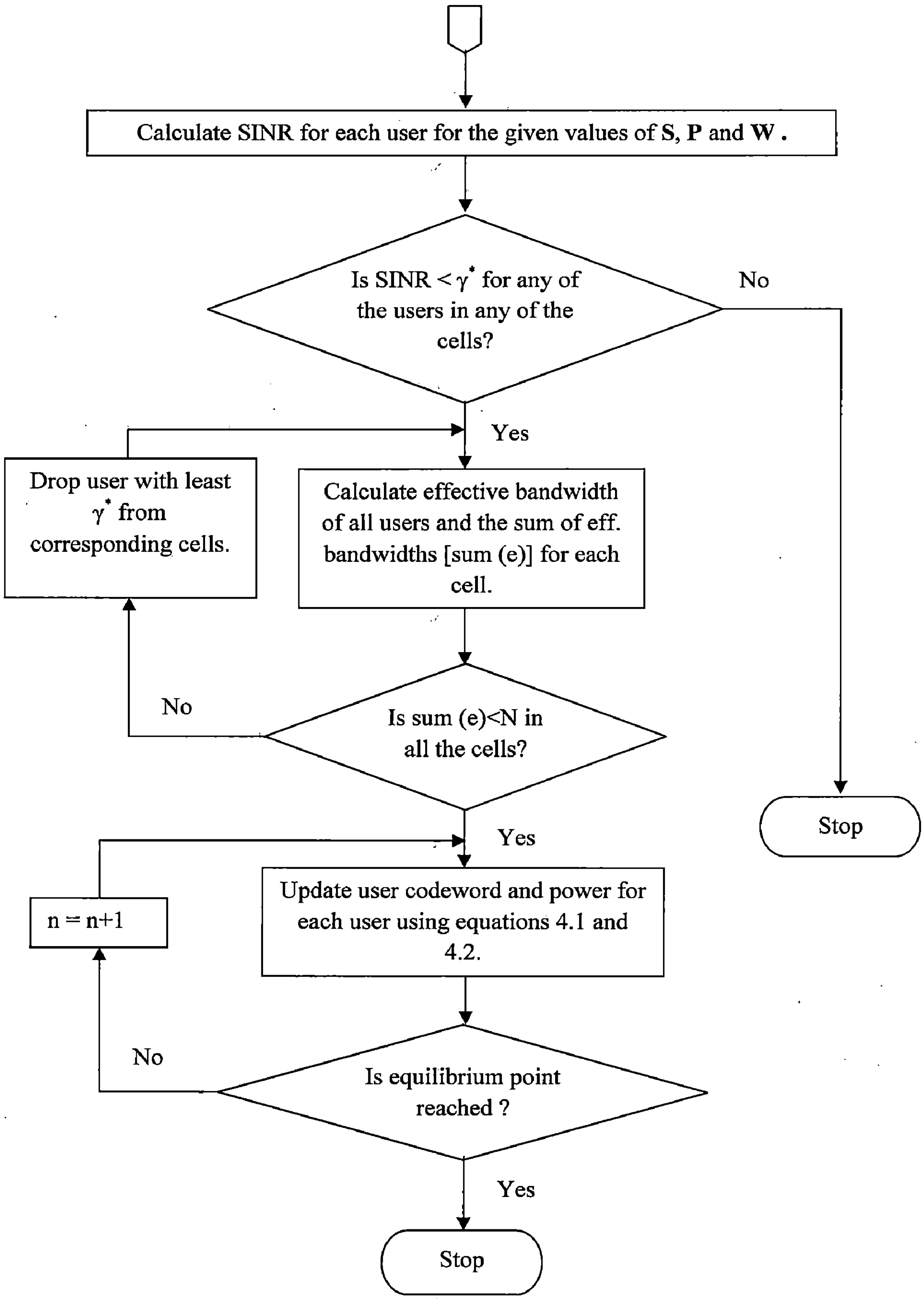
3. *Admissibility check*: Go to step 4 if admissibility condition in eq. 3.3 is satisfied else drop the users with least SINR requirement and again check for admissibility.

4. *Adaptation Stage*: set $n=1$. For each user in each cell, Do
   (a) Compute $\boldsymbol{R}_k(n)$ and determine its minimum eigenvector $\boldsymbol{x}_k(n)$.
   (b) Update user codeword using eq. 4.1.
   (c) Update user power using eq. 4.2.
   (d) Compute user cost function and check for equilibrium.

   If equilibrium is achieved STOP else n=n+1 and go to step 4(a).

The flowchart for codeword and power update for multi-cell CDMA system is shown here.





The algorithm is similar for quantized codeword and power except a quantization step is added after codeword and power update.

CHAPTER 5

RESULTS AND DISCUSSION

The results of simulation for joint power control and codeword adaptation performed for single cell and multi-cell synchronous CDMA systems are presented in this chapter. Equilibrium powers, SINRs and costs are taken as performance parameters for evaluating the adaptation algorithm. These parameters are plotted against number of iterations of the adaptation algorithm. Single cell CDMA system is studied for variable QoS, variable number of users and quantized codewords and powers. Multi-cell CDMA system is simulated and studied for intercell interference modeled as colored Gaussian noise process and for intercell interference calculated using path loss model. The effects of variation in signal space dimension and quantization of codewords are studied for the latter scenario.

5.1 SINGLE CELL CDMA SYSTEM

5.1.1 VARIABLE QoS AND FIXED NUMBER OF USERS

Fig. 5.1 (a), (b) and (c) show the variation of received power, SINR and cost function respectively with the number of iterations. The simulation is performed for 5 active users with target SINR requirement of one of the users changing with time. The users reach at equilibrium with initial target SINR values. At iteration 350, a user changes its target SINR from 1.5 to 2. The system reaches new equilibrium point at iteration 487. The user again changes its target SINR back to 1.5 at iteration 700 and equilibrium is reached at iteration 813. The powers, SINRs and cost obtained at equilibrium are same as those obtained in *ref.* [24]. The equilibrium codewords at SINR=1.5 and SINR=2, **S1** and **S2** respectively, are as shown below:

$$\mathbf{S1} = \begin{matrix} 0.2034 & -0.1993 & 0.7682 & 0.7234 & -0.2640 \\ 0.2041 & 0.9766 & 0.3648 & -0.1218 & 0.1649 \\ 0.8903 & -0.0553 & -0.2561 & -0.1940 & -0.5558 \\ 0.3527 & 0.0591 & -0.4596 & 0.6514 & 0.7708 \end{matrix}$$

S2 =

0.1945	-0.1902	0.7680	0.7383	-0.2706
0.2137	0.9801	0.3712	-0.1306	0.1687
0.8823	-0.0407	-0.2792	-0.1708	-0.5636
0.3716	0.0389	-0.4409	0.6393	0.7620

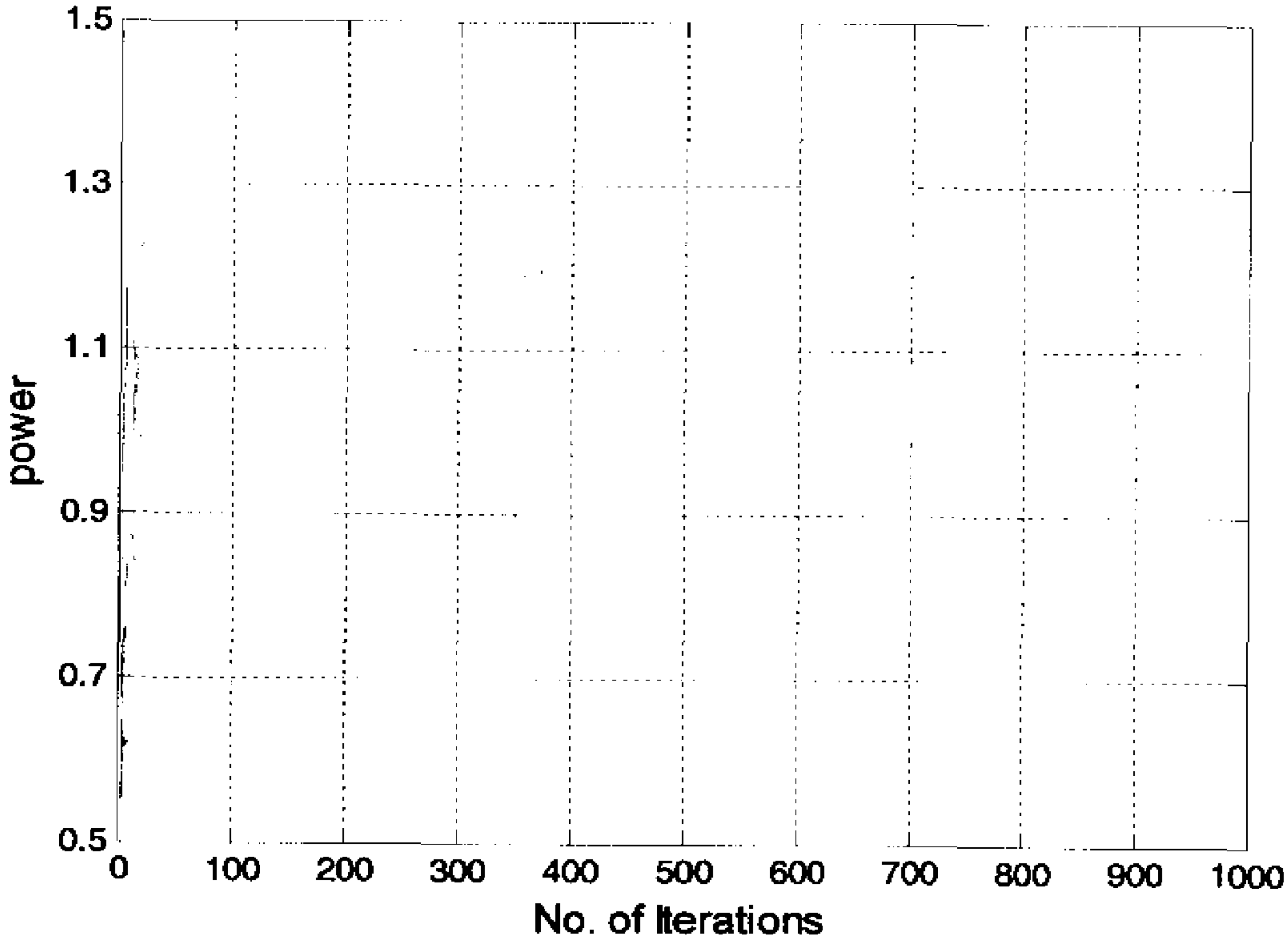


Figure 5.1(a) Variation of Power

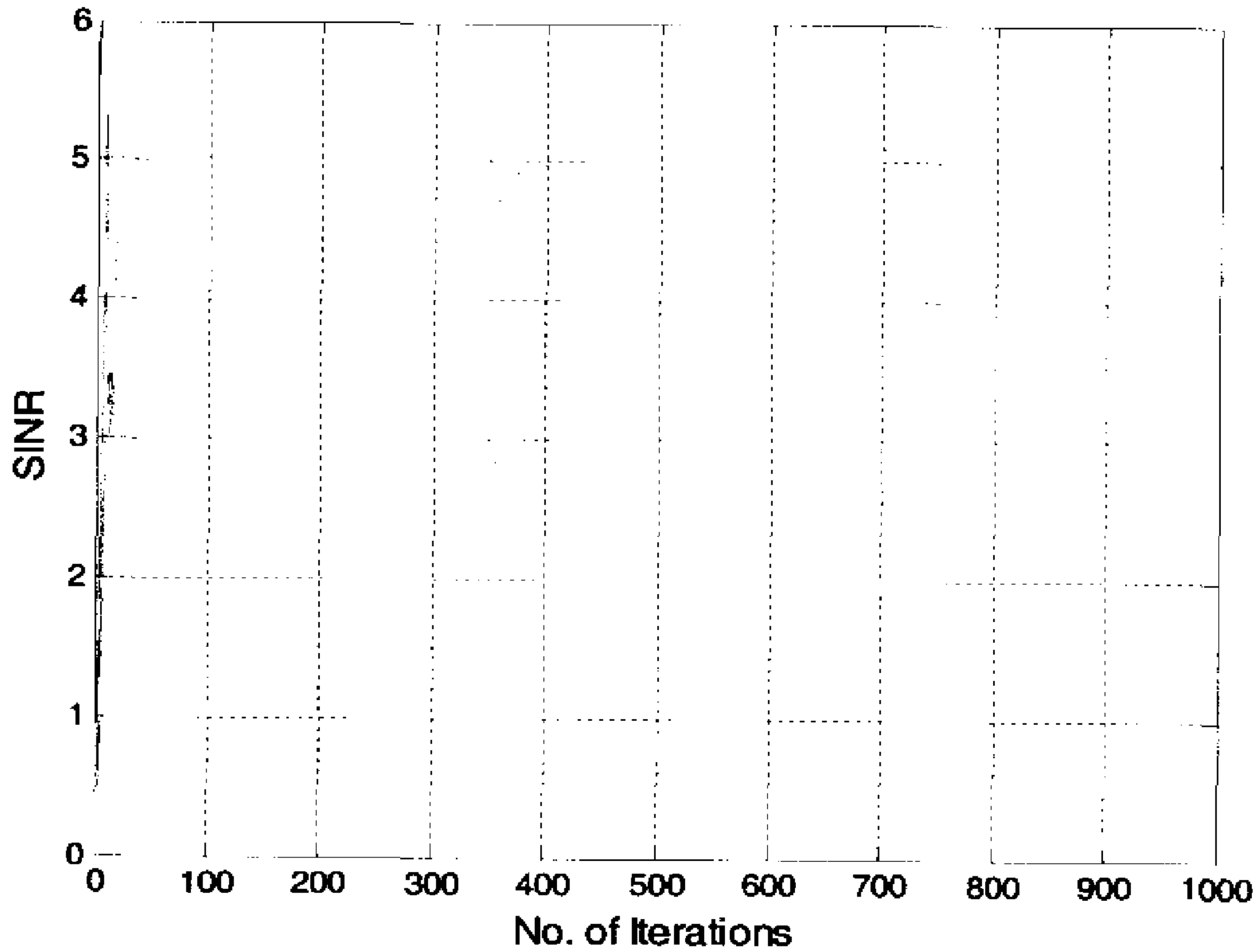


Figure 5.1(b) Variation of SINR

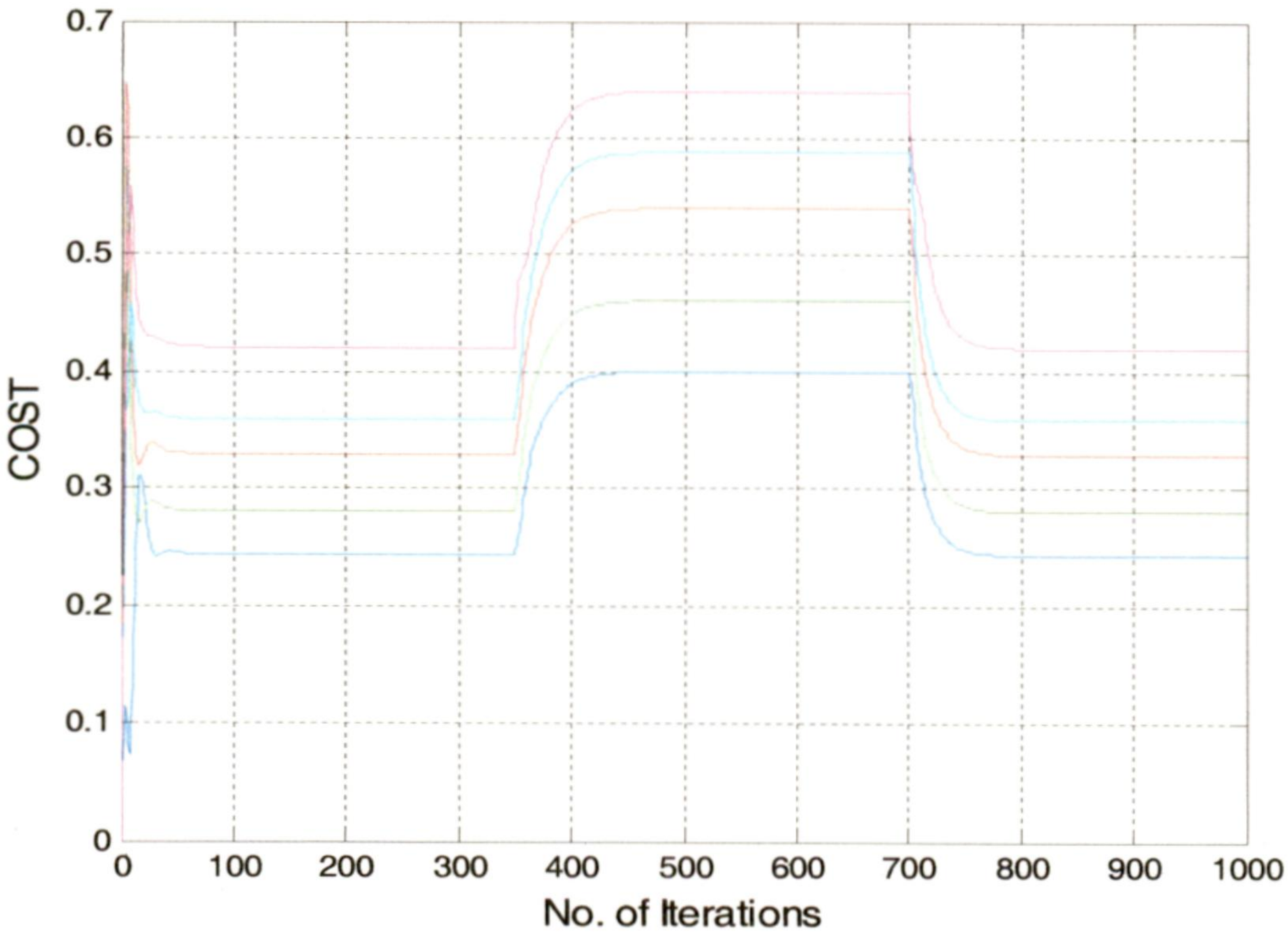


Figure 5.1(c) Variation of Cost

It is clearly visible from the results that user with higher target SINR transmits with higher power and the system updates itself from one system configuration to other configuration without any significant change in user SINR. Thus, the QoS of any user does not suffer much while system adjusts itself to the changes.

5.1.2 VARIABLE NUMBER OF USERS

Fig. 5.2 (a), (b) and (c) show the variation of received power, SINR and cost function with the number of iterations respectively for variable number of users. The system reaches equilibrium with 6 users. At iteration 300, user with target SINR equal to 1 becomes inactive and is dropped from the system. The system reaches new equilibrium point at iteration 358. A new user with target SINR equal to 1.1 joins the system at iteration 600 and system obtains equilibrium at iteration 716. It is clear from the results that the power of each user is proportional to their target SINR. As the users get dropped from the system, a sudden drop in interference causes remaining users' SINRs to increase. Similarly, inclusion of new users causes SINRs to drop because of increase in interference caused by new users. The equilibrium powers, SINRs and costs are same as those obtained in *ref.* [24]. Codeword matrix at equilibrium for different equilibrium states as discussed above are represented as S1, S2 and S3 respectively and are as shown below:

S1 =

0.5392	-0.3024	0.0487	-0.8976	-0.4039	-0.3816
0.1779	0.6697	0.3331	-0.4161	0.8459	-0.1479
0.8041	0.1550	-0.5955	0.1451	0.1042	0.6563
-0.1760	0.6604	-0.7294	-0.0094	-0.3325	-0.6339

S2 =

0.4413	-0.1477	0.1053	-0.8852	-0.5157
0.1768	0.6930	0.3412	-0.3806	0.7037
0.8245	-0.0458	-0.6398	0.2236	0.2730
-0.3069	0.7041	-0.6805	-0.1470	-0.4053

S3 =

0.3713	-0.2573	0.2896	-0.8940	-0.4826	0.4499
0.1449	0.7457	0.5121	-0.2713	0.7323	0.2171
0.7607	-0.1517	-0.5339	0.3190	0.3463	0.6166
-0.5123	0.5956	-0.6073	-0.1594	-0.3331	0.6085

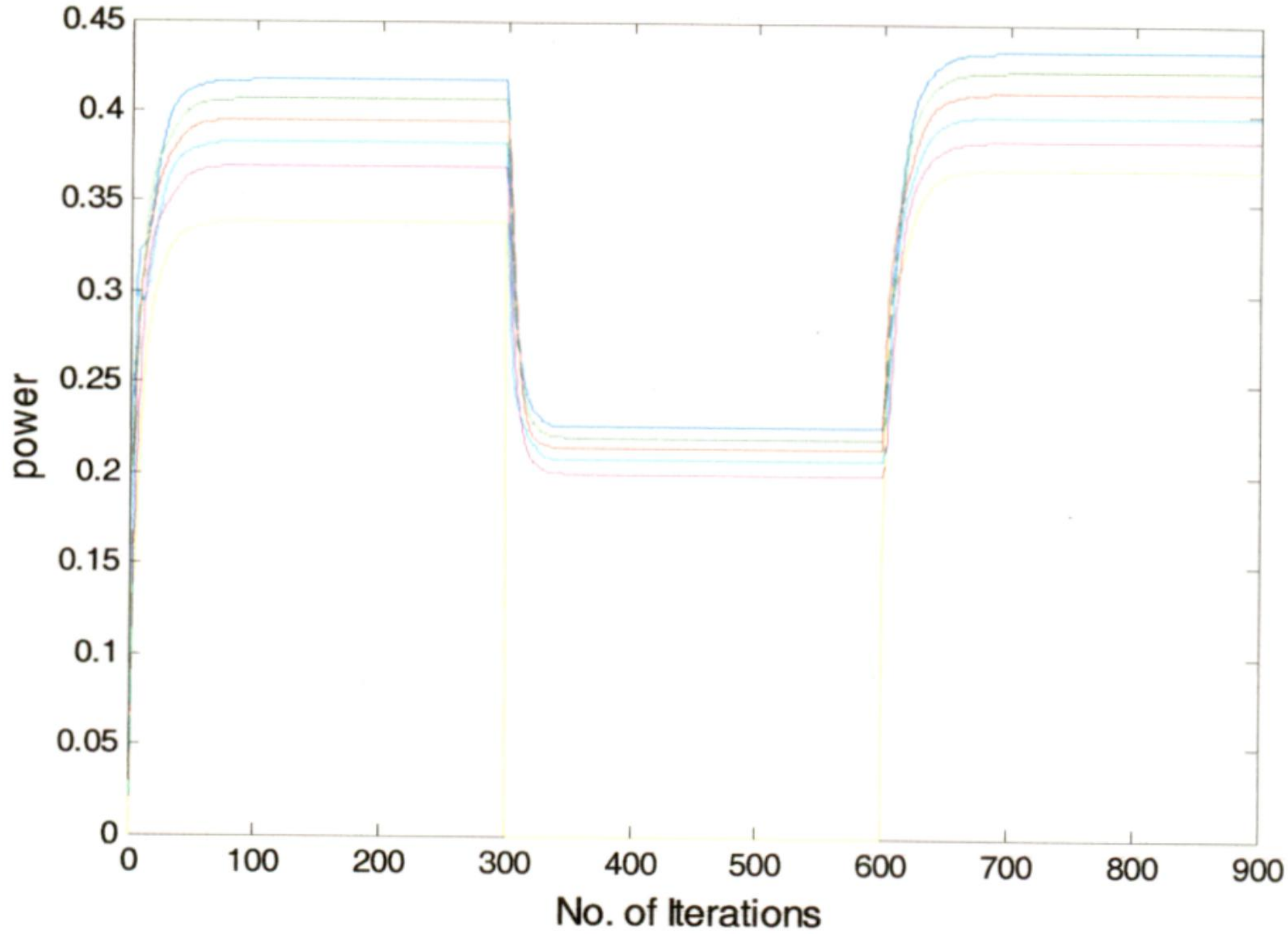


Figure 5.2(a) Variation of Power

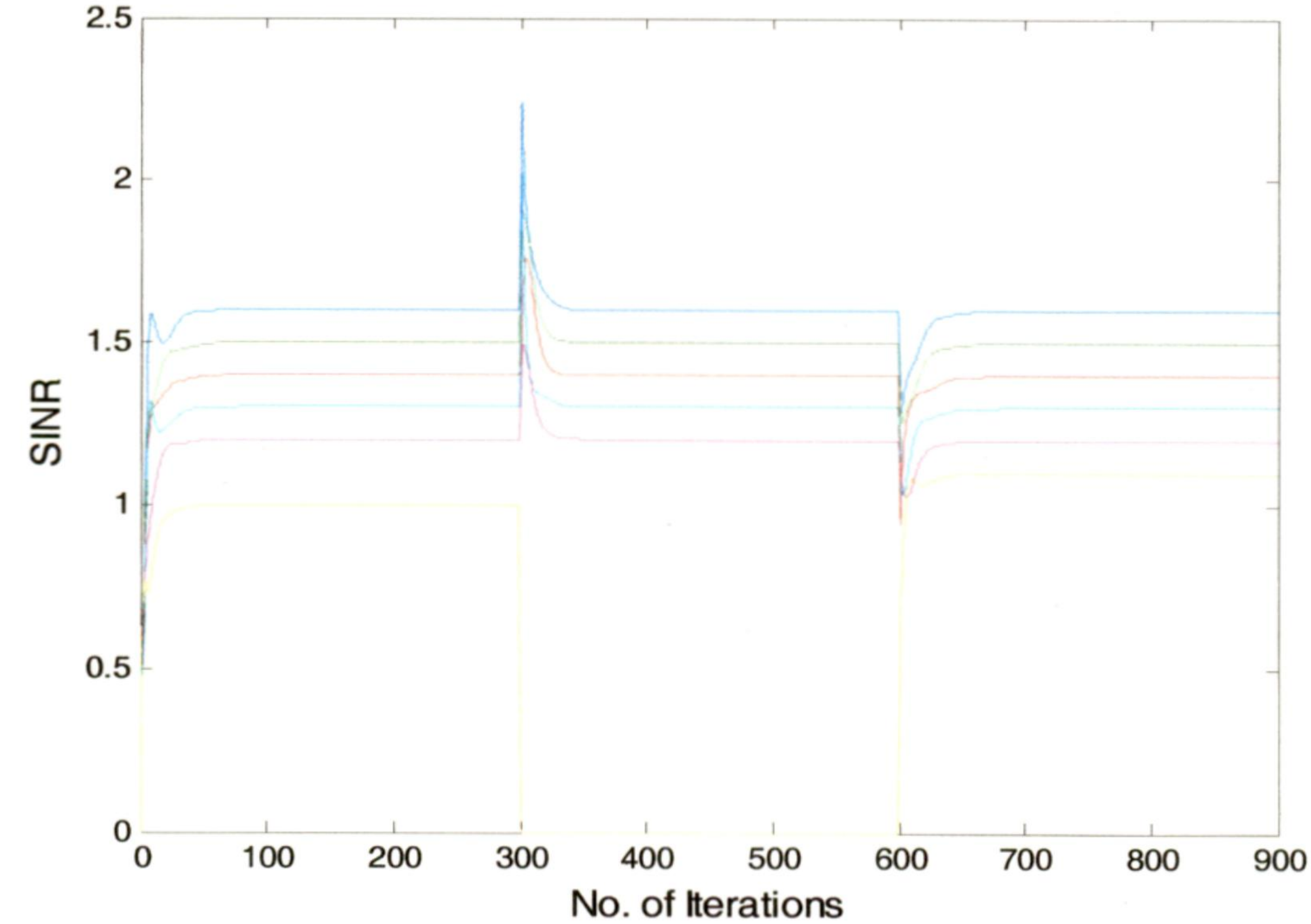


Figure 5.2(b) Variation of SINR

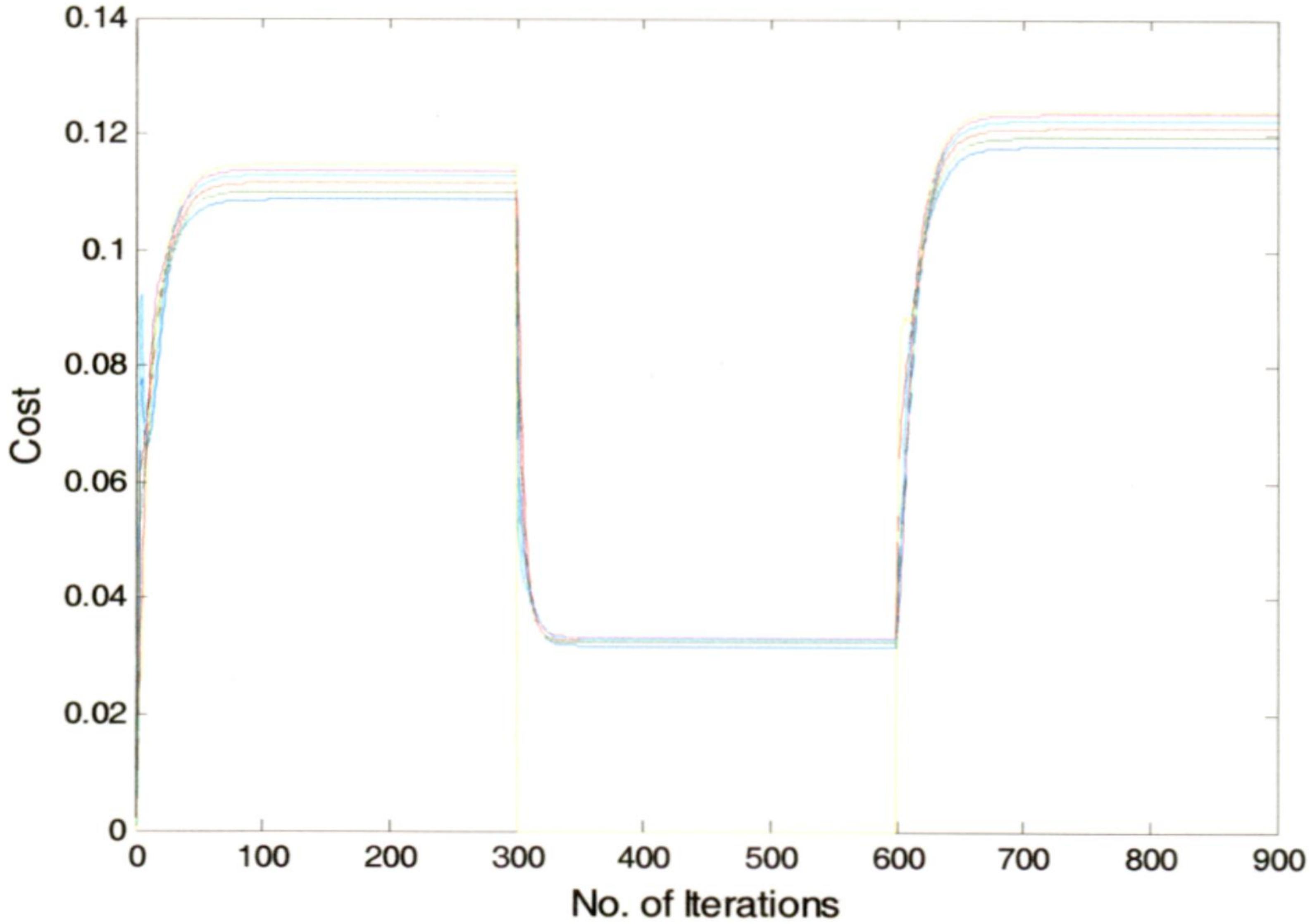


Figure 5.2(c) Variation of Cost

In this case also, we see that power is proportional to target SINR and system update to any change in number of users is smooth and without any significant reduction in QoS.

5.1.3 QUANTIZED CODEWORD AND POWER

The variation in user received powers and costs are shown in Fig. 5.3 (a) and (b) respectively. The system configuration is same as initial system configuration in section 5.1.1. The user codewords at equilibrium are given below:

$$S1 = \begin{matrix} 0.6094 & -0.2031 & 0.6406 & -0.4844 & 0.4219 \\ 0.1406 & -0.1406 & 0.6094 & 0.8594 & -0.3594 \\ 0.6406 & 0.7656 & -0.2031 & 0.1094 & -0.2031 \\ -0.4531 & 0.6094 & 0.3906 & 0.1406 & 0.7969 \end{matrix}$$

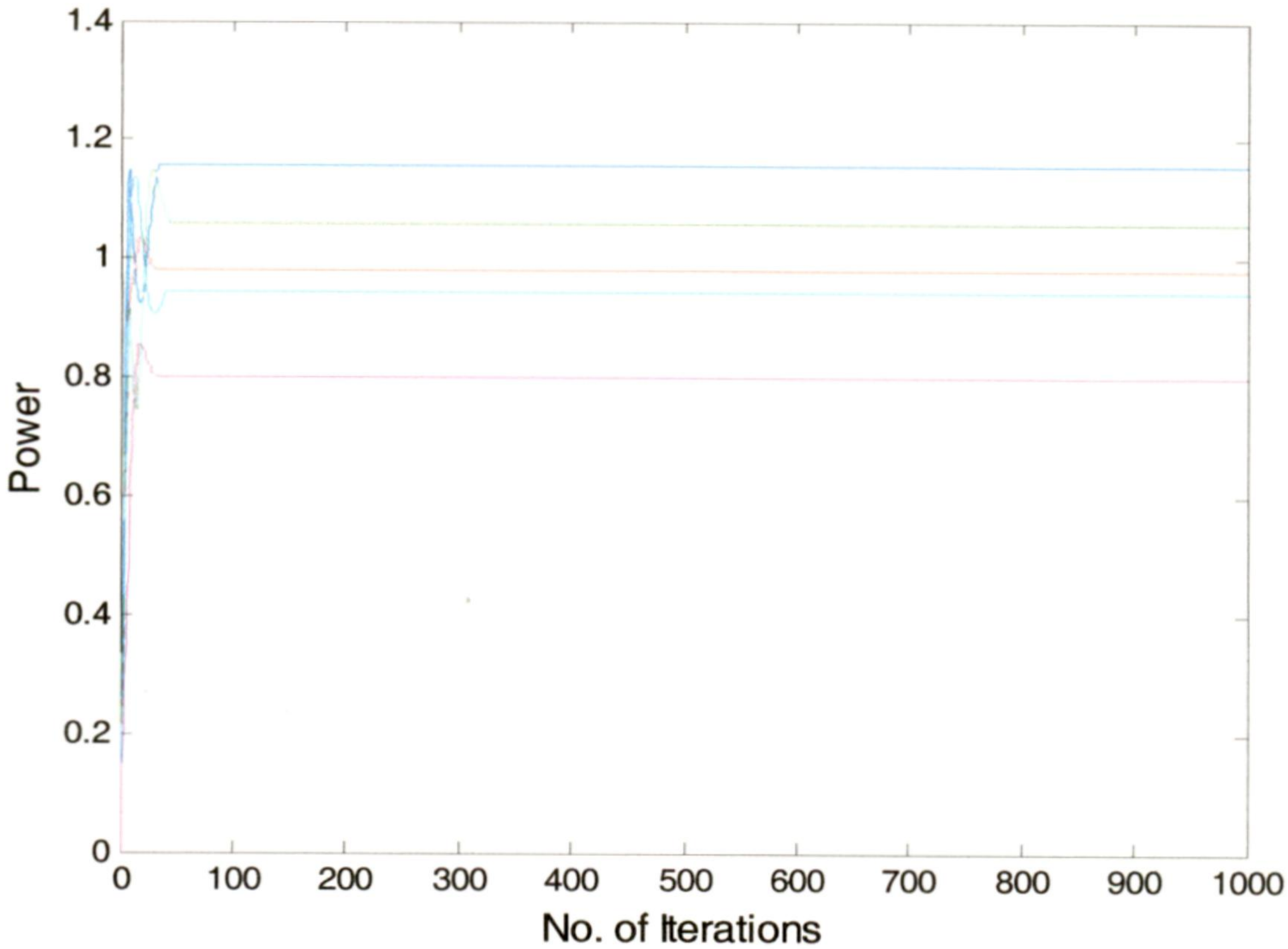


Figure 5.3(a) Variation of Power for N=4 with q = 1/32.

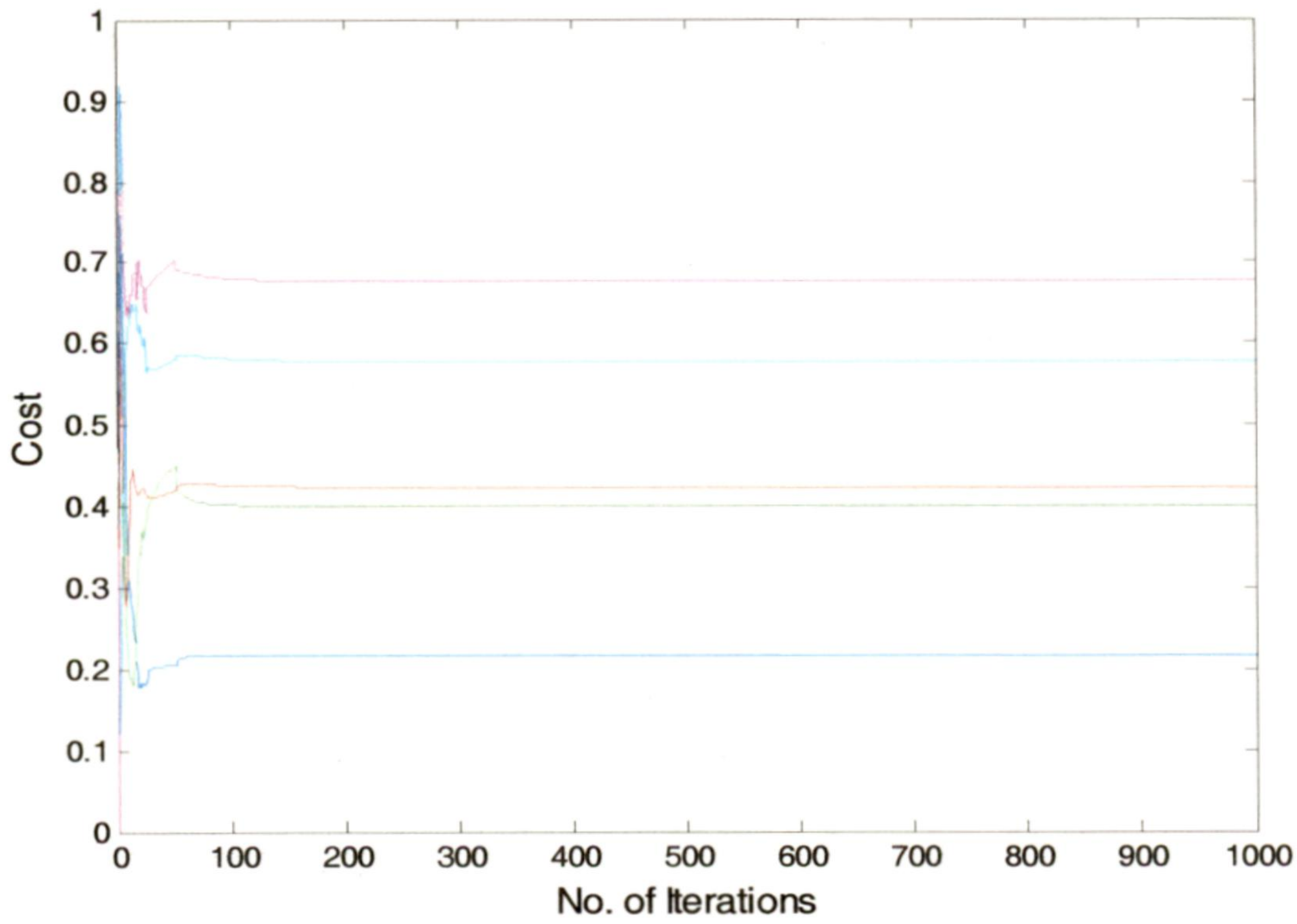


Figure 5.3(b) Variation of Cost for N=4 with q = 1/32.

5.2 MULTI-CELL CDMA SYSTEM

In this section, we present the results obtained for multi cell synchronous CDMA system. First we discuss at the results obtained for intercell interference modeled as colored Gaussian noise and then, for intercell interference calculated using path gain model with propagation exponent of 3.6. The latter scenario is simulated for 4 cell synchronous CDMA and studied for effects on evaluation parameters for:

(a) change in signal space dimension,

(b) continuous and quantized codewords.

5.2.1 CONTINUOUS CODEWORD AND POWER

(a) ***Adaptation for intercell interference as colored noise*****:**

A single cell CDMA system is considered and multicell scenario is introduced by modeling intercell interference as colored Gaussian noise process. System with 5 users and signal space of dimension 4 is considered. The variation of user received powers and costs are shown in Fig. 5.4 (a) and (b) respectively. The codeword matrix at equilibrium is

S1 =	-0.5292	0.3177	0.2701	0.8249	0.1078
	0.6187	0.7813	-0.2390	0.2317	-0.2141
	0.0884	0.3666	0.5138	-0.3721	0.9423
	0.5739	-0.3927	0.7784	0.3570	-0.2338

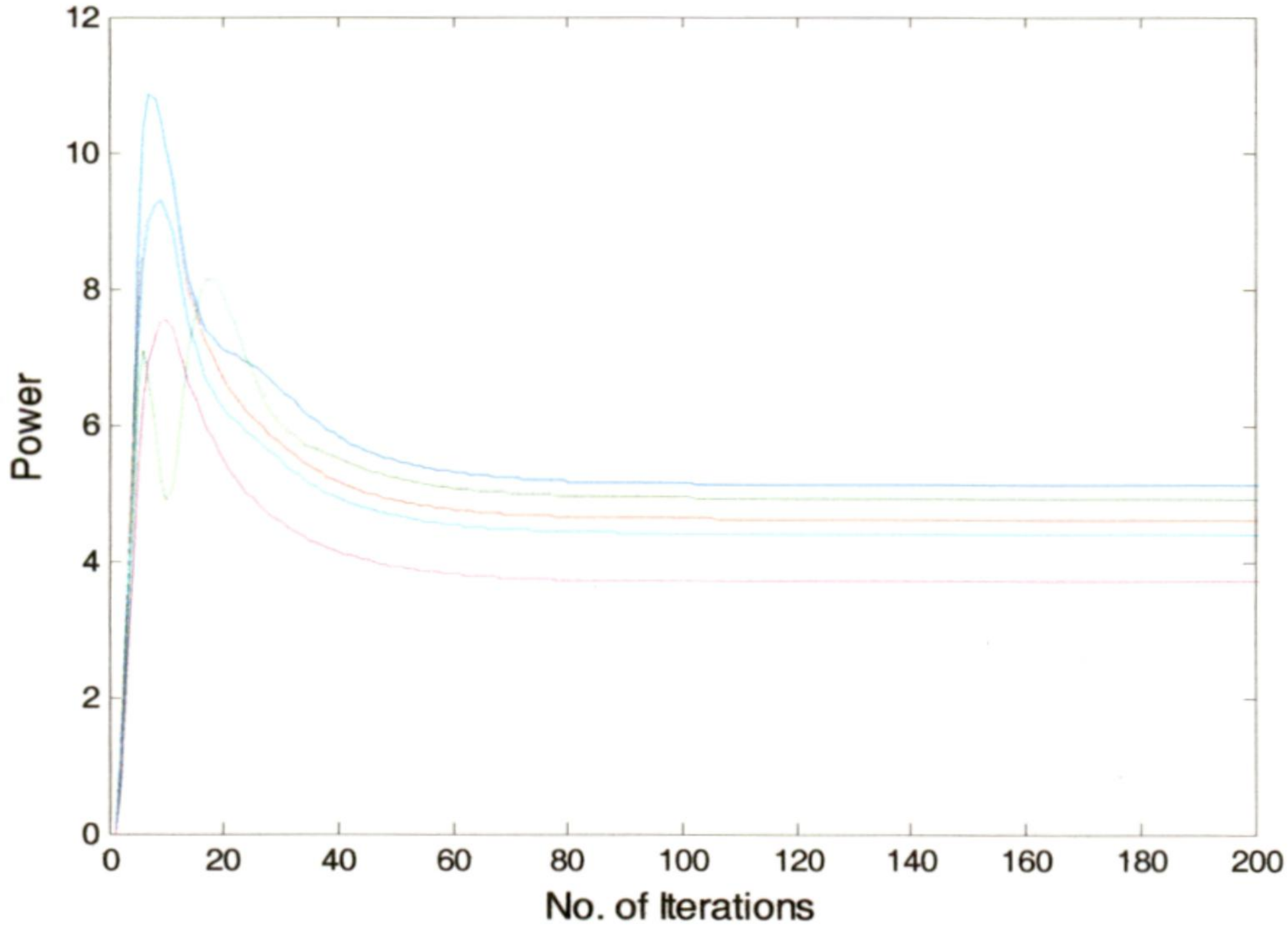


Figure 5.4(a) Variation of Power

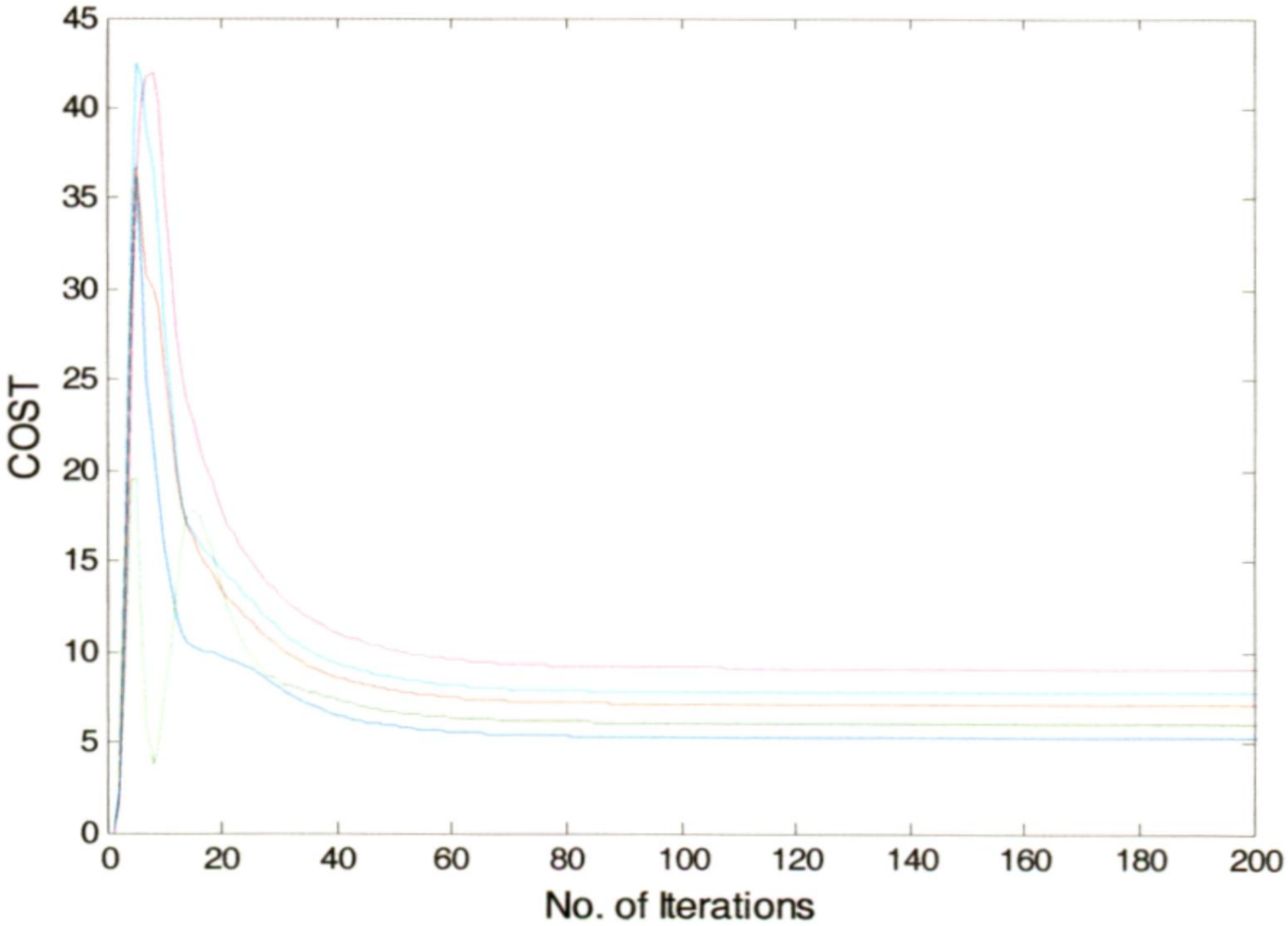


Figure 5.4(b) Variation of Cost

(b) ***Adaptation for intercell interference with path gain model:***

A 4 cell synchronous CDMA system with 5 users per cell is considered. The user locations are shown in Fig. 5.5. Cells are taken as square grids with a base station at the centre of each cell. Cell size is 100m×100m.

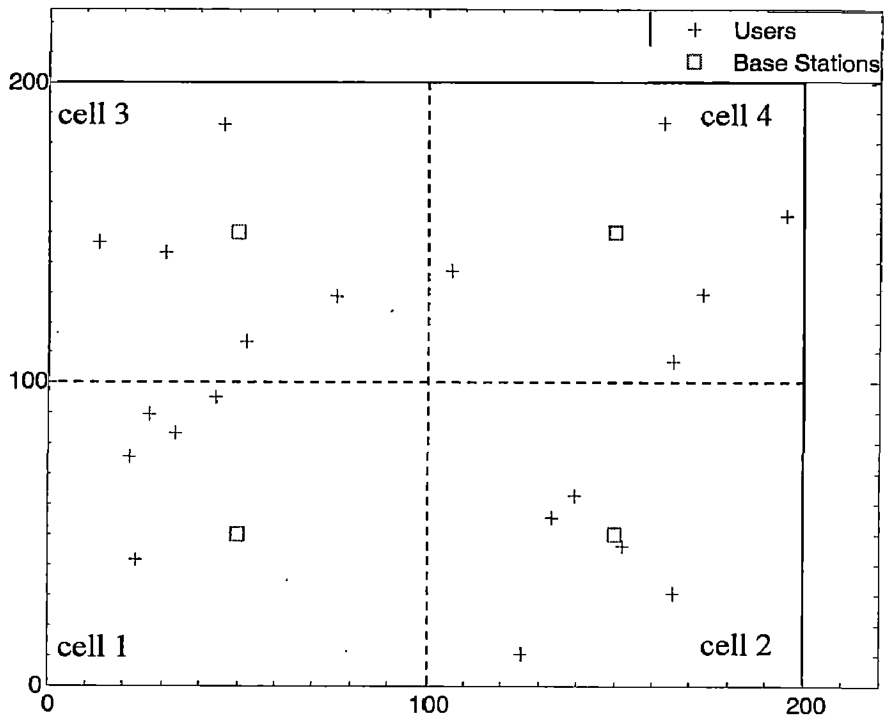


Figure 5.5 Distribution of Users

NPCG is performed for above user configuration with signal space dimensions of N=4 and N=6 to study the effect of change in signal dimension to the convergence properties of algorithm. The results with N=4 and N=6 are plotted in Fig. 5.6 and 5.7 respectively. Fig. 5.6 (a), (b) and(c) show variation in transmit powers, SINRs and costs respectively for N=4 and Fig. 5.7 (a), (b) and (c) show variation for same parameters for N=6. Results indicate faster convergence with increase in signal space dimension.

It is evident from the results that, for N=4, the system does not reach an equilibrium but even in this case, the performance is algorithm is satisfactory in that the SINRs of users are very near to their target SINRs and even though the powers do not converge for some users, they oscillate around a certain value.

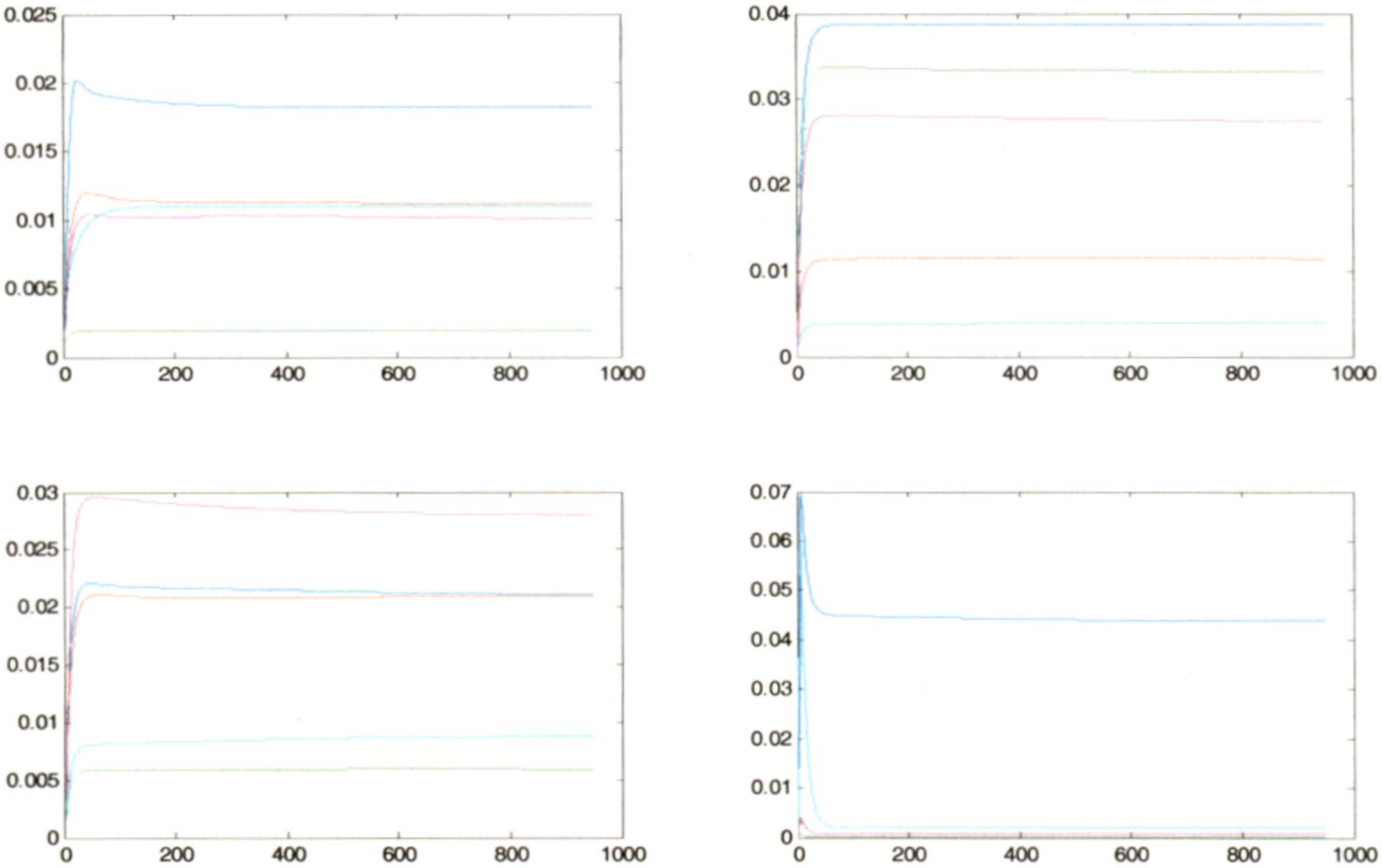


Figure 5.6(a) Variation in Transmit Power for N=4

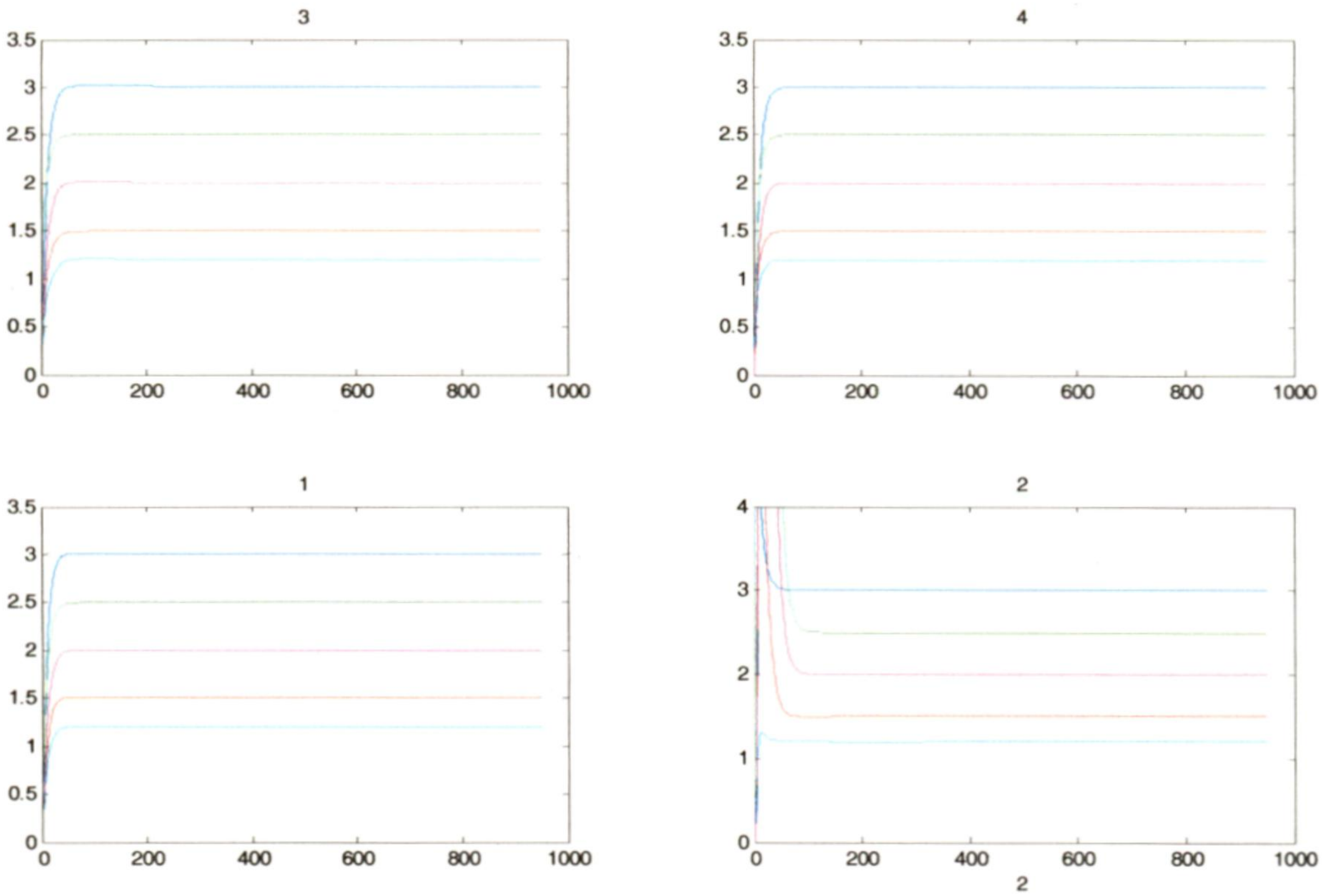


Figure 5.6(b) Variation in SINR for N=4

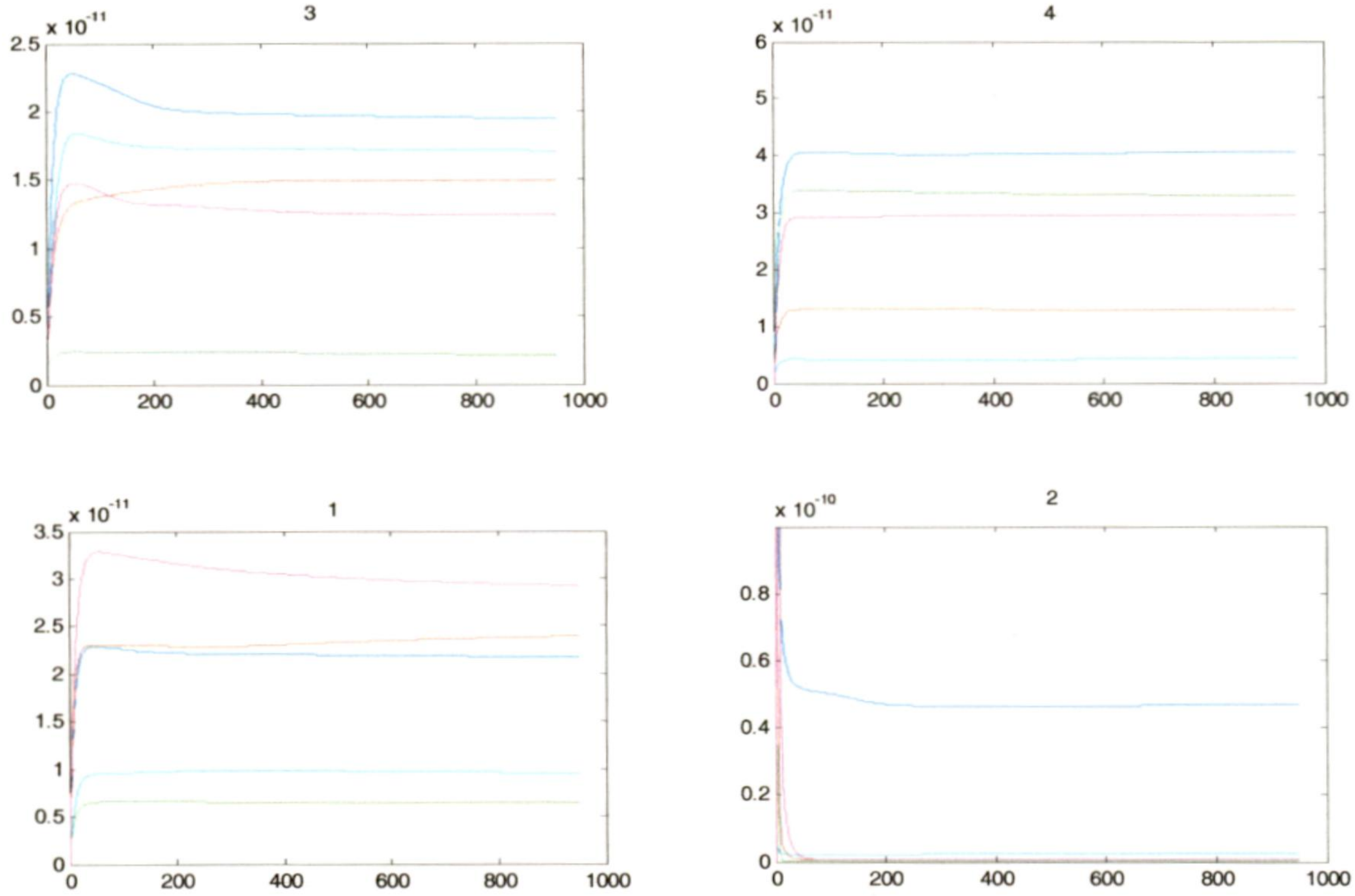


Figure 5.6(c) Variation in Cost for N=4

The cross-correlation matrix for users of cell 1for N=4 is

$$
\mathbf{SS^T} = \begin{matrix} 0.9441 & -0.1015 & -0.0719 & -0.1176 \\ -0.1015 & 0.7563 & -0.1365 & -0.2605 \\ -0.0719 & -0.1365 & 0.9265 & -0.1601 \\ -0.1176 & -0.2605 & -0.1601 & 0.7334 \end{matrix}
$$

It can be seen that the user codewords have good auto-correlation with lower cross-correlation values. Cross-correlation matrices for users of other cells also exhibit similar properties. Next we show cross-correlation matrix for users of cell 1 for N=6. Codewords for users from other cells also show similar cross-correlation properties.

$$
\mathbf{SS^T} = \begin{matrix} 1.2065 & 0.1005 & -0.0675 & -0.0690 & 0.0413 & 0.0948 \\ 0.1005 & 1.2939 & 0.0888 & 0.0169 & 0.1210 & -0.0592 \\ -0.0675 & 0.0888 & 1.2421 & -0.1135 & 0.0734 & 0.1494 \\ -0.0690 & 0.0169 & -0.1135 & 1.2574 & 0.1048 & 0.0827 \\ 0.0413 & 0.1210 & 0.0734 & 0.1048 & 1.2185 & 0.0798 \\ 0.0948 & -0.0592 & 0.1494 & 0.0827 & 0.0798 & 1.1834 \end{matrix}
$$

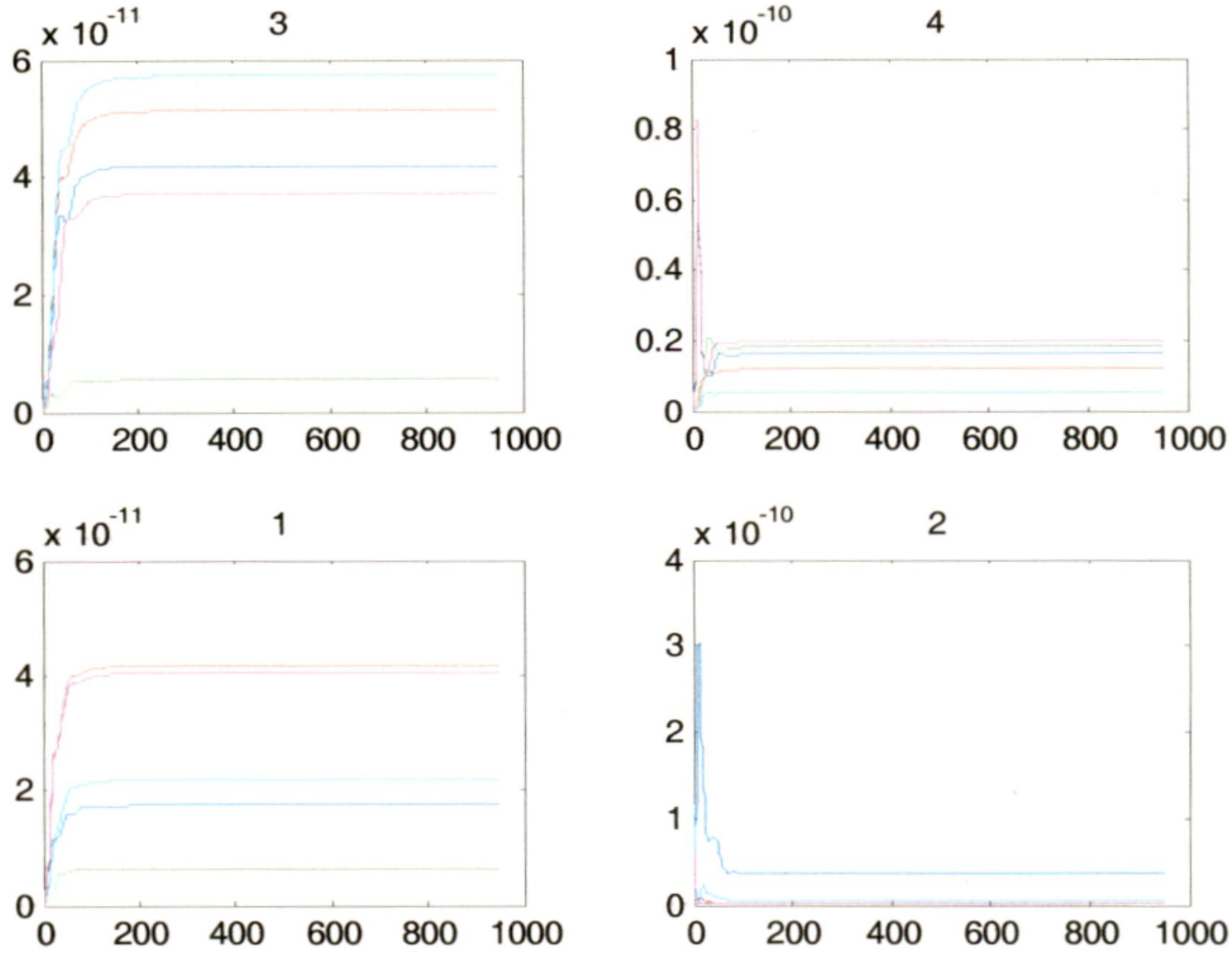


Figure 5.7(c) Variation in Cost for N=6

From the results given above, we can see that with the increase in signal space dimension to N=6, the system attains equilibrium and the transmit power levels also decrease as compared to N=4 which results in reduction in value of cost function. The drawback of increase in signal space dimension is increase in signal bandwidth and also increase in the amount of feedback data. This problem can be somewhat tackled by introducing quantization of codeword value.

5.2.2 QUANTIZED CODEWORD

(a) ***Adaptation for static CDMA system:***

Simulation is performed for same user configuration shown in Fig. 5.5 for signal space of dimension N = 4 and N = 6 with quantization level q = 1/32 and q = 1/16 respectively. The results are analyzed for change in signal space dimension and quantization level. Variations in transmit powers, SINRs and costs for N=4 and q=1/32 are plotted in Fig. 5.8 (a), (b) and (c) respectively. Fig. 5.9 (a), (b) and (c) show variation in transmit powers, SINRs and costs respectively for N=6 and q=1/16.

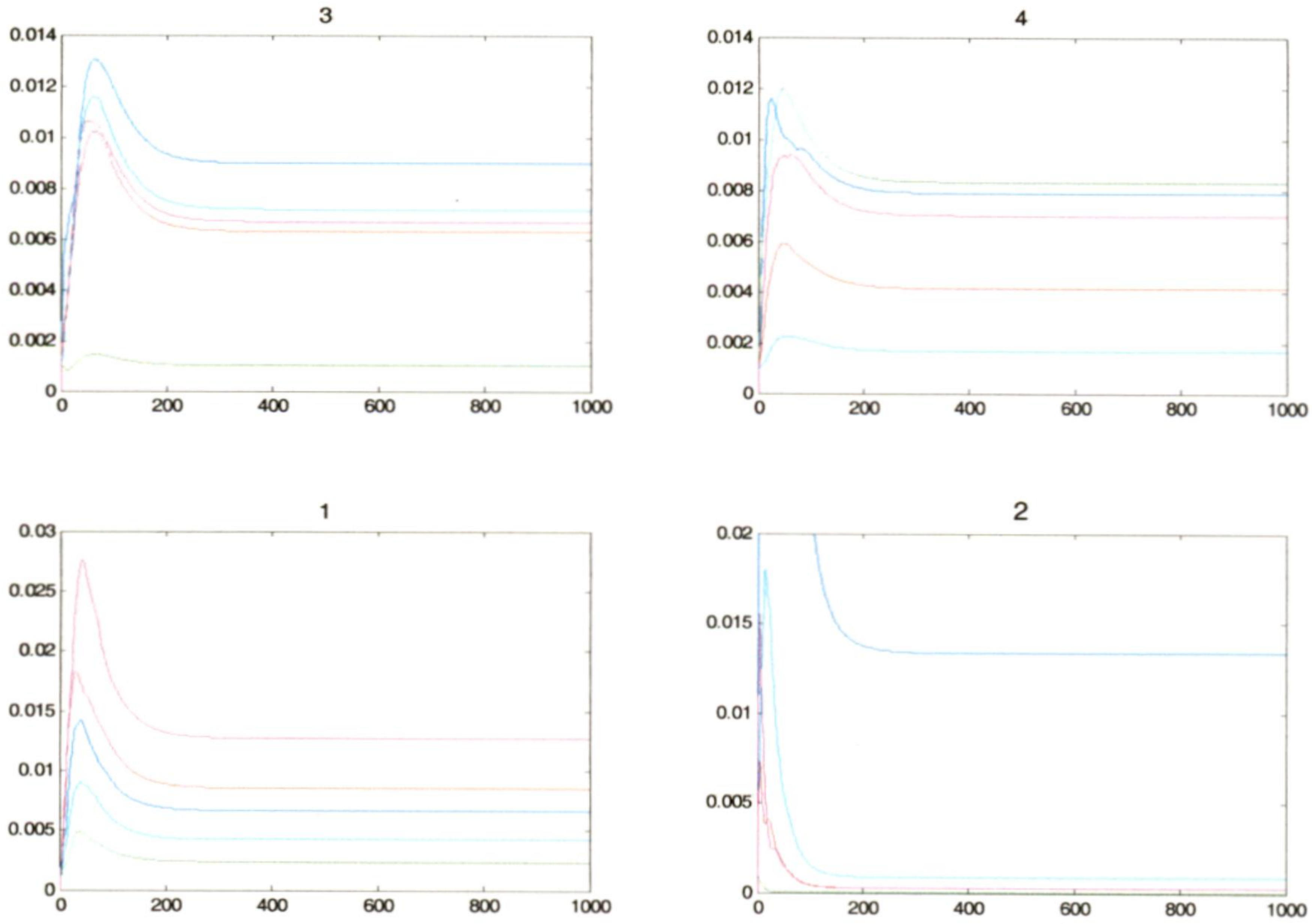


Figure 5.8(a) Variation in Transmit Power for N=4 with q = 1/32.

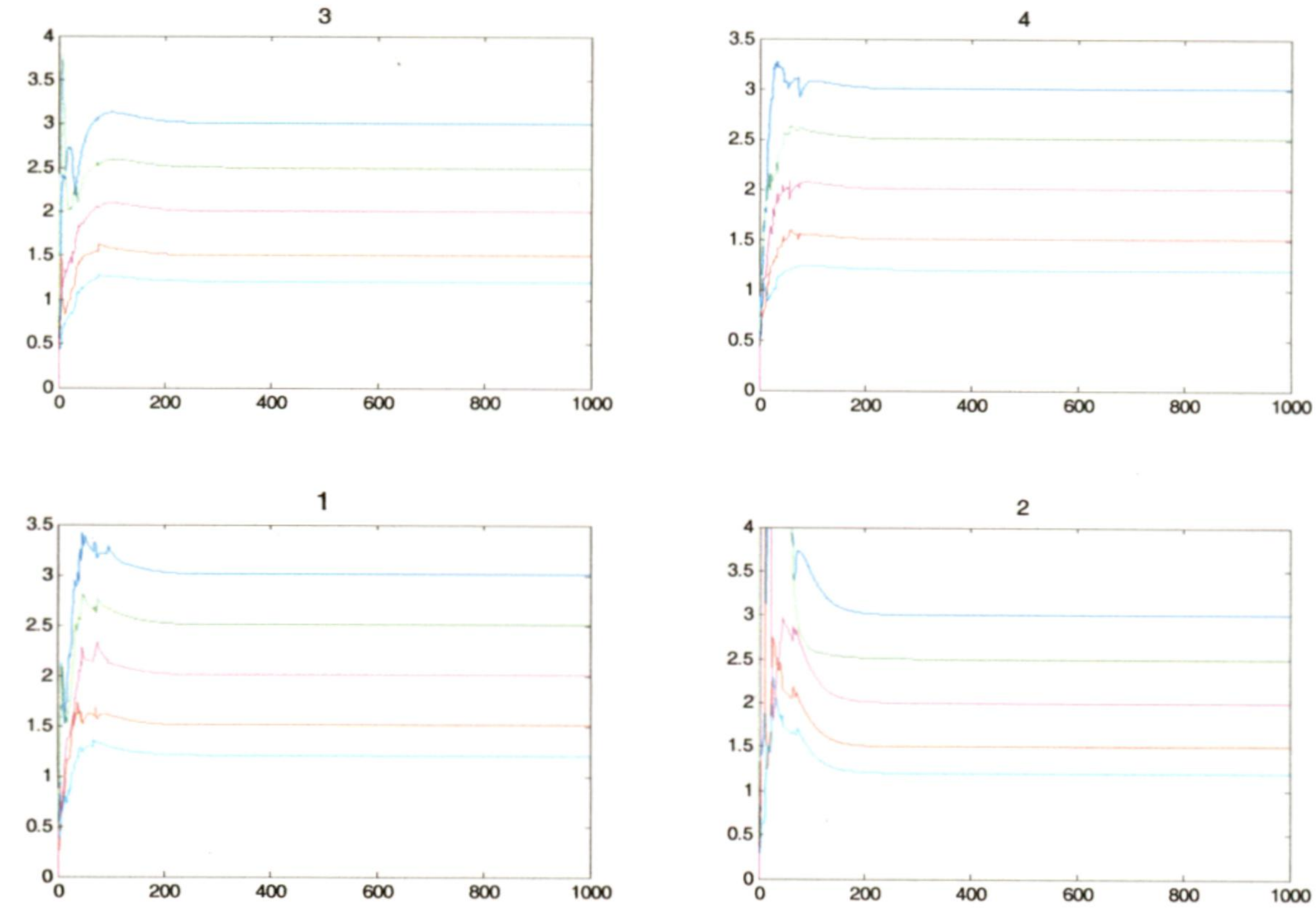


Figure 5.8(b) Variation in SINR for N=4 with q = 1/32.

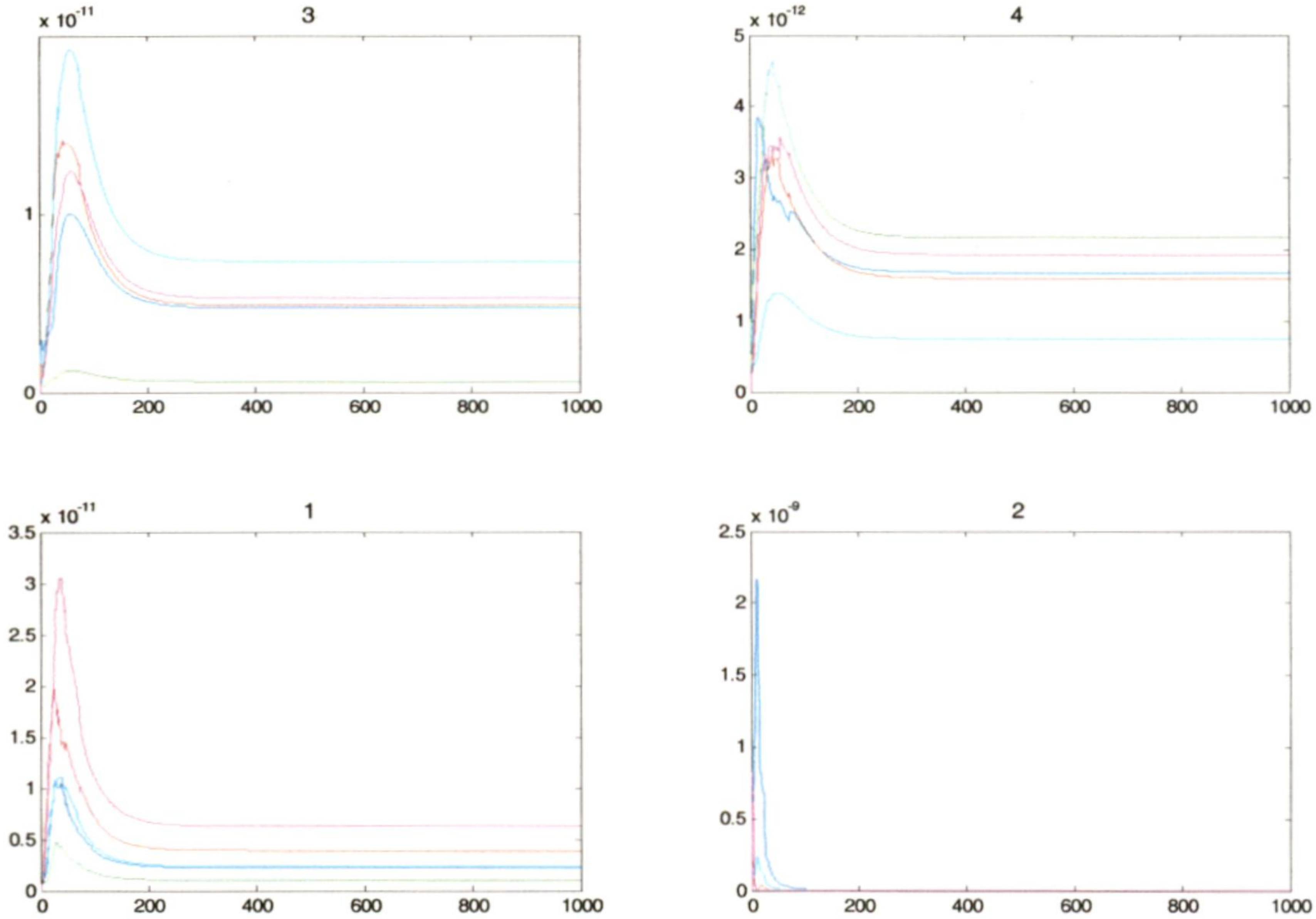


Figure 5.8(c) Variation in Cost for N=4 with q = 1/32.

The cross-correlation matrix for users of cell 1for N=4 and q=1/32 is

$$SS^T = \begin{matrix} 1.1790 & 0.1799 & -0.0037 & 0.1140 \\ 0.1799 & 1.3879 & 0.0090 & -0.1028 \\ -0.0037 & 0.0090 & 1.2786 & -0.0930 \\ 0.1140 & -0.1028 & -0.0930 & 1.1458 \end{matrix}$$

The cross-correlation matrix for users of cell 1for N=6 and q=1/16 is

$$SS^T = \begin{matrix} 0.9824 & 0.0518 & -0.0626 & 0.0205 & 0.0693 & -0.0381 \\ 0.0518 & 0.9877 & 0.0986 & 0.0205 & -0.0713 & -0.0264 \\ -0.0626 & 0.0986 & 0.9736 & 0.1069 & 0.1151 & 0.1271 \\ 0.0205 & 0.0205 & 0.1069 & 0.9933 & -0.1185 & -0.1123 \\ 0.0693 & -0.0713 & 0.1151 & -0.1185 & 0.9814 & -0.1268 \\ -0.0381 & -0.0264 & 0.1271 & -0.1123 & -0.1268 & 0.9861 \end{matrix}$$

The codewords show good autocorrelation with lower cross-correlation values, Codewords of users from other cells also show similar correlation properties.

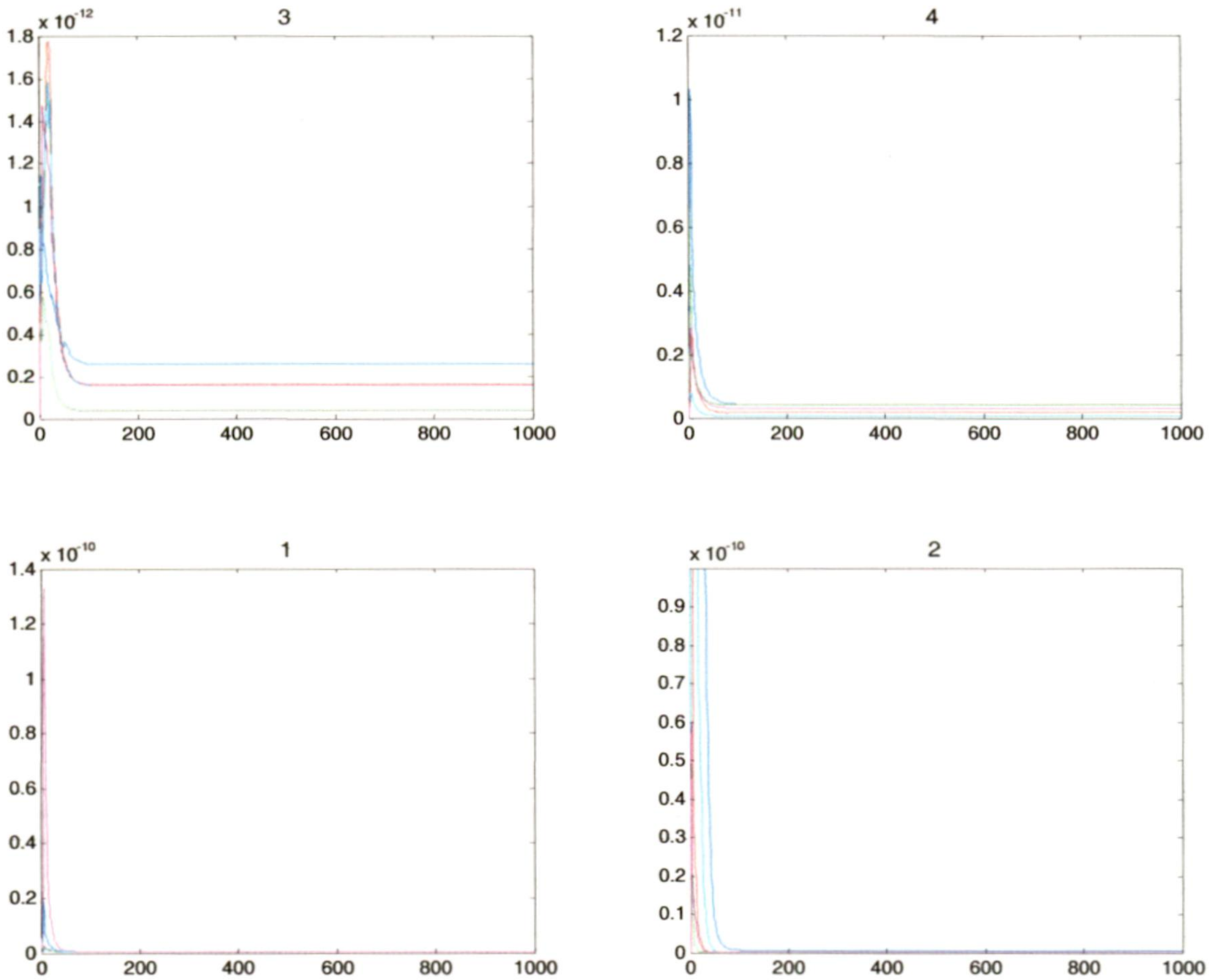


Figure 5.9(c) Variation in Cost for N=6 with q = 1/16.

We see that with quantization, the system attains equilibrium not only for N=6 but also for N=4. This makes us to believe that the non-convergence in continuous codeword scenario was caused due to some minor perturbations in codeword values which are not present when codewords are quantized. The system converges faster with N=6 than N=4 and the transmit power and cost function are also lower with N=6.

(b) ***Adaptation for dynamic CDMA system:***

The user configuration shown in Fig. 5.5 is now used to study the effect of variation in the number of users for signal space of dimension N = 6 and quantized codewords with q = 1/16. The system reaches equilibrium with 5 users. At iteration 400, a user from cell 4 with target SINR equal to 2 becomes inactive. All the users adapt to this change and achieve a new equilibrium to satisfy their QoS. At iteration 600, a new user joins cell 4 with target SINR of 2.2. The system again reaches to a new equilibrium state. The variation in users' transmit powers, SINRs and costs for this scenario are plotted in Fig. 5.10 (a), (b) and (c) respectively.

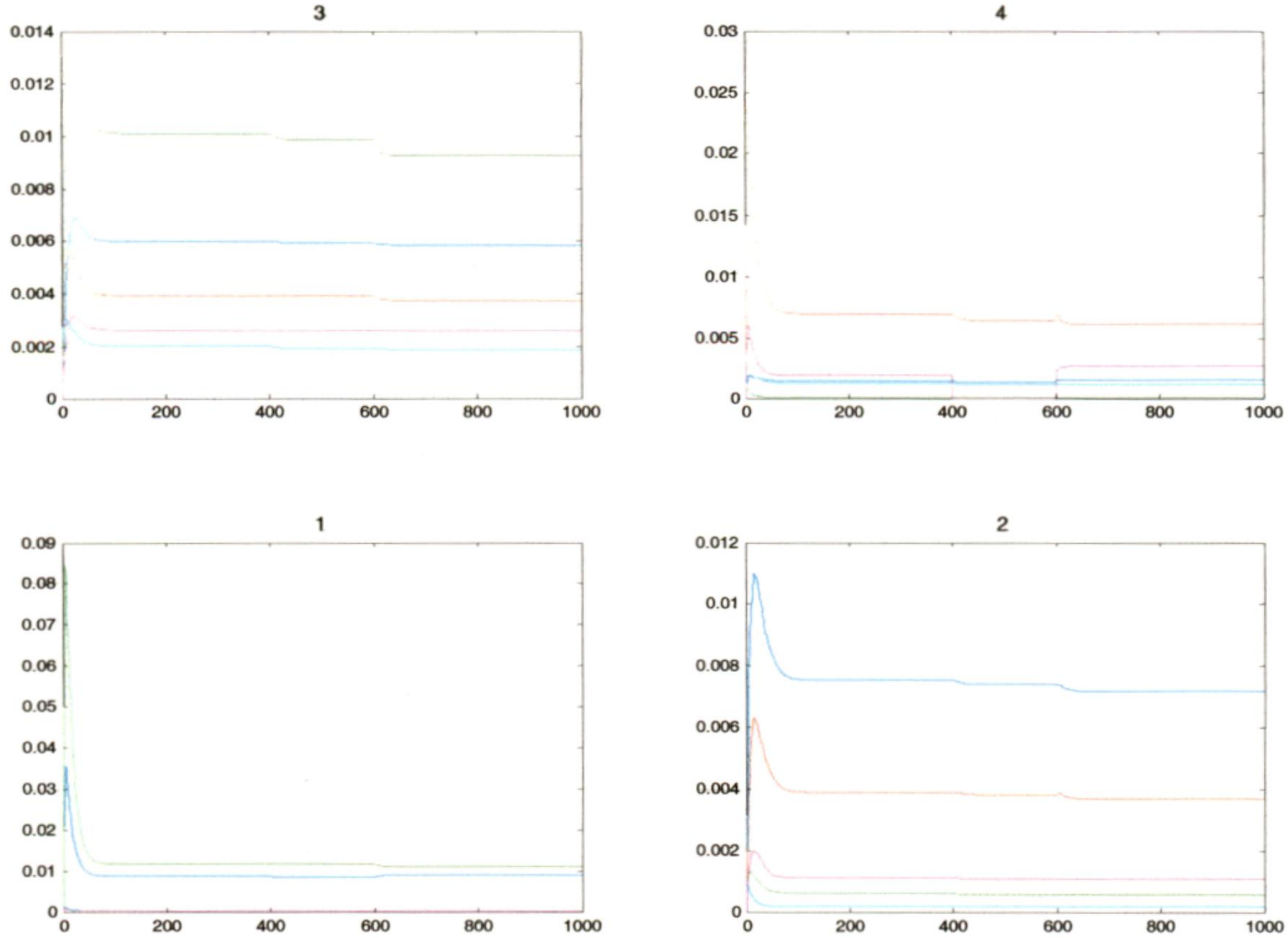


Figure 5.10(a) Variation in Transmit Power for N=6 with q = 1/16.

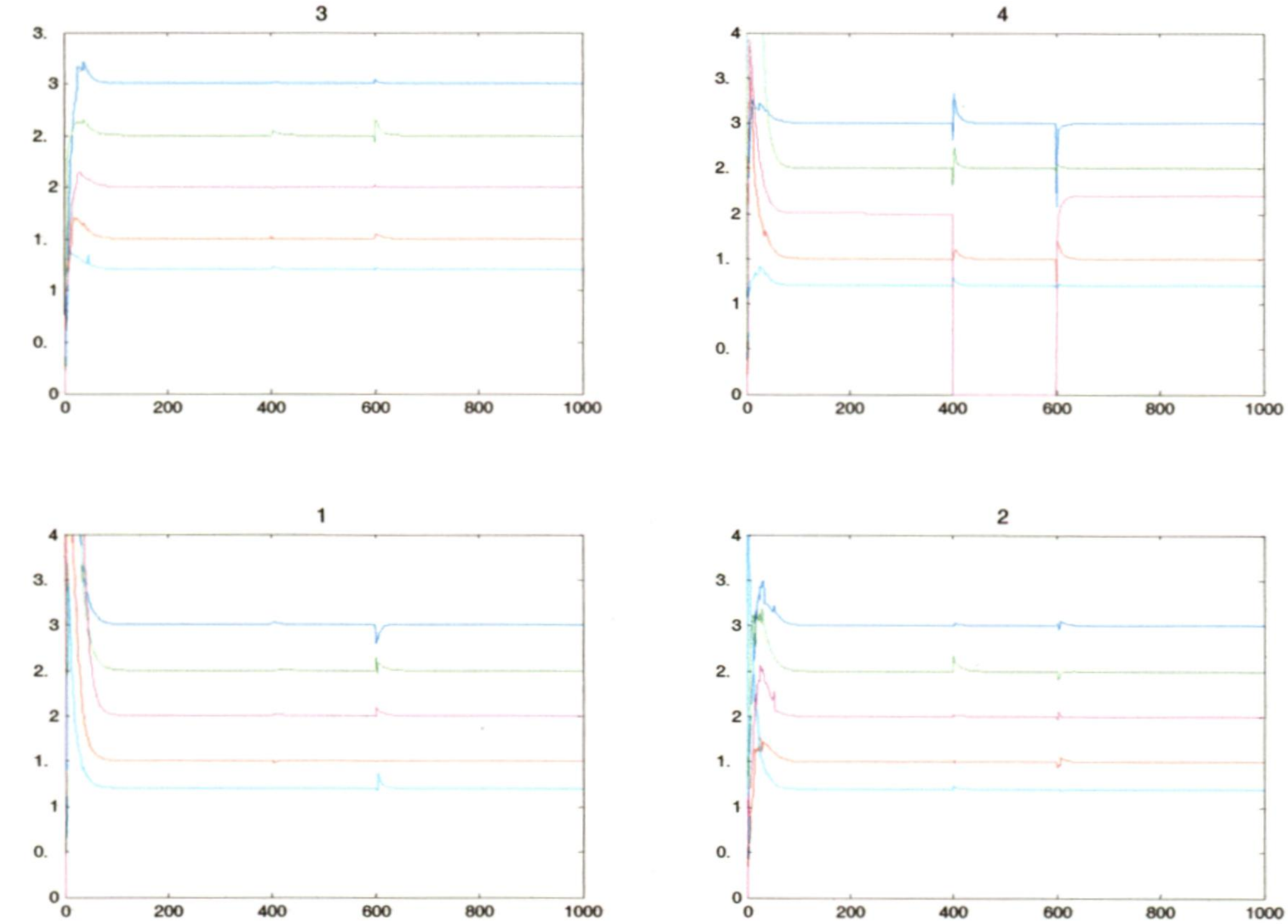


Figure 5.10(b) Variation in SINR for N=6 with q = 1/16.

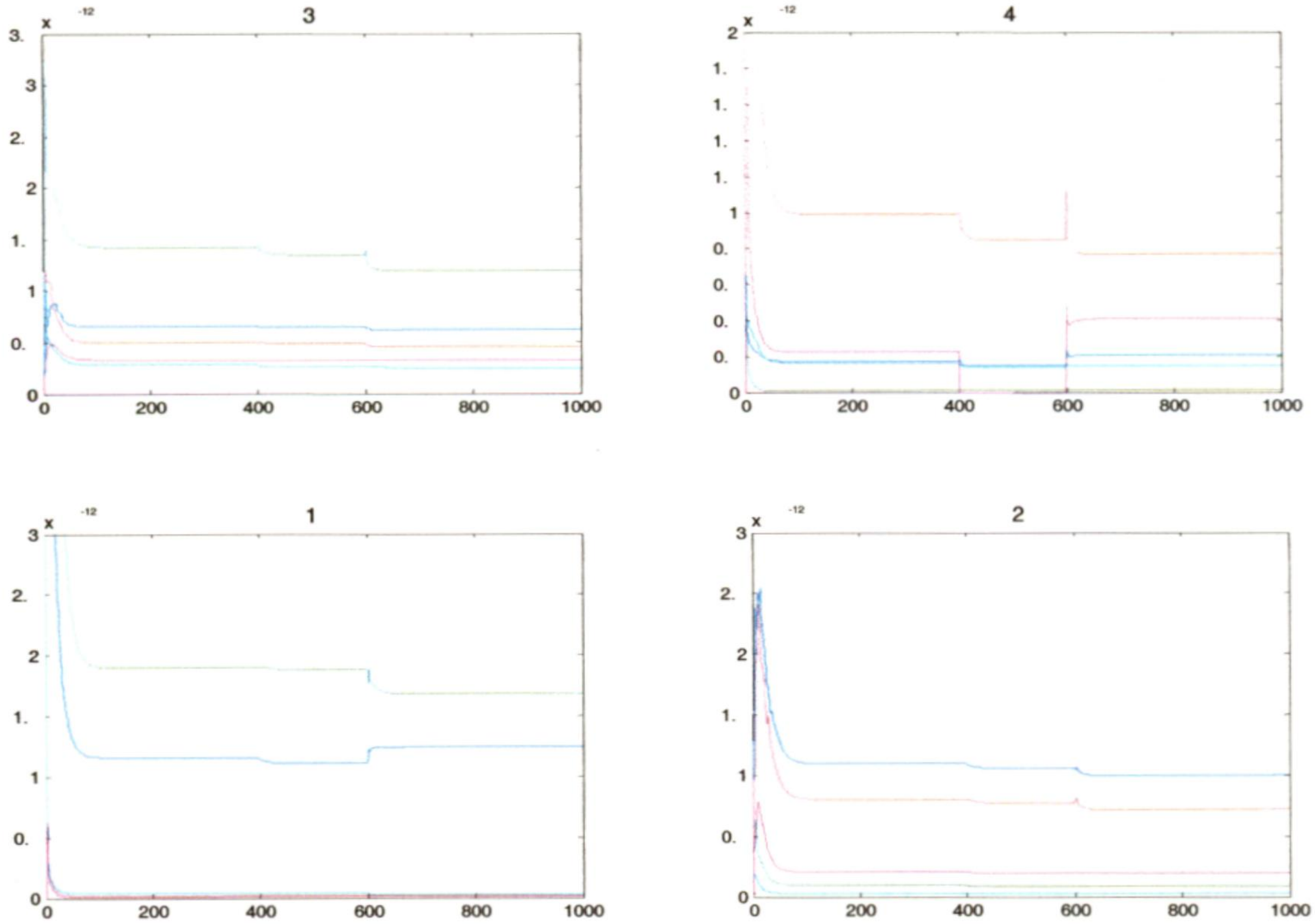


Figure 5.10(c) Variation in Cost for N=6 with q = 1/16.

It is clear from the results that deletion or inclusion of a user has very little effect on QoS for other users and the system very quickly reaches to equilibrium after any change is made. Thus, the algorithm tracks the changes in the system very effectively.

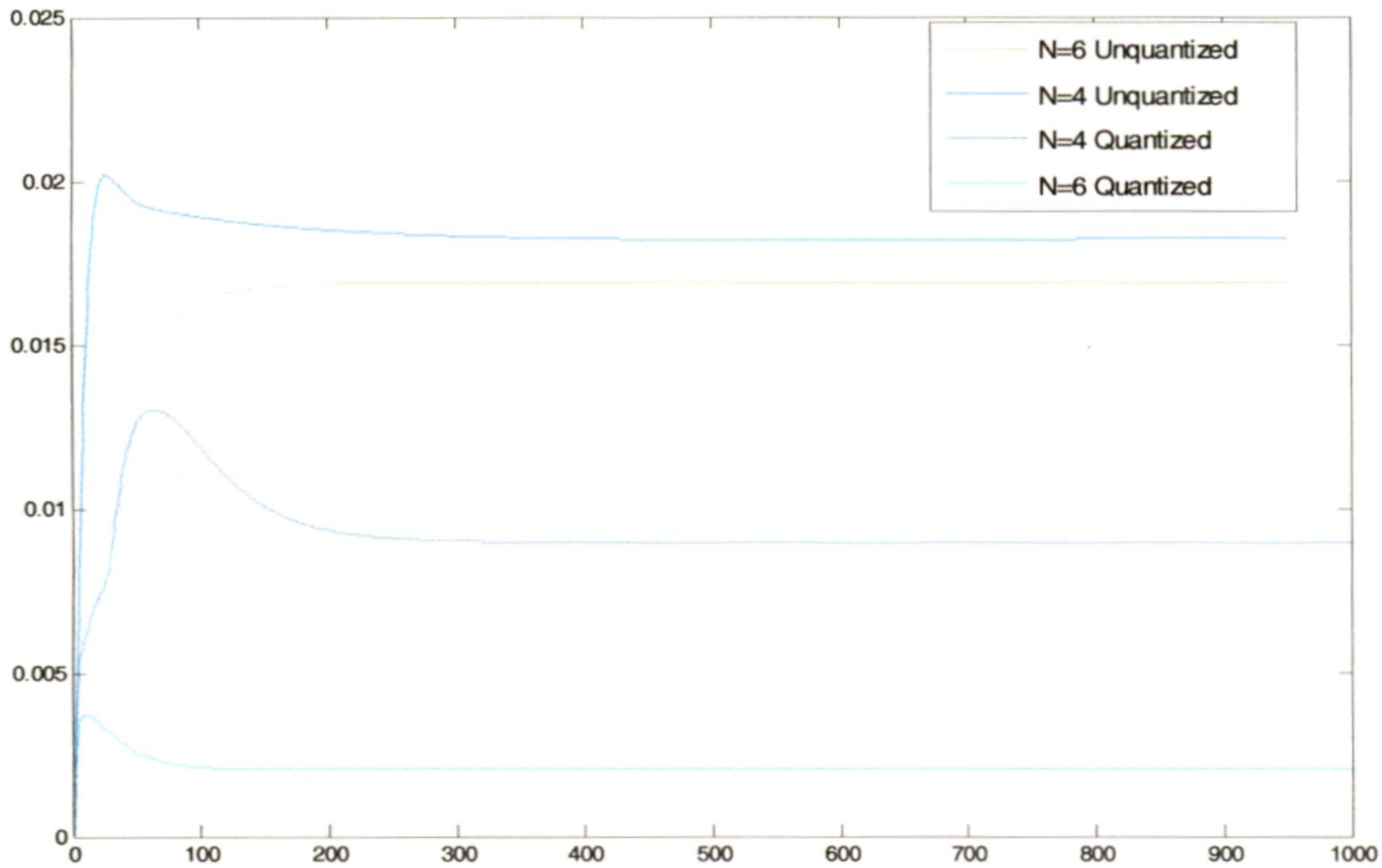


Figure 5.11 Comparison of different schemes

For comparing the performance of various schemes used for multi-cell CDMA system, we show a snapshot variation in transmit power in all the schemes in Fig. 5.11. The figure shows variation in convergence of transmit power for user with target SINR equal to 1.5 in cell 3. It is evident from the figure that increase in signal space dimension results in performance improvement in terms of convergence rate of the algorithm. Transmit power levels also reduce with increase in dimension of signal space. The bandwidth expansion due to increase in signal space dimension is compensated by using coarse quantization of codewords. Similar behavior is exhibited for convergence of cost function.

CHAPTER 6

CONCLUSION

Energy efficiency and capacity maximization are two important concerns of cellular CDMA systems. A proper adaptation of user power and codeword to network conditions can help in increasing both of these while providing desired QoS to all the users. Joint adaptation of user power and codeword for single cell and multi-cell CDMA systems has been studied in this dissertation. The simulation results for single cell systems show that the algorithm for power control and codeword adaptation is able to adapt to changing environment of the system. If the users with their target SINRs are admissible then algorithm always converges to GWBE codewords. Algorithm reaches equilibrium with quantized codewords but with slight increase in user powers because codeword cross-correlation worsens with quantization.

For multi-cell CDMA systems, it is observed that algorithm does not reaches equilibrium for certain link gains but increase in signal space dimension improves convergence property in this scenario. Effect of quantization is studied because practical implementation usually uses a finite number of values corresponding to scalar quantization of codewords. Though quantization reduces the autocorrelation, it is observed that increase in signal space dimension improves convergence property even with coarser quantization compared to quantization levels at lesser signal space dimension. The transmit power levels at equilibrium also reduce under this scenario. Thus, bandwidth efficiency of the system does not get drastically affected with increase in signal space dimension while performance of algorithm gets improved.

This dissertation work can be extended for future work in many ways. Some of them are as follows:

(a) In this dissertation, users are considered as static. Work can be done considering mobility of users with shadowing and fading channels and its effect on convergence property of algorithm can be studied.

(b) Joint power control and codeword adaptation can be studied for downlink of multi-cell CDMA system with total power constraint.

(c) The algorithm can be studied for multi-cell system with some change in cost function such that it converges for all link gains.

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