DISTRIBUTED SPECTRAL ACCESS AND ENERGY EFFICIENT COGNITIVE RADIO SYSTEM

Thesis Submitted towards the partial fulfillment of requirement for the award of degree of

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Submitted by

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DECLARATION

I, Chirag hereby declare that the work which has been presented here in the dissertation entitled, **Distributed Spectral Access and Energy Efficient Cognitive Radio system** by me in the partial fulfilment of the requirement for the award of degree of Masters of Engineering in Electronics and Communication Engineering from Thapar University, Patiala, is an authentic record of my own work, carried out under the supervision of Dr. Surbhi Sharma, Assistant professor, ECED. Other researcher's work have been duly listed in the reference section. The matter presented in this dissertation has not been submitted in any other Institute, University for the award of any other degree.

Date: 15/07/2015

(Chirag verma)

Signature of Student

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

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ABSTRACT

Cognitive Radio (CR) systems are the upcoming technology in the wireless communication where we have to utilize our spectrum available in the best and the efficient way. The tasks to be covered in the CR technology are broadly classified into two categories .They are efficient utilization of the available spectrum and secondly energy efficiency in the wireless transmission. As said above that in the wireless communication system we have major two challenges are to utilize the spectrum efficiently by also keeping in mind that the least power gets wasted during this process.

In this work, we have presented different algorithms like that of Shared Carrier Assignment (SCA) Iterative water-filling algorithm (SCA-IWF) algorithm for efficient utilization of spectrum by sensing it keeping in concern the interference from the other secondary users. Secondly we have provided the energy efficiency of the MIMO system by using Iterative Power Allocation Scheme (IPAS) that converges as the number of iterations increased. Finally we have plotted the result of both the capacity and energy efficiency with respect to number of iterations in both the graph and bar-graph form.

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LIST OF ABBREVIATIONS USED

FCC	FEDERAL COMMUNICATION COMMISSION
CR	COGNITIVE RADIO
SU	SECONDARY USERS
PU	PRIMARY USERS
OFDM	ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING
QOS	QUALITY OF SERVICE
EE	ENERGY EFFICIENCY
SE	SPECTRAL EFFICIENCY
MAC	MEDIUM ACCESS CONTROL
PHY	PHYSICAL LAYER
CFP	CONCAVE FRACTIONAL PROGRAMMING
CCT	CHARLES COOPER TRANSFORMATION
WLAN	WIRELESS LOCAL AREA NETWORKS
CSI	CHANNEL STATE INFORMATION
SCA	SHARED CARRIER ASSIGNMENT
ECA	EXCLUSIVE CARRIER ASSIGNMENT
DSL	DIGITAL SUBSCRIBE LINE
OSB	OPTICAL SPECTRAL BALANCING
ISB	ITERATIVE SPECTRAL BALANCING
SNR	SIGNAL TO NOISE RATIO
OFDMA	ORTHOGONAL FREQUENCY DIVISION MULTIPLE ACCESS

MIMO	MULTIPLE INPUT MULTIPLE OUTPUT
DSM	DYNAMIC SPECTRUM MANAGEMENT
GR	GREEN RADIO
FEXT	FAR END CROSSTALK
ASB	AUTONOMOUS SPECTRAL BALANCING
LINPACK	LINEAR SYTEM PACKAGE
EISPACK	EIGEN SYSTEM PACKAGE

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Wireless communications have experienced a rapid growth in the past decades. The demands for providing high-rate and high-quality services have been increasing. In order for coping with these demands, various new wireless communication technologies have been emerging, for instance, fourth generation (4G) cellular networks and beyond, wireless Ad Hoc networks, software-defined radio, wireless regional area networks (WRANs). All the wireless communications need radio spectrum as the medium for transmission. The electromagnetic radio spectrum is a precious natural resource, which currently is regulated by the government agencies, such as the Federal Communications Commission (FCC) in the United States and the Electronic Communications Committee (ECC) in Europe. The frequency use of the wireless systems, e.g. cellular systems, are characterized by statistic spectrum allocations. As a consequence, one serious problem is arising that there is a spectrum scarcity at usable bands. The FCC's frequency allocation chart indicates that most of the available spectrum are allocated[1]. However, the recent studies by the FCC's Spectrum Policy Task Force showed that large portions of the licensed bands remain unused temporally and geographically for as much as 85% (FCC 2002). In order to utilize these spectrum "white spaces" and "sparse use spaces", the FCC in (2003b) has issued a Notice of Proposed Rule Making and Order (ET Docket No. 03-322) advancing *cognitive radio* (CR) technology as a candidate to implement opportunistic spectrum sharing. The CR technology also makes new and improved communication services available to the public. In addition, CR is a promising green technology for human being [2]. Figure (1.1) to illustrate the current command-and-control spectrum allocation strategy. Although, there are some free parking slots, they are reserved. The concept of CR coined by Mitola et al.[3] emerged from the application of software-defined radio. Since then cognitive radio has received much research interest, such as dynamic spectrum access, spectrum sensing, information-theoretic analysis. There are a few slightly different versions of the definition of cognitive radio in several classic and highly-cited publications on CR, for instance, as following:

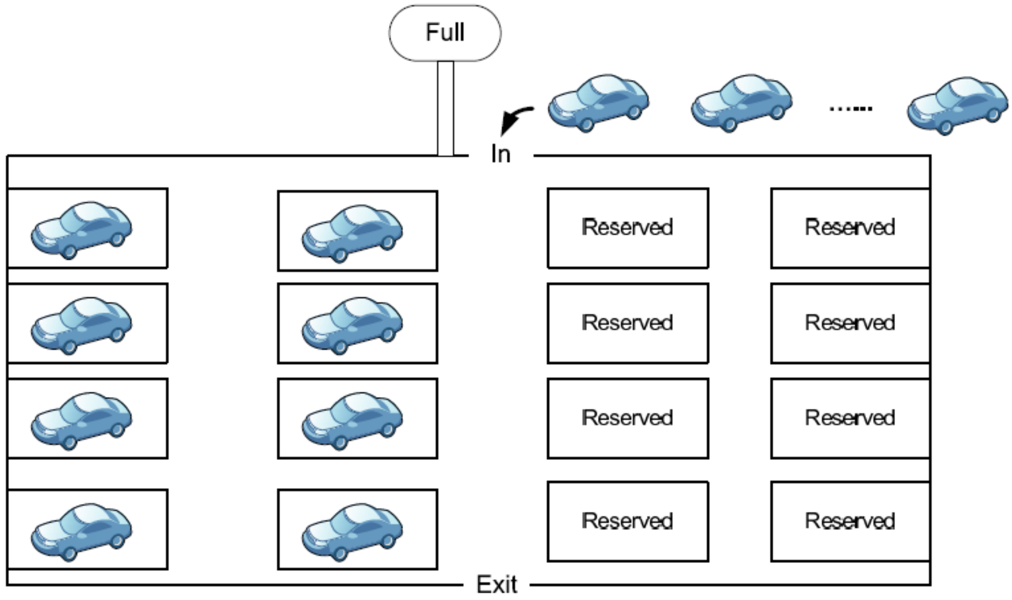

Fig 1.1 An illustration of current spectrum allocation using parking lot[4].

“The term cognitive radio identifies the point at which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to: a) detect user communications needs as a function of use context, and b) to provide radio resources and wireless services most appropriate to those needs.

“Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (for instance, transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind: a) highly reliable communications whenever and wherever needed, b) efficient utilization of the radio spectrum.” [5-7].

“A cognitive radio is a wireless communication system that intelligently utilizes any available side information about the a) activity, b) channel conditions, c) codebooks, or d) messages of other nodes with which it shares the spectrum.”

Although the above definitions are slightly different, the common key points are that the CR systems/devices should be smart, adaptive, able to utilize the diver-sities as many as possible without causing harmful interference to the primary users. In [3], the concept and the architechture are developed in details provides and develops the details of cognitive radio based on the signal-processing and adaptive procedures, where a modified basic cognitive cycle is proposed focusing on three fundamental cognitive tasks: 1) radio environment estimation including interference estimation and spectrum sensing, 2) channel estimation and capacity prediction, 3) transmit power control/allocation and dynamic spectrum management. In the authors survey the dynamic spectrum access protocols and present a definition, functions and some research challenges of the DARPAs approach on Dynamic Spectrum Access network, the so-called NeXt Generation (xG) program .In[6], the survey is mainly from the information-theoretic point of view that the cognitive radios may improve their achievable transmission rate. This thesis provides guidelines for analyzing and designing the promising technology for mitigating the spectrum scarcity. Therefore, some new methods need to be defined for cognitive radios on managing and qualifying the interference to the primary users caused by the secondary users. The reason is that the traditional method for controlling interference is based on the transmitter operations. However, for spectrum sharing networks between the licensed users, or primary users, and the unlicensed users, or secondary users, the approach for assessing the interference should take into consideration both the transmitters and receivers. From the information-theoretic point view, Gastpar pointed out in [8] that interference constraints at the transmitter side and the receiver side can be much different. The FCC established an interference temperature metric in ’Notice of Inquiry and Notice of Proposed Rulemaking to quantify and manage interference and to expand available unlicensed operation in certain fixed, mobile and satellite frequency bands. The interference temperature introduced by the FCC is depicted in Figure (1.2) for measuring interference. This interference temperature could be beneficial to the licensed users through providing some transmission opportunities to the unlicensed users if the aggregated interference plus noise is well controlled.

From Figure (1.2), it is shown that the interference temperature limit provides a maximum cap, or worst case, on the cumulative interference plus noise.

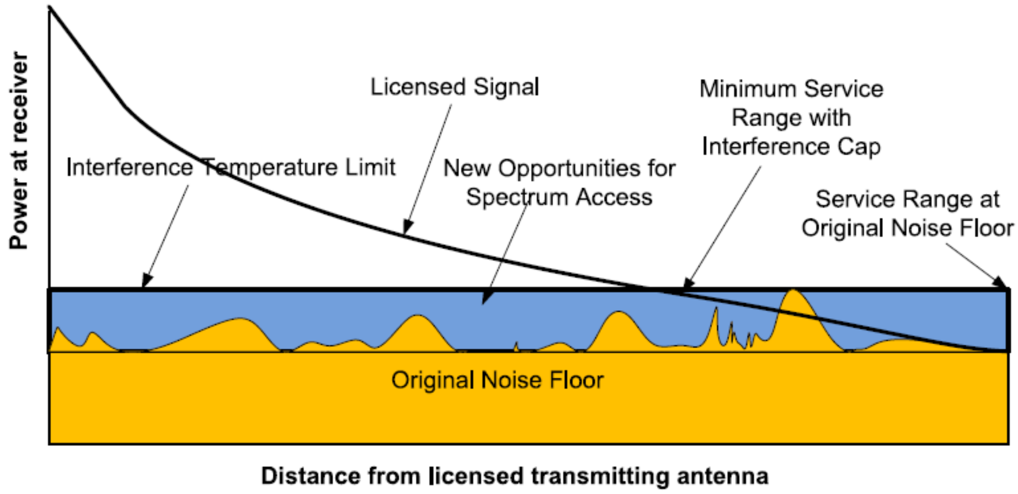

Fig 1.2 Interference Temperature [4]

the concept of interference temperature, other interference constraints for the secondary users have been proposed in literature, for instance, average interference power, primary outage probability constraint, and primary user capacity loss. We will study the influence of these constraints on the performance of the secondary users in the following chapters of this thesis.

1.2 COGNITIVE RADIO NETWORK PARADIGMS

There are three cognitive radio paradigms in literature: underlay, overlay, and Interweave . This classification is based on the available network side information and the regulations.

In *underlay parade*,[6] the secondary and primary users could transmit simultaneously, if the interference caused by the secondary users to the licensed users is below a predefined threshold. This paradigm assumes that the secondary user has the channel state information (CSI) of the interference channel from the secondary transmitter to the primary receiver, which can be gathered by the spectrum manager, primary receiver or a third-party device and then fed back to the secondary transmitter [9]. Of course, this CSI can be assumed to be perfect for simplicity. However, in practice it is always imperfect due to, such as, fading, Doppler, limited feedback channel, and measurement error. The interference can be regulated by the interference temperature.

In *overlay paradigm*, the secondary users need to assist the primary users in maintaining or improving performance through using sophisticated signal processing and coding techniques in order to obtain some resources from the primary users for their own transmission. Therefore this paradigm requires that the cognitive users have the codebook side information and the message of the primary users, e.g. the secondary users may use some of the transmit power to relay the primary users' message. Figure (1.3) graphically illustrates the three paradigms.

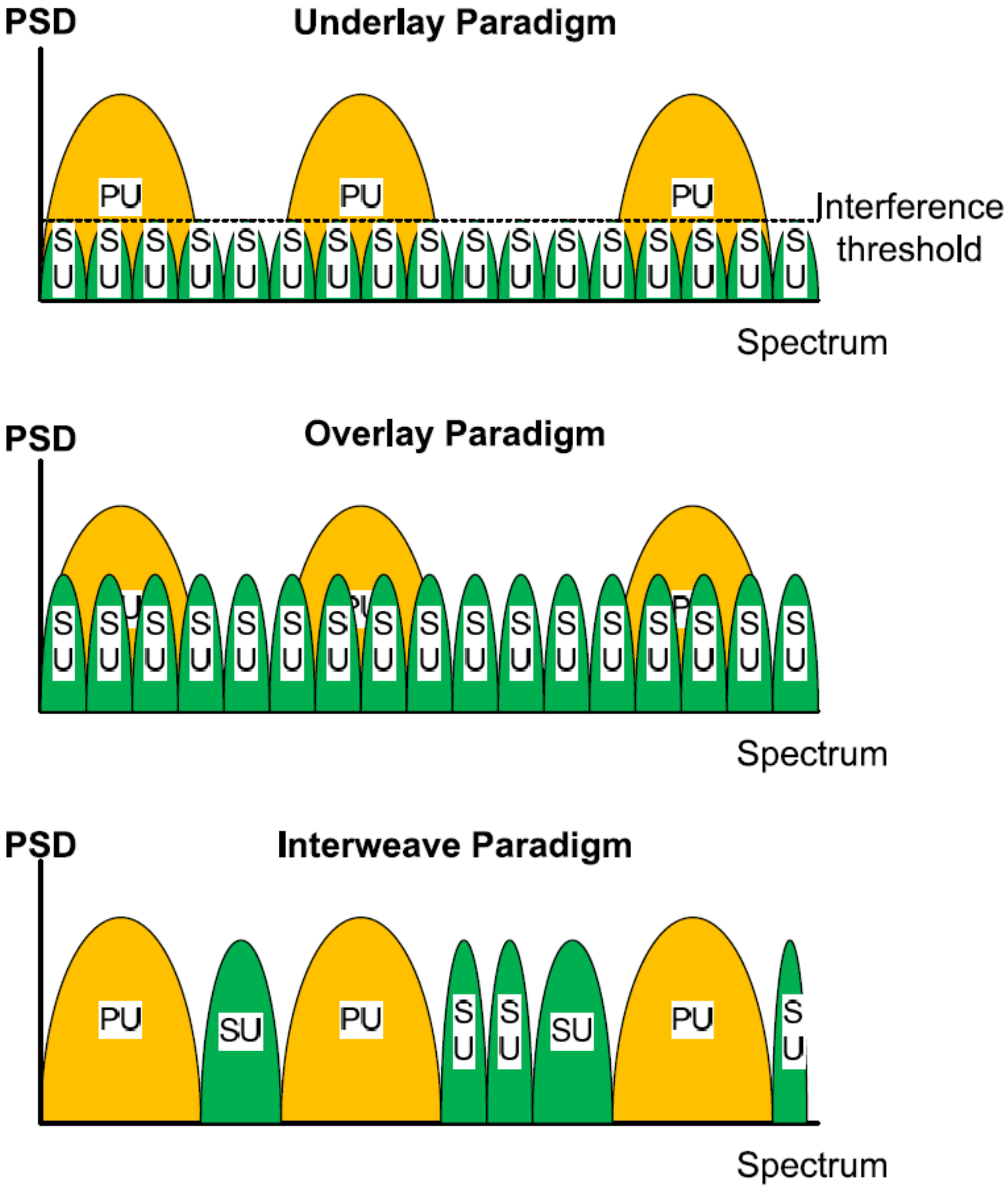

Fig.1.3 Cognitive radio network paradigms [4]

Interweave paradigm,[2]on the other hand, is different from the previous two paradigms that the secondary users require accurate information of the spectrum use. In other words, the secondary users opportunistically transmit exploiting spectrum holes in time, space, or frequency.

1.3 Challenges in Cognitive Radio Networks

The improvement of spectrum underutilization problem by cognitive radio technology comes at the price of causing additional interference to licensed users. In the underlay scenario, under some constraints what is the performance that the secondary network can achieve. In addition, for interweave paradigm cognitive radio network, how accurate a secondary user monitors and detects spectrum holes. For overlay cognitive radio networks, how the secondary users assist the primary communication, and the proper resource allocation schemes.

1.4 SIGNAL MODEL OF COGNITIVE RADIO

We assume that in a CRN there are K active transmit and receive pairs (links) located in an area, and they compete for a set of N available frequency bands B_i, $i = 1, \ldots, N$ at each time slot[8]. If more than one pairs access the same carrier n, they will cause interference to each other as shown in Figure (1.4)

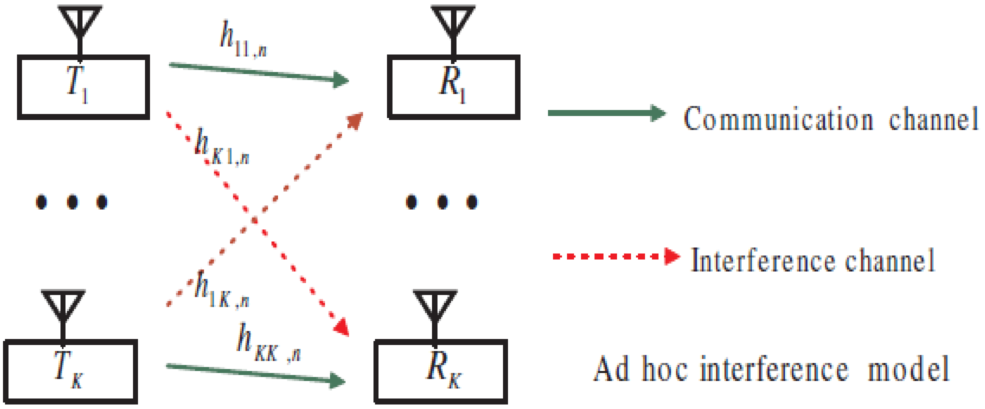

Fig 1.4 Multi-carrier interference channel model in a CRN[22]

Each pair has a single transmit antenna and single receive antenna. The received signal at receiver k on carrier n, $y_{k,n}$, consists of desired signal from transmitter k, interference signals from the remaining $K-1$ transmitters ,and background noise and is given by(1.1):

$$y_{k,n} = h_{kk,n}x_{k,n} + \sum_{k'=1,}^{K} h_{kk',n}x_{k',n} + \varepsilon_{k,n} \quad (1.1)$$

where $h_{kk',n}$ is the frequency domain channel gain from transmitter k to receiver k, and $x_{k,n}$ and $\xi_{k,n}$ are the transmitted signal from user k and the noise at receiver k, all at carrier n. The transmission power and noise power are given by $P_{k,n} = |x_{k,n}|^2$ and

$N_{k,n} = E[|\xi_{k,n}|^2]$, respectively. We assume that over the N available multi-carrier channels, all the K users experience independent but not necessarily identically distributed Rayleigh fading channel gains. At time t, the channel SNR of pair k at carrier n is given by $\gamma_{k,n}(t) = |h_{kk,n}(t)|^2/N_{k,n}$. We suppress the index t when no confusion arises. The maximum transmit power for pair k is given by $P_{T,k}$, which is split among the N_k carriers that are assigned to transmitter k. The signal-to-interference-plus-noise ratio (SINR) of user k at carrier n may be defined as

$$\gamma_{k,n}^{SINR}=[h_{kk\prime,n}]\text{^}2/[\textstyle\sum_{k\prime}[h_{kk\prime,n}]\text{^}2P_{k',n} + N_{k,n}] \tag{1.2}$$

For Share Carrier Assignment

$$\textstyle\sum_{k\prime}[h_{kk\prime,n}]\text{^}2\ P_{k',n} > 0 \tag{1.3}$$

For Equal Carrier Assignment

$$\textstyle\sum_{k\prime}[h_{kk\prime,n}]\text{^}2\ P_{k',n}=0 \tag{1.4}$$

1.5 THESIS OBJECTIVE

For the wireless communication using the cognitive radio(CR) technique we have to consider both of the energy efficiency during the transmission as well as the maximum utililization of the spectrum, keeping in consideration the interference to the primary user by the other secondary users trying to access the same channel allocated to the primary user. Here in this thesis we have shown separately:

1. Algorithm for the detection of spectrum available and then allocating the spectrum efficiently
2. Algorithm for maximization of the energy efficiency of the network

Here both of the algorithms converge with the number of iterations and reaches to its maximum performance are shown.

1.6 ORGANIZATION OF THESIS

This thesis includes six chapters. An outline of each chapter is given below:

Chapter 1 gives how the spectrum is allocated and the introduction about what are cognitive radios, cognitive radios network paradigms-underlay, overlay and interleave methods, challenges in CR systems and then the signal model.

Chapter 2 dealt with literature survey. The research work relevant to the thesis work has been discussed here in detail.

Chapter 3 presents the power allocation algorithms in cognitive radio systems: Water-filling power allocation scheme, Optimal power allocation scheme with reference to Machine to Machine technology, Sub-optimal power allocation schemes.

Chapter 4 deals with methodology and the proposed design for the thesis work, Iterative Power Allocation (IPAS) Scheme for the energy maximization, Shared carrier assignment Iterative water-filling algorithm (SCA-IWF) for the spectral allocation purpose and their corresponding algorithms are given in this chapter.

Chapter5 included the results obtained, the spectrum allocation and energy efficiency is plotted for the number of iterations, it is shown clearly that the plot converges as the number of iterations increases. Also it is shown in bar-graph form the corresponding variations with the iterations.

Chapter6 concluded the thesis work, what we have analysed from our work and observed. Future Scope is also given in the same chapter.

In end section the important references that have been referred throughout the thesis and without which the thesis work could not have been accomplished.

CHAPTER 2

LITERATURE REVIEW

Gaurav Bansal *et al*. [10] investigated the optimal power allocation techniques in the OFDM based cognitive radios. The downlink transmission capacity of the system is maximized while keeping the interference to the primary users within the tolerable range. The performance of the optimal and suboptimal schemes is then compared with the classical power loading schemes for example water-filling and uniform power loading algorithms. These results also shows that the suboptimal schemes have certain degradation as compared to optimal schemes but they are far better than the classical power loading algorithms.

Hichan Moon *et al.* [11] see that the waterfilling power allocation schemes for general fading distributions converges pointwise to the functions in which power allocated to all the non-zero channel gains is fixed as the SNR approaches towards infinity.Here the convergence speed for the above scheme is also investigated.

Daniel Pérez Palomar *et al.* [12]proposed in MIMO systems power will be allocated to all the channels adaptively when the channel state information is available at the transmitter to achieve the large channel capacity.The maximum value of the difference between the channel capacity of the conventional water-filling algorithms and non-optical power allocation algorithms is also derived here. Compared with the simple constant power allocation scheme,the constant power waterfilling scheme achieve more capacity to the system with the reduced complexity.

Wei Yu *et al*. [13] proposed that the resource allocation for the uplink orthogonal frequency division multiple access (OFDMA) networks which coexists with the primary networks will be studied. Here with the objective of maximizing secondary users sum rate we investigate both the joint subcarrier and power allocation approaches in consideration with both the transmit power constraints and the interference of the power limit to the primary users. After simulation of the above technique we observed that the water-filling algorithm which is based on the above proposed model yields the good performance gains as compared to the classical water-filling algorithm for the single secondary user and the multi PU spectrum sharing case.

Gesualdo Scutari *et al.* [14]shows that most of the engineering problems that are also considered as constrained optimization problems mostly result in solution given by the waterfilling structure,the classical example is the capacity achieving solution for the frequency selective channel. For the waterfilling solutions with single waterlevel and a single constraint, typically a power constraint, some algorithms are proposed to compute the solutions of these problems numerically, but some of the other optimization problems results in the more complicated waterfilling solutions with the multiple waterlevels and the multiple constraints. But it is still be possible to obtain the practical algorithms to evaluate the solutions numerically but only after the inspection of the particular waterfilling structure.

S. M. Mishra *et al* [15]shows that we have seen the performance of constant power-waterfilling algorithms for the independent identically distributed faded channels and the intersymbol interference channel where a constant level of power is used for the for a properly choosen subset of channels. The performance analysis shows the upper bound of the maximum achievable rate under the true waterfilling and the constant power waterfilling schemes. Here it is shown that for the Rayleigh fading channels the spectral efficiency for the constant power waterfilling schemes is maximum upto 0.266b/s/Hz. Also the performance bound allow us logarithm free, very low complexity, power adaptation algorithm to be develop. The worst case here is that after analysis and simulation it is shown that the approximate waterfilling scheme is very close to the optimum scheme.

Raphael Cendrillon *et al*. [16]shows that we have studied the non-coperative maximization of mutual information in the vector Gaussian interference channel in the fully distributed fashion with the help of game theory. This technique is very much used and studied in the number of works in the last decade for frequency selective channels, and even recently for multiple input multiple output(MIMO) case in which the state of art results are valid for the nonsingular square channel matrices,but these results have some limitation and hence cannot be true for rectangular and rank deficient matrices. The aim of this paper is to provide complete characteristic of MIMO game theory for the arbitrary channel matrices with the conditions guaranteeing both the uniqueness of convergence of the asynchronous distributed iterative waterfilling algorithms and the Nash equilibrium. Here all of our analysis is based on the new technical intermediate results like that of mean value theorem for complex matrix-valued functions, MIMO waterfilling projection valid for singular matrices and a general contraction theorem for the multiuser MIMO waterfilling mapping valid for all arbitrary channel matrices.The surprising result of the above technique is that uniqueness or convergence conditions for all the cases of tall channel matrices are more restrictive than those which are required for fat channel matrices.Here it is also proposed a modified game algorithm with the milder conditions for the uniqueness of the equilibrium and the convergence and same performance in terms of the original game.

Wei Yu *et al.* [17]shows that the major issue in communication is crosstalk in the modern digital subscriber lines (DSL) systems such as ASDL and VDSL. The traditional way of ensuring spectral compatibility that is static spectral management employs spectral masks that is very much conservative and will lead to poor performance. Here we have discussed centralized algorithm for the the optimal spectral balancing in DSL. Here the algorithm used uses dual composition method to optimize the spectra in an efiicient and tractable way.The algorithm used here shows the significant performance gains over the existing Dynamic Spectrum Management (DSM) techniques, eg here in one of the cases studied the centralized proposed algorithm leads to the increase in the data rate over the distributed DSM algorithm iterative waterfilling by the factor of four.

Jiho Jang *et al.* [18]shows that the total throughput of the communication subject to the system resource constraints often carried out by the design and optimization of multicarrier communication systems. The problem of optimization is generally difficult to solve when the problem do not have a convex structure. Here to make progress toward solving the optimization problem we can see that under certain condition called the time sharing condition, the duality gap is approximately zero regardless what is the convexity of the objective function. Also we can see that the time sharing condition is satisfied for the practical multiuser spectral optimization problems with the limit that the number of carriers in the system goes to infinity. Here the result of these computations is that we can use the efficient numerical algorithms that solve the non convex problem in the dual domain.Also we can see that the recently what proposed optimal spectrum balancing algorithm for the digital subscriber lines can be also interpreted as the dual algorithm. This new interpretation can also tell us about the more efficient dual update methods. Here it also gives us the ways in which the dual objective function can be evaluated to the approximate extent which further improve the numerical efficiency of the algorithm. We have presented the low complexity spectral balancing algorithms based on the above ideas and show that these new algorithms leads to achieve near optimal performance in many of the practical situations.

Simon Haykin *et al.* [19]shows that we will be going to develop the transmit power adaptation method which maximizes the total data rate for the multiuser orthogonal frequency division multiplexing (OFDM) systems for the downlink transmission. Here we can formulate the data transmission maximization problem by making allow that the subcarrier will be shared by multiple users. The transmit power maximization scheme is done by using the two steps: power allocation for carriers and subcarrier assignment for users. Now we have also found that the data rate of the multiuser OFDM systems is maximized when each subcarrier is assigned to only one user that is having the best channel gain for that of the subcarrier and the whole of the transmit power is distributed to the subcarriers by using the waterfilling policy. Now to reduce the computational caoacity to calculate the waterfilling level in the proposed transmit power adaptation method, we will be proposing a very simple method in which the user having the best channel gain is selected among all the subcarriers and the transmit power is equally distributed among all the subcarriers. Now the results shows that the total data rate for the said transmit power adaptation methods will increase significantly with the number of users that owes to multiple user diversity effects and is greater than that of the conventional frequency division multiple access like that of transmit power allocation schemes. Also we can see that the total data rate of the multi-user OFDM system with the help of proposed transmit power adaptation methods is even higher than the capacity of AWGN channel when the number of users is very large.

Cong Xiong *et al*. [20]shows that cognitive radio is the latest upcoming and very effective approach to use the natural resource which is very precious that is : the radio electromagnetic spectrum. The cognitive radio that is built on the platform of software-defined radio is defined as an intelligent wireless system that is also aware of its surroundings and uses the methodology of understanding and then building to learn from the environment and also it adapts to the variations in the input stimuli with the two primary objectives in the mind and they are: very highly reliable communication whenever needed and also efficient use of the radio spectrum.

Ziaul Hasan *et al*. [21]shows that after the discussion of the interference temperature as a new matric for the management and quantification of the interference, here this paper addresses three important tasks.

1) Radio-scene analysis
2) Channel state estimation and predictive modeling
3) Control of the Transmit power and dynamic spectrum management.

Here it is also discussed about the emergent behavior of the cognitive radios.

Adisorn Lertsinsrubtavee *et al.* [22]discusses the main focus of the wireless network technology in the past years is on capacity and spectral efficiency(SE).As the green radio(GR) is becoming an inevitable trend, the wireless networks are becoming more and more focused towards the energy efficient technology, therefore here the relation between the energy efficiency and the Spectral efficiency in wireless network technology in the downlink Orthogonal frequency division multiple access is studied. Now here firstly general EE-SE tradeoff framework is made where the quality of service (QOS), SE,EE are all considered simultaneously and we will prove that EE is quasi-concave in the SE. Also we will provide an upper limit on EE-SE curve for the general scenario by which we can show the actual EE-SE relation .Now after that the focus is on the spectral case such that the fairness and priority are considered simultaneously and we will develop a low complexity but practically but near optimal resource allocation algorithmin the EE-SE tradeoff. The numerical results will collaborate the theoretical findings and then find the effectiveness of the proposed resource allocation schemes only to achieve desirable and flexible tradeoff beween EE and SE.

J. Nicholas Laneman *et al*. [23]discusses that reliable and the efficient power allocation to the orthogonal frequency division (OFDM) based cognitive radio networks is a challenging problem. Traditional approaches for power allocation such as water-filling is inefficient for such networks due to limitation of the interference introduced to the primary users. It is presented the solution to the above problem which is energy efficient resource allocation which maximizes the cognitive radio capacity by considering the availability of the subcarriers and also within the interference introduced to the primary users. Now we will consider an capacity expression which is aware of energy by talking into account an another factor called as subcarrier availability. Now optimization of such an expression saves valuable resources that are battery life by allocating the power to underutilized subcarriers selectively. Now based on the risk return model we will formulate an convex optimization problem in which we will incorporate a linear average rate loss function to optimize that also includes the effect of subcarrier availability. Here we have proposed three suboptimal schemes due to the complex structure of the optimal solution namely step-ladder, nulling and scaling schemes. Also the performance of the optimal and suboptimal schemes are compared with the performance of the classical water-filling schemes.Finally it is concluded that the water-filling is worst among all the schemes discussed here due to its unability to satisfy the interference criteria.

Yan Chen *et al.* [24]gave the available spectrum handoff techniques for handoff purposes for the cognitive radios perform handoffs solely based upon channel availability. This can results in the very frequent number of channel handoffs and cannot makes sure about the quality requirements of applications called as delay bounds. This paper proposes the the use of the cumulative probability that are based on the past backlog measurements to measure how to perform handoffs .Now in order to prevent the unnecessary handoffs operations ,secondary users must keep the same channel till the cumulative probability estimation does not violates the some bound. However the estimations from the past observations may or may not predict the real behavior in the immediate future even if the efficient prediction models are employed. Therefore we propose the use of the backup channels to alleviate this problem. We analyse all of the above strategies through the extensive simulations and then we compare them to random as well as the classical approaches. Finally the results shows that the proposed strategies will significantly reduce the number of channel handoffs that goes uto 76% while still supporting the delay bound requirements.

Vasile Horia MUNTEAN *et al.* [25]shows that we will develop and analyse the low complexity cooperative diversity protocols that will handle the fading which is induced by the multipath propagation in the wireless networks. The techniques here exploit the space diversity that is available through the cooperating terminals that are relaying signals for one another. Here also we discuss the several strategies employed by the cooperating radios including all of the fixed relay schemes like amplify and forward and decode and forward. The selection of the relaying schemes that we adapt are based upon the limited feedback from the destination terminal. Here we also discuss the performance characterizations in terms of the associated outage probabilities and the outage events that measure the robustness of the transmission to fading also by focusing on the high SNR regime. Except for the fixed decode and forward relaying scheme all of the other algorithms are efficient in the way that they achieve full diversity and more than that they are close to the optimum value which is within 1.5db in certain regimes. And so by using distributed antennas we can also provide the powerful benefits of the space diversity without the need of the physical arrays, though at the loss of the spectral efficiency due to the half-duplex operation and also at the cost of the additional receiver hardware. Another advantage is that it is applicable to any wireless setting, including the cellular or ad-hoc networks-wherever the space constraints preclude the use of physical arrays, the performance of these protocols reveal that the large energy and power savings will result from the use of these protocols

Guowang Miao *et al*. [26]said in the previous days the designof the wireless communications have the main purpose to provide large capacity and ubiquitous access. However as the global demand of the wireless communications shifts towards the energy efficiency and the environmental protection, wireless communication engineers shifts their focus towards the energy efficiency communication design that is called green radio. Here we will discusss the fundamentals of the green radio research and also will discuss the fundamental issues regarding this technology. The skeleton of this framework consists of the four fundamental tradeoffs: deployement efficiency tradeoff, energy efficiency tradeoff, spectrum efficiency, delay-power tradeoff and the bandwidth-power tradeoff. With the help of above mentioned tradeoffs we will demonstrate that the key network performances and the cost indicators are still stingled with each other

Guowang Miao *et al.* [27]says that today energy efficiency is becoming increasing demanding for the small form factor mobile devices as the battery technology is not be able to kept up with the growing requirements stemming from the ubiquitous multimedia applications. We addresses the link adaptive transmission to maximize the energy efficiency as measured by the throughput per joule metrics. As we can see in the existing power allocation schemes like that of water-filling that maximize the throughput subject to the fixed overall transmit power constraint, here in this paper we have discussed the techniques which maximize the throughput as well as energy efficiency of the entire communication system according to the circuit power consumed and the channel states. Here we will discuss the unique globally optimal link adaptation algorithms. Here we will also discuss the flat fading channels to discuss the upper bound of the energy efficiency and also its variations with the channel gain bandwidth and the circuit power. Finally our results shows that of huge energy savings with the energy optimal link adaptation as well as we will discuss the fundamental tradeoffs between the spectrum efficient and the energy efficient transmission.

Zukang Shen *et al.* [28]said that energy efficient wireless communications requirement is more dominant in the battery constrained gadgets like mobile devices. For the mobile devices the uplink power requirement will dominates the wireless power budget as of the radiofrequency power requirements for wireless devices for the long distance wireless communication. All of the previous works done focused on maximizing the energy efficiency by maximizing the instantaneous bit per joule metric through the iterative approaches which results in the significant increase in the energy savings for the uplink cellular OFDMA transmissions. We have discussed the energy efficiency schemes with the significantly lower complexity as compared to the iterative approaches by using the time averaged bits per joule matrices. Here we consider the uplink transmission approach where number of users communicate to the central scheduler over the frequency selective channels with high energy efficiency. Here the scheduler will allocate the system bandwidth among all the users such as to optimize the energy efficiency throughout the network. Using the time averaged metrics here we will derive the energy efficient techniques in the closed form for per user link adaptation and also resource scheduling across the users. finally the results of simulation shows that the proposed algorithms not just only have low complexity but it also performs close to the globally optimum solutions that are obtained through the exhaustive research.

Yuan-Bin Lin *et al.* [29]says that the transmit diversity with the help of the user cooperation is is an attractive proposal for the performance enhancement in the mobile communication systems. Now we have given the multiple transmission channels from the multiple users we will always concerned with the channel power and rate assignment schemes that offers the maximum capacity while satisfying also the multi-rate multimedia requirements. Earlier the cooperative schemes oftenly assume that there is some central processing device is there to find the suboptimal and optimal solutions. Hence the high computing complexity in these cases makes the implementation of the enrgy efficient cooperation transmission not be able to done practically. Here in this paper we have presented the simple resource allocation scheme that enables each participant user to find the optimal channel assignment matrix and the power allocation vectors under the given constraints. Here our technique is used in both mono-rate and multi-rate applications. For the formal case it is optimal and also it gives near to optimal for the later case.

Kuhn Chang Lin *et al*. [30]discussed the energy efficient scheduling in the wireless communications. Here we have proposed two general near optimal schedulars that are having simple structures for the general hard delay constraint scenario. Here both the multiusers and single users cases are considered. The first scheduler is formatted on Gaussian approximation while the second one is inspired from inverse water-filling approach. The scheduling processes here takes consider the channel awareness as well as delay awareness term. Here the numerical results of the above scheduling processes shows that they achieve near optimal proformance when the total required transmit bits R is very large. Now here for the multiuser scenario scheduling strategy includes initial resource allocation that is number of time slots allocated and then slot-by –slot user selection and then finally bit loading algorithm. The former depends on the priori knowledge of the user dependent channel stastic and the rate requirement while the latter uses the ordered approach stastic based to minimize the total energy consumption.

Yen-Shuo Lu *et al.* [31]said that the capacity as well as the coverage of the orthogonal frequency division multiple access (OFDMA) channels can be greatly improved by dynamically allocating the radio transmission resources. Now by including the radio resources of the cooperative nodes and also taking into account the fairness issues we will present the simple suboptimal solution to the the problem of the resource allocation in the relay based OFDMA cellular systems. Here we restrict the investigation to the single cell system with the several cooperative mobile stations and relay stations. Here we will be using IEEE 802.16e-like TDD scenario and also only the uplink transmission with the base station that will handle the resource allocation is of our major concern. Also we propose two suboptimal algorithms that will assign power, subcarriers and the cooperative relay stations to the MSs to meeth their quality of service (QOS) and also its minimum rate requirements. Here these low complexity solutions will maximize the sum rate and also the fairness index while also satisfying the total power constraint and the the quality of service (QOS). All of the numerical solutions shows that the above proposed algorithms provides the robust fairness and also achieves near the optimal sum rate performance.

Raphael Cendrillon *et al*. [32]discusses an important technique to mitigate crosstalk in DSL is dynamic spectrum management (DSM). One of the DSM algorithms proposed iterative waterfilling is having the low capacity and also tells about the spectral gains performances that are possible. Unfortunately the IW tends to be highly sub-optimal in the mixed upstream VDSL and CO/RT deployements. Also one another DSM algorithm optimal spectral balancing (OSB) use the weighted sum to find the transmit spectra in the optimal value, but unfortunately the capacity of this technique scales exponentially with the number of lines N in the binder. Typically it contains about the 25-100 lines for the intractability of the OSB. Here iin this paper we have shown the new iterative algorithm for the spectrum management in DSL. This algorithm optimizes the the weighted rate-sum in an iterative fashion that leads to the quadratic rather than the exponential capacity in N. The algorithm we have used can be tractable for the large values of N and also can be used to optimize the entire binders. The simulations here shows that the algorithms performs very close to that what we achieve from the theoretical optimum achieved by OSB.

Giovanni Cherubini *et al.* [33]gave the problem we will be going to tacle is the multiuser detection for the upstream very-high-speed digital subscriber line (VDSL) transmission, where we will receive the far end crosstalk (FEXT) signals at the input of a VDSL receiver as the interferers that shares the same channel as the remote user signal, is addressed. Here the knowledge of the FEXT impulse responses at the central office as well as the transmission upstream that are based on the multicarrier modulation by all the remote users are assumed. Here the joint application of the reduced capacity decision feedback (DFE) multiple detector and the upstream power back off where only those crosstalk interferers that are most significant are considered and the coefficient of the minimum mean square errors structure is determined. After that a novel power backoff algorithm is introduced and then its performance based upon individual rates is then evaluated. Finally then the numerical results showing the impact of power back off on the achievable performance on the VDSL system with the multiuser detection are then presented.

Jianwei Huang *et al.* [34]shows for the frequency selective interference channels where we treat interference as the noise so distribute attaining the boundary of the rate region is an open problem in this situation, and is also very important for the broadband DSL access. What we have to do is to develop and analyse and simulate a different and new algorithm for power allocation for the frequency selective interference channels which is called as Autonomous Spectral Balancing (ASB). Here it will use the concept of reference line that minimizes the victim line in the interference channel. When compared with the state of art Iterative Water-filling and other methods like the Optimum Spectrum Balancing, the ASB algorithm is completely autonomous that is having linear complexity in terms number of users and the tones, and hence gives close to the near to optimal performance. Also the convergence of the version of the Autonomous spectral balancing is used for any number of users.

Brian Wiese *et al.* [35]shows that the performance losses and their mathematical proofs due to the use of the reference noise method that is bounded. Here it is shown that when the two lines of arbitrary lengths are considered then the performance losses that is the application of reference noise method will results in the upstream signal to noise (SNR) ratio degradation of less than 3db relative to when the two transmitters are of same length and remote transmitters transmit at the maximum allowed power spectral density. Here as this above discussed technique provides the service providers to determine a apriori the worst case impact of the upstream power backoff on the upstream bit rates without taking consideration of the loop plant technology and hence the result is very much significant for very-high speed digital subscriber line applications.

Krista S. Jacobsen *et al.* [36]provides the near and the far problem in the upstream direction of VDSL which comes when the lengths of the VDSL loops in the binder will vary significantly. Now the methods of the upstream power backoff techniques to mitigate the near-far problem is then described here. After that the simulation results are presented in the end and the performances of the methods are then discussed.

Lin Xiao *et al.* [37]shows in all the wireless networks the optimal routing of the data depends upon the link capacities which are then dependent on how to allocate all of the communication resources to the links. So the optimal performance of the wireless network can only be achieved by the simultaneously optimization both the routing and the resource allocations. Here in this paper simultaneously optimization of the routing as well as the resource allocation problem is done and problem structure is analysed and different solution methods are then presented. A capacitated multi-commodity flow model is presented to describe the data flows in the network. It is assumed that the capacity of the wireless links is an concave as well as the increasing function of the communication resources that are allocated to the corresponding links and also for all the links the communication resources are limited. All of the above assumptions done above tells us to know that the SRRA problem is the convex optimization problem of the network flow variables and also the communication variables. Both of these variables are dependent on the link capacity constraints. This separate structure is then explained by the duo-decomposition. Finally in the resulting solution method it is attained the optimal coordination between the data routing in the network layer and the resource allocation in the radio control layer by also considering the pricing on the link capacities.

Wei Yu *et al.* [38]gave a numerical algorithm for the computation of the sum capacity for the Gaussian broadcast channel is discussed. The sum capacity computation here depends upon the duality of both of the Gaussian vector broadcast channel as well as the sum- power constrained Gaussian multiple access channel. The numerical algorithm, discussed here is based upon the laganngian dual composition technique and it also uses the waterfilling approach for the Gaussian multiple access channels. Finally the algorithm, converges into the sum capacity computation both globally and efficiently.

Cem U. Saraydar *et al.* [39]gave the distribution of the power in the multi-cell wireless communication system as well as their pricing is discussed. Now considering our earlier work we formulate here that the quality of service (QOS) of the data user via the utility function measured will be in bits per joule. Here we will consider the distributed power control called as the non cooperative gain where all of the users will be able to maximize their utility in the multi-cell system. Here now the base station requirement with the received signal strength as well as the received signal to noise ratio(SNR) are considered jointly with the power controlling. Here the results indicate that with the above discussed assignment schemes, this procedure resulted into an inefficient operating point(NASH EQUILIBRIUM) for the entire system. We also introduced that the pricing of the transmit power to be checked as the mechanism for influencing the data user behavior and hence the results obtained shows that the distributed power control that is based on the maximizing the network utility results in the improvement of the pareto efficiency of the resulting operating point. The variation in the pricing of the loading of the both of the global and the local cells are considered as the factor in improvement in the efficiency of the wireless networks. Now finally it is discussed the improvement in the utilities through a centralized scheme in which each base station calculates the best SIR possible by the terminals assigned to every base station.

Jiho Jang *et al.* [40]discussed the effect of the frequency offset in the multicarrier code-division multiple access system that are also theoretically analysed as well as verified by the computer simulations for the downlink channels. Here both of the maximal ratio combining as well as the equal gain combining are considered in the combining techniques of the subcarrier signals in the whole analysis.

CHAPTER 3

OPTIMIZATION ALGORITHMS FOR POWER ALLOCTION

Here in this section we are discussing some algorithms for power allocations .These algorithms are different in the sense of their efficiency and performance.They are:-

3.1 POWER ALLOCATION USING WATERFILLING IN CR SYSTEMS

In the water-filling algorithm for power allocation [10], we allocate power to different sub-carriers of the CR band like filling of water in a sectioned vessel. Here in this algorithm we allocate power by taking the average of the sum of total power to be allocated and inverse of the channel gain through the sub-carriers.

Hence power allocated is given below:-

$$\text{Power-allocated} = \frac{\mathrm{Pt}+\sum_{i=1}^{n} 1/H_i}{\sum channels} - 1/\,H_i \tag{3.1}$$

As it is known that Multiple-Input Multiple-Output (MIMO) systems are used to get higher data rate as compared to a normal SISO system where we keep the same power budget and SNR. A comparison of MIMO system with a SIMO reveals that the MIMO system need lesser transmit power than the SISO system in order to achieve the same capacity .As we need to minimize the energy consumed by the circuit and want to maximize the capacity of a system and that is possible only if we use multiple MIMO system. The capacity of the system increases with the increase in the number of transmit and receive antenna.

The capacity of a MIMO system can further be increased if we know the channel parameters both at the transmitter and at the receiver and assign extra power at the transmitter by allocating the power according to the water filling algorithms to all the channels. In the MIMO-OFDM system we use the water filling algorithm and the results of this algorithm are better as compared to the successive water filling algorithms.

WATER FILLING ALGORITHM

The process of waterfilling is similar to pouring the water in the vessel. The unshaded portion of the graph represents the inverse of the power gain of a specific channel.The portion representing the shadow represents the power allocated or the water and also shows the maximum water level.

The total amount on water filled (power allocated) is proportional to the Signal to noise ratio of the channel.

Power allocated by the individual channel is given by the Eq (3.2), as shown in the following formula.

$$\text{Powerallocated}= \frac{\text{Pt} + \sum_{i=1}^{n}\frac{1}{H_i}}{\sum channels} - \frac{1}{H_i} \tag{3.2}$$

Where Pt is the power budget of the MIMO system which is allocated among the different channels and H is the channel matrix of the systems. The Capacity of a MIMO system is algebraic sum of the capacities of all channels and is given by the Eq (3.3).

$$\text{Capacity} = \sum_{i=1}^{n} \log\left(1 + Powerallocated * H\right) \tag{3.3}$$

We have to maximize the total number of bits to be transported. As per the scheme following steps are followed to carry out the proposed water filling algorithm.

Algorithm Steps :-

1. We do not need to Reorder the MIMO-OFDM sub channel gain realization in a descending order
2. Take the inverse of the channel gains.
3. Water filling has non uniform step structure due to the inverse of the channel gain.
4. Initially take the sum of the Total Power Pt and the Inverse of the channel gain .It gives the complete area in the waterfilling and inverse power gain.

$$\text{Pt} + \sum_{i=1}^{n}\frac{1}{H_i} \tag{3.4}$$

5. Decide the initial water level by the formula given below by taking the average power allocated (average water Level)

$$\frac{\text{Pt} + \sum_{i=1}^{n}\frac{1}{H_i}}{\sum channels} \tag{3.5}$$

6. The power values of each subchannel are calculated by subtracting the inverse channel gain of each channel .

$$\text{Powerallocated}= \frac{\text{Pt} + \sum_{i=1}^{n}\frac{1}{H_i}}{\sum channels} - \frac{1}{H_i} \tag{3.6}$$

7. In case the Power allocated value becomes negative stop the iteration process.

Figure (3.1) shows the mean capacity of a MIMO system increases with the increase in the power budget at the input of the transmitter.

It is observed that the water filling algorithm has 2-3bps improvement as compared to the system when no water filling is done at 20db SNR and approximate 10bps improvement in capacity at 20db SNR as compared to the successive water filling algorithm.

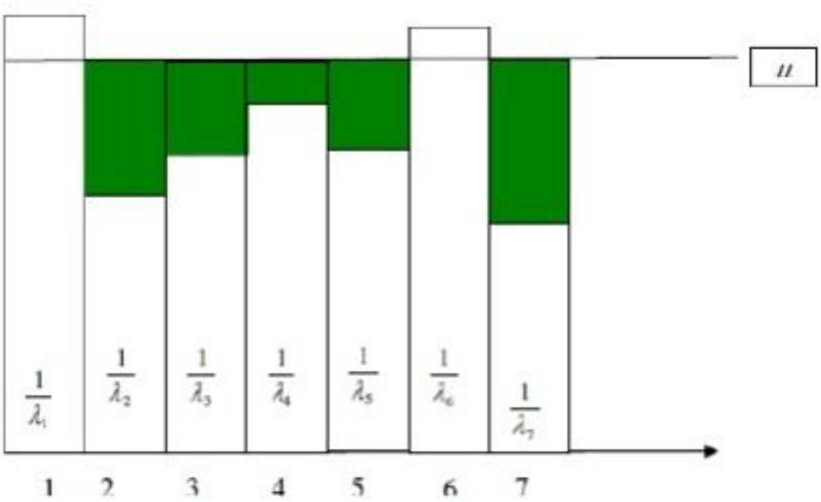

Fig 3.1 Waterfilling power allocation model [10]

3.2 OPTIMAL POWER ALLOCATION SCHEME IN M2M SYSYTEMS

In optimal power allocation scheme, we allocate the power to the sub-carriers in such a way so that the interference to the primary user band should remain below a certain threshold.

Optimal power allocation is explained with context to machine-to-machine (M2M) communications.M2M communications are rapidly developing based on the large diversity of machine-type terminals, including sensors, mobile phones, consumer electronics, utility metering, vending machines, and so on. With the dramatic penetration of embedded devices, M2M communications will become a dominant communication paradigm in the communication network, which currently concentrates on machine-to-human or human-to-human information production, exchange, and processing. M2M communications is characterized by low-power, low-cost, and low-human intervention.

M2M communications is typically composed of billions of wireless identifiable infrastructure sensors which will be developed and deployed over the coming years. The diversity of the M2M network structures, protocols, and standards, combined with even more diverse application services from users, pose big challenges for M2M network integration and service integration. The capabilities of sensors are generally limited which puts several constraints in M2M communications, including communication spectrum, energy, computation, and storage. These constraints pose a number of unique challenges in the design of network architecture and spectrum usage to achieve a highly connected, efficient, and reliable M2M communication.

The first challenge in M2M communication is the spectrum scarcity. Massive M2M terminals accessing wireless network require lots of spectrum resources, but the exploitable spectrum is becoming scarce resource. Thus, there should be a mechanism to solve the problem of imbalance between the M2M spectrum requirement and the spectrum scarcity.

Another main issue challenges the M2M communication is ever more intensive interference with more radio systems in M2M communication, including unlicensed systems operating in the industrial, scientific, and medical (ISM) frequency band, electronic equipment, and domestic appliances

M2M(Machine to machine network consists of different layers, Subrover and Subunder layers. Subrover layers are closer to the Primary User band and hence causes more interference by the devices present in the SubRover layer and the power allocated to the devices in this layer corresponds to the interference to the Primary User band and hence the more closer the devices, least the power allocated to the channels by the devices in SubRover band. Another layer present around the SubRover is SubUnder layer which is far away from the Primary user and hence the channels for the devices in the SubUnder layer can be allocated more power because their interference to the band of primary users is least.Fig(3.2) shows the layout of the design of the Machine to Machine network.

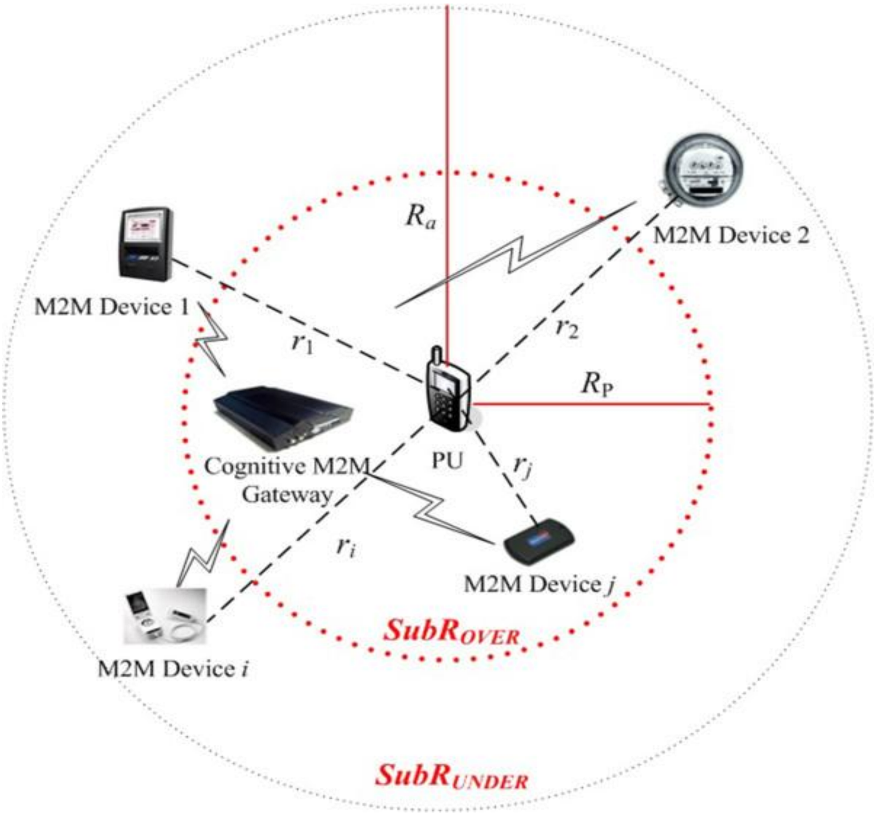

Fig 3.2 Cognitive radio based M2M network scenario [12]

The performance of M2M communications may be seriously degraded due to the self-existence/coexistence interference. Moreover, wireless channels in M2M communications are notoriously unreliable due to channel fluctuations and noise, which may become even worse due to the complicated construction in an indoor environment.

The cognitive-based M2M network we considered here is shown in Figure (3.2). The proposed M2M network is composed of a number of M2M devices, a licensed user (PU), and a dedicated cognitive M2M gateway, and the PU is not the M2M device. Now here to allocate the power optimally, it follows following steps:

1. Firstly the PU who has the main license band transmits the data in the spectrum allocated.

2. Now the M2M devices that are under SubRover range that are closer to the transmitter are allowed to transmit but as they are closed to the PU, they are allocated the less power due to the interference by the PUs.

3. Now the M2M devices that are far-away from the PU are allowed to take the free PU band in case of its not in use to transmit but as they are far away from the PU and hence they are allocated more power as their interference to the primary users (PU) is less.

4. Now finally all the machines are allocated power optimally by keeping in consideration the interference to the primary user should be least.

3.3 SUB-OPTIMAL POWER ALLOCATION SCHEME IN CR SYSTEMS

In the optimal power allocation scheme, we get the required transmission capacity with the interference to the primary user band below a certain threshold but the optimal power allocation scheme requires very high no of iterations equals to N(LOGN) which is not acceptable in some cases and hence sub-optimal power allocation scheme is proposed whose no of iterations are reduced to 1. Power profile for suboptimal schemes is shown in Fig (3.3)

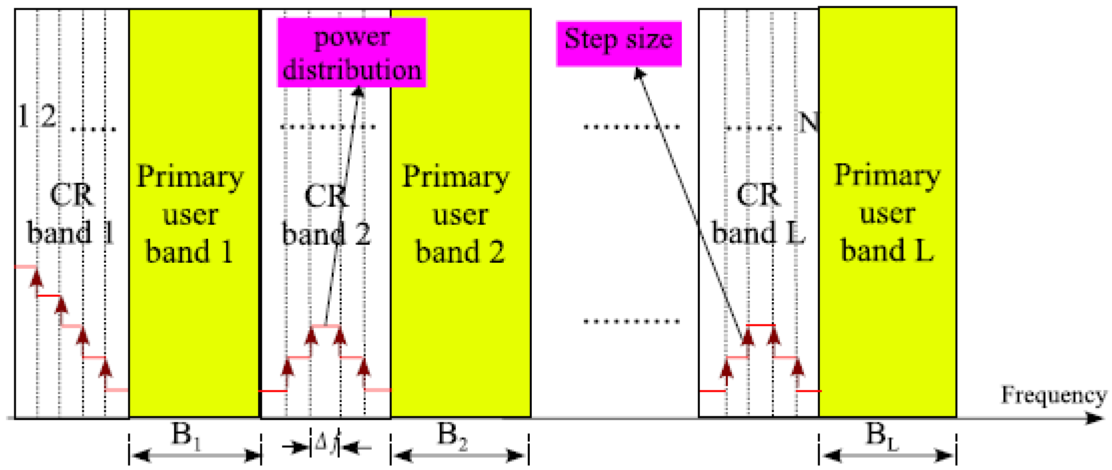

Fig 3.3 Power profile for suboptimal schemes[10]

3.3.1 Scheme A

While allocating power using Scheme A for a particular CR user subcarrier, we consider the effect only on the PU band where it causes the most amount of interference, i.e., the PU band to which it is closest. Power is distributed such that the subcarriers that are adjacent to the PU bands are given power P[1]. Then we increase the power by P as we move away from the PU bands. Hence, to subcarriers that are adjacent to the PU bands we allocate power P, to those that are right next to them we allocate 2P , and so on. For proposing this scheme, without loss of generality we assume that each CR user band occupies N/L >1 subcarriers. Hence, we can write the power profile as follows in (3.7). Here from the distribution shown below we can see how the power is allocated. The power profile shown below is in accordance with the Fig (3.3) shown above and hence we can see how there is gradual change in power profile, the adjacent primary user bands are given least power and then as we go from one band to other power increases and when we start approaching the second primary user band, the power allocated then again starts decreasing and it gets minimum again as we come close to second PU band and then again from second PU to third PU band it increases again ,attains a maximum value and then starts decreasing to minimum when comes close to fourth band and hence this process of power allocation goes on.

$$\begin{aligned}
P_i^{A} &= \left(\frac{N}{L}+1-i\right)P \\
&\quad \forall i \in \left\{1,2,\ldots\frac{N}{L}\right\} \\
&= \left(i-\frac{N}{L}\right)P \\
&\quad \forall i \in \left\{\frac{N}{L}+1,\ldots\left\lceil\frac{3N}{2L}\right\rceil\right\} \\
&= \left(\frac{2N}{L}+1-i\right)P \\
&\quad \forall i \in \left\{\left\lceil\frac{3N}{2L}\right\rceil+1,\ldots,\frac{2N}{L}\right\} \\
&\;\vdots \\
&= \left(i-\frac{(L-1)N}{L}\right)P \\
&\quad \forall i \in \left\{\frac{(L-1)N}{L}+1,\ldots\left\lceil\frac{(2L-1)N}{2L}\right\rceil\right\} \\
&= (N+1-i)\,P \\
&\quad \forall i \in \left\{\left\lceil\frac{(2L-1)N}{2L}\right\rceil+1,\ldots,N\right\}
\end{aligned} \tag{3.7}$$

3.3.2 Scheme B

In this scheme, the step size of the ladder is taken to be inversely proportional to $\sum_{l=1}^{L} K_{i,l}$. Hence, the power in the subcarrier can be written as below [1]

$$P_i^B = \mathrm{P}/\sum_{l=1}^{L} K_i^{(l)} \tag{3.8}$$

where P will be determined by the value of I_{th}, as follows:

$$P=I_{th}/N \sum_{l=1}^{L} K_i^{(l)} \tag{3.9}$$

Hence from equation (3.9), given the value of I_{th} that is the threshold value of the current we can calculate the power allocated P and then using the this value we will calculate the power allocated to the subcarriers keeping step size of the ladder in consideration.

CHAPTER 4

ANALYSIS AND METHODOLOGY

Let d_m denote the distance between the SU base station and the m^{th} PU, and R_m denote the radius of the protected circular area around the m^{th} PU. The channel from the source to m^{th} PU in kth SU band can be written as:

$$g_{m,k} = \frac{\tilde{g}_{m,k}}{(d_m - r_m)^\wedge\beta} \quad (4.1)$$

Where $g_{m,k}$ is the small-scale fading and β is the path loss exponent of the wireless channel. Without loss of generality, we assume that $R_1 = R_2 = \cdot\cdot\cdot = R_M = R$.

Let us consider a wireless network with one transmitter, one relay, K SUs and M PUs. Each SU receives the data on a separate pre-assigned frequency band. The relays transmit and receive data on pre-assigned frequency bands. The central controller decides the power allocation to the relay and the secondary users. We denote by $p_c = p_c^s + p_c^r$, the total static circuit power of the source and the relay in the transmit mode, p_k^s is the source transmit power to serve kth SU, and p_k^r, the relay transmit power to serve kth SU. We denote by h_k^s, the channel gain from the source to the kth SU, h_k^r, the channel gain from the relay to the kth SU, $h_{r,k}^s$, the channel gain from the source to the relay in the kth SU band, $g_{m,k}^s$ the channel gain from the source to mth PU in kth SU band, and $g_{m,k}^r$the channel gain from the relay to the mth PU in the kth SU band.

The channel model for cooperative communication (e.g., relay channel) is the same as mentioned [29] .

$$C_k^1 = \log(1+\frac{p_k^s h_{r,k}^s}{N}) \quad (4.2)$$

Eq(4.2) shows the capacity is for the transmission through source only.

$$C_k^1 = \log(1+\frac{p_k^s h_{r,k}^s}{N}+\frac{p_k^r h_k^r}{N}) \quad (4.3)$$

Eq(4.3) shows the capacity for the transmission when it takes place through both of the source as well as the relay.

The energy efficiency[29] for the co-operative communication system is given by:

$$\Gamma_{DF}\ (p_s,p_r) = \frac{\sum_{k=1}^{K} \min\,(C_k^1, C_k^2)}{pc+\sum_{k=1}^{K} p_k^s + p_k^r} \quad (4.4)$$

Now to maximize the energy efficiency given in Eq(4.4),

$max_{\ p_r, p_s}\ \Gamma_{DF}\ (p_s, p_r)$

$$\text{C1: } \sum_{k=1}^{K} p_k^s\ g_{m,k}^s < I_m \tag{4.5}$$

$$\text{C2: } \sum_{k=1}^{K} p_k^r\ g_{m,k}^r < I_m \tag{4.6}$$

$$\text{C3: } p_k^s > 0,\ p_k^r > 0 \tag{4.7}$$

Above the constraints C1 and C2 assure that interference from the source and relay to primary users is less than a specified threshold respectively. By introducing new variables τ_k, k = 1, 2, ……, K.

4.1 ITERATIVE POWER ALLOCATION SCHEME (IPAS)

In this section, we present an iterative power allocation scheme (IPAS)[41] to solve the optimization problem. The proposed algorithm is based on ε-optimal algorithm. Therefore, for any ε > 0, ε-optimal algorithms guarantee the solution within ε of the optimal solution. The objective function of the FP problem is transformed into a parametric optimization problem. Let us first consider the following optimization problem:

$$max_{x \in S}\ \frac{f(x)}{g(x)} \tag{4.8}$$

where $x \in R^n$. The parametric problem associated with for $q \in R$ can be written as

$$max_{x \in S}\ \text{f(x)-q*g(x)} \tag{4.9}$$

The following algorithm ε-optimal algorithm shows the optimization.

Initialization
q=0, epsi =10^-6,i=0,convergence=false
Define
$\gamma_{DF}^{\tau}(p_s, p_r, \tau, q) = \sum_{k=1}^{K} \tau_k - q(p_c + \sum_{k=1}^{K}(p_k^s + p_k^r))$
while (convergence=false)&(i< imaxitr) **do**
if $\gamma_{DF}^{\tau}(p_s, p_r, \tau, q) = 0$ **then**
$p_{so} = p_s$

p_{ro}= p_r

τ_o= τ

Convergence=true

Else if

$\gamma_{DF}^{\tau}(p_s,p_{r,}\tau, q) \leq \varepsilon$

$p_{s\in}$=p_s

$p_{r\in}$ =p_r

$\tau_{\in}$ =τ

Convergence=true

Else

q=$\frac{\sum_{k=1}^{K}\tau_k}{p_c+\sum_{k=1}^{K}(p_k^s+p_k^r)}$

i=i+1

end if

end while

4.2 SHARED CARRIER ASSIGNMENT ITERATIVE WATERFILLING ALGORITHM (SCA-IWF)

The rate maximization subject to the instantaneous sum-power constraints may be defined as

$$max_{a_{k,n},P_{k,n}} \sum_{n=1}^{N} a_{k,n}\, C_{k,n}(P_{k,n})$$

$$\text{s.t. } \sum_{n\in S} a_{k,n}\, P_{k,n} < P_{T,k}\ \ , \sum_{k=1}^{K} a_{k,n} < 1 \qquad (4.10)$$

where $a_{k,n} = \{0, 1\}$ and $a_{k,n} = 1$ when user k accesses channel n. S_k is the set of carriers assigned to user k, and $P_{\text{mask},n}$ is the maximum power allowed at carrier n to avoid interference to primary users. $S_1, .. . , S_K$ are generally overlapping sets for SCA. The capacity of user k at carrier n is given by Eq (4.11)

$$C_{k,n}^{SCA}(P_{k,n}) = B_n log_2(1+\Gamma_k P_{k,n}\gamma_{\Gamma,n}^{SINR}) \qquad (4.11)$$

Where $\gamma_{\Gamma,n}^{SINR}$ was given by SINR at the channel n, Γ_k is an SNR gap due to modulation format and bit error rate (BER) requirement.

When $\Gamma_k = 1$, Eq (4.11) gives the Shannon capacity when $\Gamma_k = -1.5/\log(5P_{e,k})$, $P_{e,k}$ is the target BER for user k assuming continuous-rate quadrature amplitude modulation (CR-QAM) , Eq(4.12) gives the throughput which satisfies the

Target BER $P_{e,k}$. The sum rate of all K pairs is given by

$$C_{tot}^{SCA} = \sum_{K=1}^{K} \sum_{n=1}^{N} a_{k,n} \ C_{k,n}^{SCA} \quad (P_{k,n}) \tag{4.12}$$

Shared Carrier Assignment [42] technique shares the given carriers available for the transmission as compared to the exclusive carrier assignment where each user is allocated a different carrier. It generally requires an N K-dimensional numerical search and the global optimization is an often in-tractable problem. Based on OSB and ISB, optimization may be implemented assuming a central controller or global knowledge of interference powers at each pair. As a suboptimal solution with distributed processing, the SCA-based iterative water-filling technique may be used, which allows all transmitters (users) to initially compete all the N carriers and then fine tune it. In each data frame duration, the first few mini-slots are used for carrier competition of K users, after which the data transmission follows. In these mini-slots each transmitter implements WF along the carriers under its own power constraint and based on the SINRs of the carriers. This method converges fast as shown by simulations. Usually, the IWF requires a numerical search. A low-complexity IWF taking into account the spectral mask at each channel n is derived below.

Define the Lagrangian(for pair k)

$$\mathrm{L}\ (\lambda_{k,}\{P_{k,n}\}_{n\epsilon S}) = \sum_{n\epsilon S} \log\,(1+P_{k,n}\gamma_{\Gamma,n}^{SINR}) - \lambda_k(\sum_{n\in S} P_{k,n}\text{-}P_{T,k}) \qquad (4.13$$

Taking derivative

$$P_{k,n}^{*} = (1/\lambda_k\text{-}1/\gamma_{\Gamma,n}^{SINR})$$

$$\text{s.t.} \qquad \sum_{n\in S} P_{k,n}^{*} < P_{T,k} \tag{4.14}$$

where $(x)^+ = \max(0, x)$, and $P_{k,n}^{*}$ denotes the water-filling optimal solution of $P_{k,n}$.

After some manipulations, we obtain an equation equivalent as

$$\lambda_k\text{=}N_k/[P_{T,k} + \sum_{n\in S} 1/\,\gamma_{\Gamma,n}^{SINR}] \tag{4.15}$$

where N_k = $|S_k|$ is the cardinality number of set S_k . After the WF power allocation, not all the carriers are used due to possibly weak channel SINRs at some carriers, which means that generally.

A very low complexity exact IWF algorithm is shown below

1. At each min slot assume that pair k has channel set S_k(with cardinality N_k) with non zero power aloocation at each of the element. Update the SINR $\gamma_{k,n}^{SINR}$ according to the interference power levels from the other links.
2. Let N_{keff}=N_k. Rank $(\gamma_{k,n}^{SINR})_{n\in Sk}$ in descending order where $\gamma_{k,1}^{SINR}$>…..>γ_{k,N_k}^{SINR}holds.
3. Find λ_k using (4.14) with N_k is replaced by N_{keff} therein.
4. Check if $\lambda_k < \gamma_{k,N_{keff}}^{SINR}$ holds. If true go to step 5. Otherwise remove $\gamma_{k,N_{keff}}^{SINR}$ from the set $\gamma_{k,1}^{SINR}$>…..>$\gamma_{k,N_{keff}}^{SINR}$,set N_{keff}=N_{keff}-1 and go to step3.
5. The λ_k and N_{keff} are now obtained for the user k. The allocated power for the carrier n of user k is given by $P_{k,n}^{IWF}$=min ($P_{k,n}^{*}$,P_{mask}) where $P_{k,n}^{*}$ is given by (4.13) for n=1…..N_{keff}
6. The instantaneous throughput for the nth carrier with the iterative water-filling(IWF) is given by

$$C_{k,n}^{IWF}=\log(1+P_{k,n}^{IWF}\gamma_{\Gamma,n}^{SINR})$$

CHAPTER-5

RESULTS AND DISCUSSIONS

5.1 GRAPHICAL REPRESNTATION OF ENERGY EFFICIENCY AND CAPACITY PLOT WITH NUMBER OF ITERATIONS IN CR NETWORKS USING IPAS SCHEME

Figure (5.1) shows the energy efficiency with the no of iterations, We have plotted graphs for different values of primary users K.it is observed that with the increase in the value of K, the energy efficiency increases. As the number of iterations increases, the energy efficiency first increases linearly and then after few iterations the energy efficiency increases at a very low rate and almost becomes a constant. This shows that the graph converges in very few iterations.

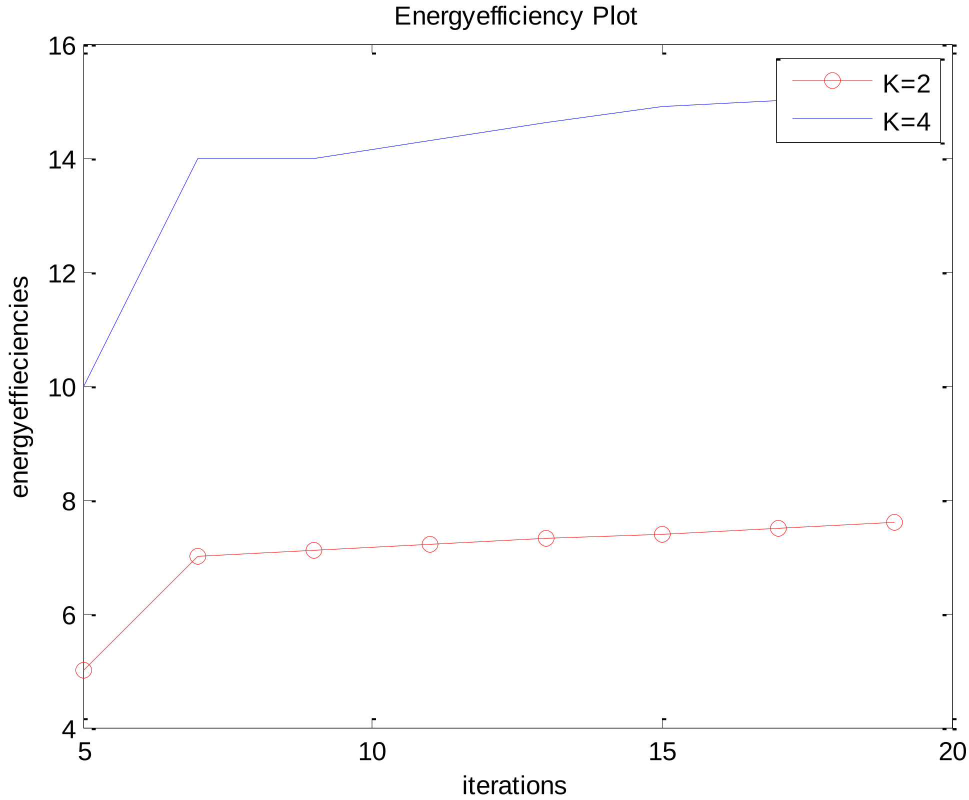

Fig. 5.1. Energy efficiency plot in the CR networks with the number of iterations at the different values of K

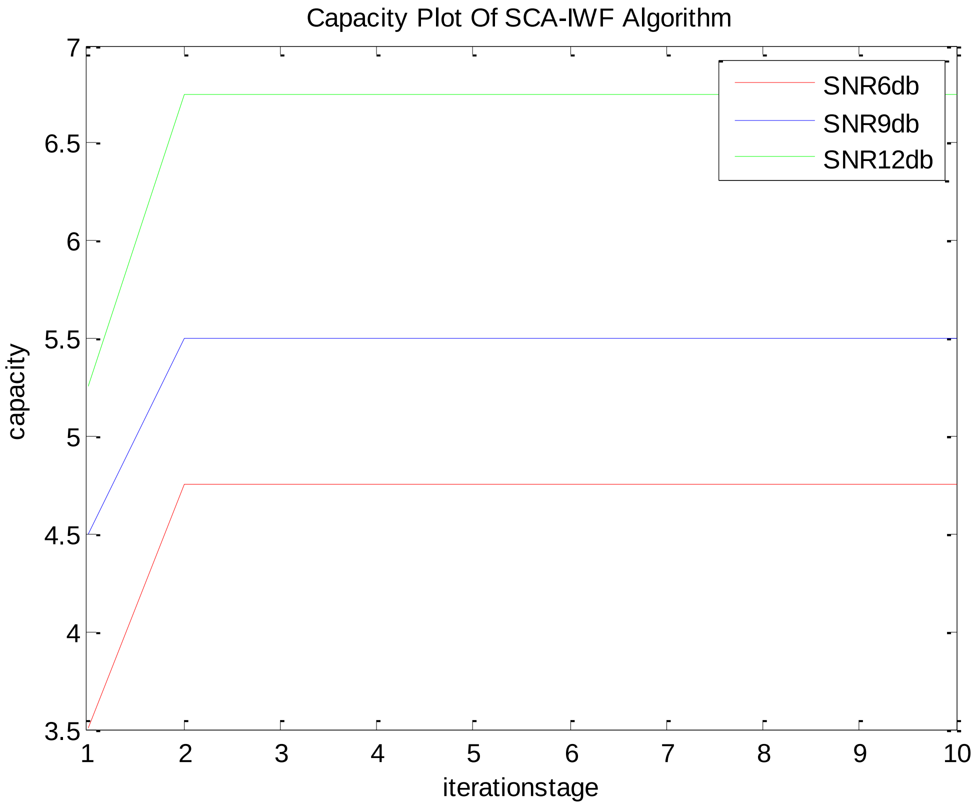

Fig. 5.2 Capacity plot of SCA-IWF Algorithm with the Number of iterations at the different SNR values of the channels

Figure (5.2) shows the capacity plot for SCA-IWF Algorithms for the different values of SNRs. Capacity plots for SNR 6db,9db and 12db are plotted. From the figure it is clear that the SNR of the channel increases as the capacity value increases for the no of iterations and it increases linearly first and then become constant for all the cases.

5.2 ENERGY EFFICIENCY AND CAPACITY PLOT IN BAR-GRAPH FORM

The variation of the energy efficiency plot with the number of iterations at the different SNR values is shown in Fig (5.3). It is shown in the bar-graph form for the better understanding of the variation of the energy efficiency with the number of iterations at the different SNR values.

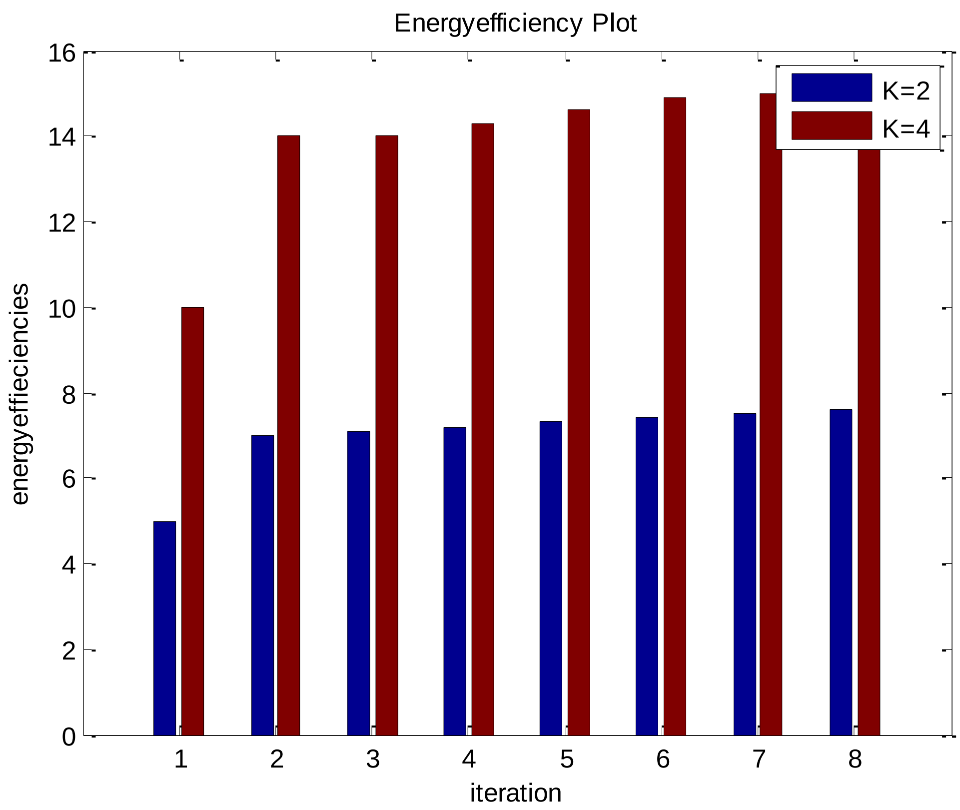

Fig 5.3 Energy efficiency plot with respect to the number of iterations in the bar-graph form.

Fig(5.4) shows the capacity plot with the number of iterations in the bar-graph form for the better understanding of the variations of capacity at different SNR with the number of iterations. In the graphical form we can see the variations of capacity at different SNR values simultaneously in descrete forms.

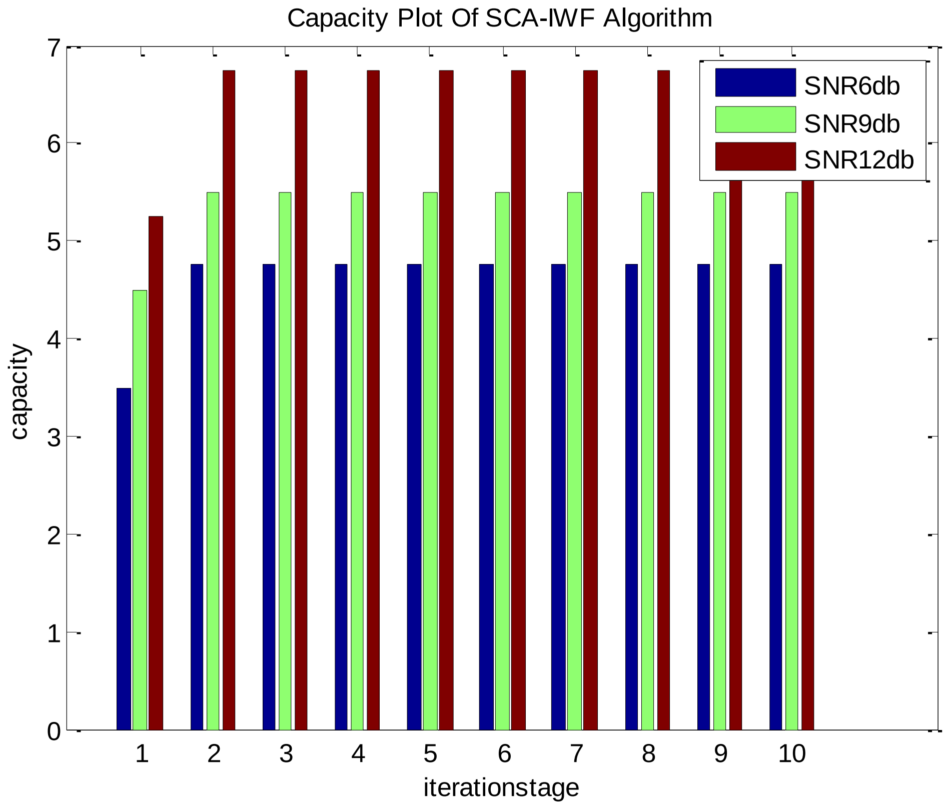

Fig 5.4 Capacity plot of the SCA-IWF Algorithm in the bar graph form with respect to the number of iterations.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

In the CR system, spectrum and power are two main resources that we need to utilize very efficiently. In this thesis we mainly focused to maximize the utilization of these resources.

In the first part of thesis, we have discussed the different algorithms by which all power is allocated in different scenarios with the channels having different SNRs and then finally we have allocated power to the channels so as to maximize the capacity by allocation the power to channels according to their SNRs. Here we have used Shared Carrier Assignment-Iterative Water-filling (SCA-IWF) approach to maximize the capacity by optimum utilization of the spectrum.

In the second part of our work, we have considered a network where we have to allocate power to the network in order to get the maximum energy efficiency of the whole scenario. Here in this case we have used the iterative power allocation scheme (IPAS) technique in which we have also considered SNR as the base to decide in which channel we have to allocate the power so as to get the maximum capacity of the system.

6.2 FUTURE SCOPE

By the use of above techniques we will be able to find out the good capacity of the wireless communication networks but here we have also got some limitations that are required to be solved in the nearby future according to the needs and requirements of the wireless communication networks. This work can be further extended

- To speed up the process by reducing the number of iterations
- To improve the performance by using cooperative communication techniques.

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