Sum Rate Comparisons with and without Simultaneous Spectrum Sharing and VQ for Rate Adaptation

A Project Report

submitted by

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

MASTER OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY MADRAS.

JUNE 2016

THESIS CERTIFICATE

This is to certify that the thesis titled **Sum Rate Comparisons with and without Simultaneous Spectrum Sharing and VQ for Rate Adaptation**, submitted by **B NAVEEN KUMAR**, to the Indian Institute of Technology, Madras, for the award of the degree of **Master of Technology**, is a bona fide record of the project work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Date: 10^{th} June 2016

ACKNOWLEDGEMENTS

First and foremost, I am deeply indebted to my advisor Prof. K. Giridhar for his guidance and encouragement throughout the course of this project. I would like to thank him profusely for giving me an opportunity to work with him, for his patient guidance and for giving me freedom to work. His dedication and keen interest and above all his overwhelming attitude to help his students had been solely and mainly responsible for completing my work. His timely advice, patience, meticulous scrutiny, scholarly advice and scientific approach has helped me to a very great extent to accomplish my task.

I also thank Dr. T. G. Venkatesh for his valuable support as a faculty advisor during my entire tenure as a student.

It is a pleasure to thank my teammates Suman Kumar, V. Vignesh Kumar, P. Sriram, C.R. Venkatesh, Vishnu O.C, M. Midhun, Umakishore G.S.V,and Deepak Saidam for their help at every stage of my work. I would extend my sincere thanks to all my classmates and hostel mates for all the fun and making my stay memorable.

I take this opportunity to express my greatest regards to my family and friends for their support, co-operation and inspiration which were the sustaining factors in carrying out my work successfully.

Finally, I would like to thank the Department of Electrical Engineering and Indian Institute of Technology Madras for providing an excellent and ideal environment for learning

ABSTRACT

KEYWORDS: MOSSSAIC, BWSim, Hata Model, ISD, Inter Operator Negotiator, FFR, AFFR, Spectral Utilization Factor, Interference Cancellation, Vector Quantization, Nearest Neighbor, Genaralized Lloyd Algorithm

Non-Orthogonal Spectrum Sharing is a technique where all the cellular operators use the entire shared spectrum. Multi Operator Simultaneously shared Synchronized Air Interface (MOSSSAIC) is one such technique which operates in TV-UHF band. MOSSSAIC system is realized using a system level simulator BWSim and we show MOSSSAIC system outperforms a single operator system. Several system level simulations were performed varying various parameters and the optimal parameters that improve sum-rate and %Gain in Spectral Utilization of MOSSSAIC system over single operator system are presented.

As a UE in the MOSSSAIC system uses a Joint Detection Receiver which is a non-linear one, Rate adaptation will be complex and needs the knowledge of interference profile. Different techniques of Vector Quantization (VQ) are presented and VQ is used to quantize the interference profiles of MOSSSAIC system and we show they can be quantized to a finite set of codewords which reduces the computational complexity of rate adaptation. But our focus here will be mainly on Vector Quantization.

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ABBREVIATIONS

OFDM	Orthogonal Frequency Division Multiplexing
BWSim	Broadband Wireless Simulator
BS	Base Station
MS	Mobile Station
UE	User Equipment
ISD	Inter Site Distance
ION	Inter Operator Negotiator
FR	Frequency Re-use
TDD	Time Division Duplexing
LLR	Log Likelihood Ratio
FFR	Fractional Frequency Re-use
AFFR	Adavanced Fractional Frequency Re-use
CDF	Cumulative Distribution Function
DL	DownLink
UL	UpLink
SUF	Spectral Utilization Factor
IC	Interference Cancellation
JD	Joint Detection
SISO	Single Input Single Output
ML	Maximum Likelihood
MI	Mutual Information
MCS	Modulation and Coding Scheme

VQ	Vector Quantization
NN	Nearest Neighbor
ZPBC	Zero Probability Bound Condition
GLA	Generalized Lloyd Algorithm
SR	Stochastic Relaxation
SA	Simulated Annealing

CHAPTER 1

INTRODUCTION

1.1 MOSSSAIC

Non-Orthogonal spectrum sharing between multiple operators can reduce the cost of ownership of frequency bands, especially in the TV-UHF band where reframing of spectrum is possible. For this purpose, Multi Operator Simultaneously Shared Synchronized Air Interface for Communication (MOSSSAIC) is proposed where all the cellular operators simultaneously uses the entire shared spectrum and also various interference management techniques are used to ensure that this scheme can provide a much higher sum rate when compared to a single operator based deployment. Different levels of co-operaton between the operators are introduced. The interworking between the base stations of different operators is facilitated by a new network element called Inter-Operator Node (ION). MOSSSAIC introduces several new techinques such as multi-utility pilots, precoding for advanced interference reduction and advanced fractional frequency re-use (AFFR). To enable a more computationally efficient rate adaptation in the presence of joint ML detector, one fraction of the resource block being with fixed modulation is proposed.

1.2 System Simulator

The Broadband Wireless Simulator (BWSim) is an OFDM technology-based wireless system level simulator. It is capable of performing system level simulations of an OFDM based system in a multi-cellular environment under different deployment scenarios with a variety of radio conditions in the presence of interference of up to two tiers.

BWSIM is an advanced 4G system simulator, capable of realizing a wide range of LTE RAN scenarios involving one or more cells and multiple users per cell, in the presence of interference and noise. It can be used to perform system level simulations of an LTE system in a multi-cellular environment under different deployment scenarios with a variety of radio conditions. It also has the Physical and Layer 2 stacks so that the simulation can cover all aspects related to these layers or which depend on these layer.

A number of propagation models corresponding to different terrains such as Urban Micro, Rural etc are supported by BWSIM. The simulator also includes a traffic generator for simulating different types of applications such as VoIP, video streaming, browsing etc.

The networks simulated can be homogeneous (macro only)or heterogeneous (HetNets) involving picos, femtos, relay eNodeBs and Remote Radio Heads overlaid on the Macro coverage area.In addition to the above, BWSIM can be used to perform link level simulations for a point-to-point link, which can be used to evaluate the performance of newly developed schemes/algorithms.

1.3 Channel - Hata Model

Path loss models like Urban Micro which are available in BWSim are not applicable in TV-UHF band. Hata Model which is valid in TV-UHF band is incorporated into BWSim and used for MOSSSAIC.

The Hata model also known as Okumura-Hata model for being a developed version of Okumura model, is most widely used radio frequency propogation model for predicting the behaviour of cellular transmissions in built up areas. The model incorporates the graphical information from Okumura model and develops it further to realize the effects of diffraction, reflection and scattering caused by city structures.

This hata model is applicable to the radio propagation within urban areas, for both point-to-point and broadcast transmissions and it is based on extensive empirical measurements taken. It is applicable over a frequency range of 150-1500 MHz, MS antenna Height being 1-10 m, BS antenna height being 30-200 m and with in a link distance of 1-10 km.
Hata model for Urban areas is formulated as follows:

$$L_u = 69.55 + 26.16 \log_{10} f - 13.82 \log_{10} h_B - C_H + [44.9 - 6.55 \log_{10} h_B] \log_{10} d \tag{1.1}$$

For small or medium sized city,

$$C_H = 0.8 + (1.1 \log_{10} f - 0.7) h_M - 1.56 \log_{10} f \tag{1.2}$$

and for large cities

$$C_H = \begin{cases} 8.29(\log_{10}(1.54h_M))^2 - 1.1, & \text{if} 150 \leq f \leq 200 \\ 3.2(\log_{10}(11.75h_M))^2 - 4.97, & \text{if} 200 \leq f \leq 1500 \end{cases} \tag{1.3}$$

where, L_u = Path loss in Urban areas

h_B = height of BS antenna in meters

h_M = height of MS antenna in meters

f = frequency of operation in MHz

C_H = Antenna Height Correction factor

d = distance between BS and MS in km.

1.4 Brief Overview of The Present Work

Several systen level simulations were performed and system sum-rate was used to bring out the efficacy of MOSSSAIC. By doing non-orthogonal spectrum sharing in TV-UHF band between four liscensed, each operator aquires spectrum not only at a much lower cost, but also can enjoy a rate which is as good if not higher than the rate obtained by the single opearator using the entire unshared spectrum

As the UE in the MOSSSAIC system uses a joint ML receiver which is a non-linear one, accurate rate adaptation becomes difficult and complex and it requires the knowledge of current interference profile. Vector Quantization is performed on the interference profiles, ending up with a group of vectors which are close to all possible interference profiles, so that rate adaptation technique can be performed on those group of interference profiles and get to the approximate rate reducing the complexity.

1.5 Objectives

- To show the improvement in Spectral Utilization in MOSSSAIC system compared to single operator system using the entire spectrum and get to optimal parameters for MOSSSAIC system.

- To show interference profiles in a MOSSSAIC system can be quantized and get to quantized vectors so that they can be used for Rate Adaptation.

1.6 Organization of Thesis

The Outline of this Thesis is as follows: Chapter 2 discusses about MOSSSAIC, its key features and how it is better compared to Single Operator system. Chapter 3 describes the basics on Vector Quantization and various VQ techniques, how it helps in Rate Adaptation. Simulation results are presented in respective chapters and finally conclusions are drawn in chapter 4.

CHAPTER 2

RATE ANALYSIS

2.1 System Architecture

A system consisting of four different cellular operators with nearly same ISD is considered. It is assumed that all the cellular operators are synchronized and simultaneously uses entire shared frequency bands. A macrocell network relying on hexagonal tessellation and on an inter cell site distance of $2R$ is realized using a system level simulator. The Base Stations (BS) of all operators are uniformly distributed inside a circle of radius $R' < R$ as shown in figure.

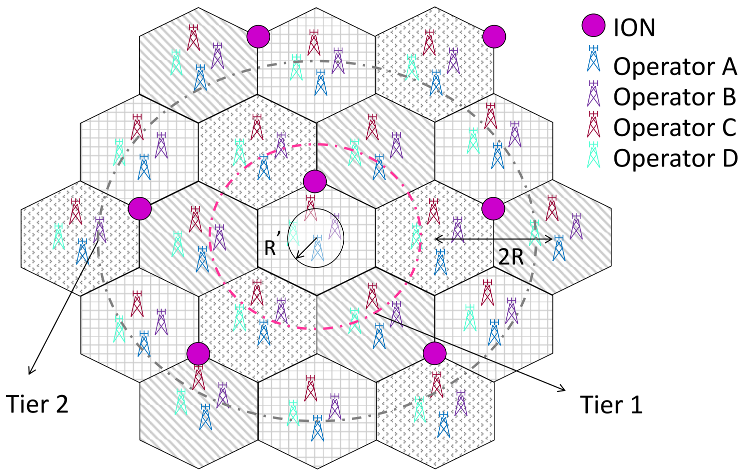


Fig. 2.1 Hexagonal structure of 2-tier MOSSSAIC system

Interference for the 0^{th} cell(in center) in FR1 system is contributed from all the neighboring 75 cells(18 * 4 Operators+3 Tier 0 interferers), while in FR3 system, it is contributed only from the similarly shaded cells.

2.1.1 SINR Expression

The SINR $\eta_m(r)$ of a user in the frequency re-use m(FRm) aided shared spectrum located at r meters from its serving BS is given by

$$\eta_m(r) = \frac{gr^{-\alpha}}{\frac{\sigma^2}{P} + I_m}, I_m = \sum_{i \in \psi_m} h_i d_i^{-\alpha_i} \tag{2.1}$$

Where P and σ^2 denote the transmit and noise power of a enodeB. Here ψ_m is the set of all interfering enodeBs in the system model considered and $|\psi_m|$ denote the number of interferers according to the chosen frequency re-use scheme. The standard path loss model $\| x \|^{-\alpha}$ is assumed where $\alpha \geq 2$ is the path loss exponent and $\| x \|$ is the distance of the user from enodeB. Here r and d_i are the distances from the user to the serving enodeB and the i^{th} enodeB. Note that unlike the single operator case, in FR1-shared spectrum system, the users experience interference from any operator. Moreover, g and h_i denote the corresponding composite channel fading power, which are independent and identically distributed (i.i.d), such a model is used in the system simulator.

2.1.2 Levels of Cooperation in MOSSSAIC

MOSSSAIC proposes different levels of cooperation between the eNodeBs and/or UEs of the different operators resulting in significant performance improvements when compared to the orthogonal (single operator) system:

1) $Level - 0$ $cooperation$: Level-0 can be viewed as the basic level of timing synchronization between the various MOSSSAIC operators who have the same air-interface. An UE registered with an operator can attach only to the strongest eNodeB of the same operator. In level-0 there is a chance of an interferer being stronger than the serving BS.

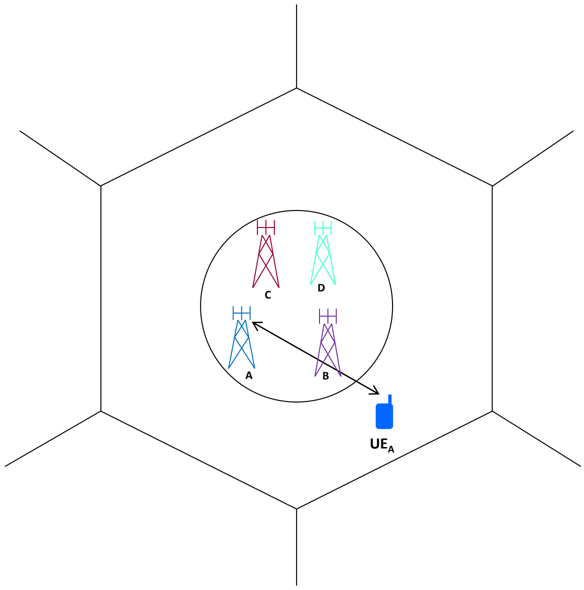


Fig. 2.2 Level-0 cooperation

Figure 2.2 shows that as the UE is of operator A it is associated to BS of operator A only even though the UE is far from the BS of A (level-0 cooperation).

2) $Level - 1$ $cooperation$: Here, in addition to Level-0 synchronization, a UE can get associated with the strongest eNodeB of any operator. We refer to this Level-1 cooperation as user sharing arrangement. The associated enodeB may be of the same cell or from neighboring cells. In level-1, there is

no chance of interferer being stronger than the associated BS as the UE gets associated to the strongest enodeB of all operators thus knocking off very strong interferers.

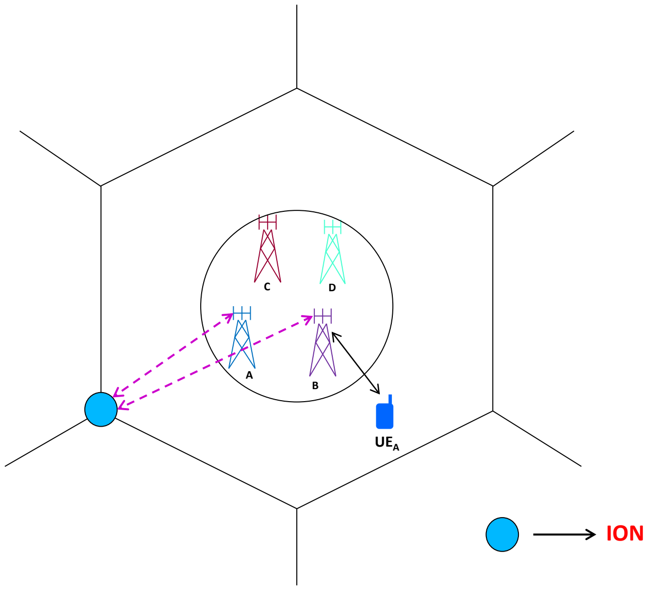


Fig. 2.3 Level-1 coopearation

Figure 2.3 shows that even though UE is of Operator A, as it close to the BS of operator B it gets associated with operator B BS which is indeed level-1 cooperation.

2.1.3 Inter-Operator Negotiator(ION)

In MOSSSAIC Levels of cooperation other than level-0 are facilitated by a ION node which can help the eNodeBs of the different operators exchange different kinds of information including LLR information (in level-1). Finally whether to cooperate or not solely lies with the particular operator. An ION node typically interacts with all the twelve eNodeBs (three of each operator) of a cell. It acts like a medium of communication between the operator enodeBs.

2.2 Frequency Re-use Techniques

As FR1 and FR3 are well known frequency Re-use techniques we start our discussion with Fractional Frequency Re-use (FFR)

2.2.1 FFR

Fractional frequency reuse (FFR)[1] is an interference management technique well-suited to OFDMA based cellular networks wherein the cells are partitioned into spatial regions with different frequency reuse factors. FFR is a combination of both FR1 and FR3. The users are clasiffied into two groups: cell center-users and cell-edge users. The cell-center users are those whose SINR values are high because of less interference or being close to the BS and are allocated a common sub-band of frequencies in all cells i.e., FR1. The cell-edge users are those having low SINR values because of high interference seen by them or being away from the BS and are served through FR3 Re-use technique. Here all the frequency bands are shared among operators.

2.2.2 Advanced FFR

Advanced fractional frequency reuse (AFFR) is proposed for MOSSSAIC, which is the modified version of the traditional FFR. Explicitly, AFFR in the OFDMA context is a combination of shared frequency resources and unshared frequency resources. Shared frequency resources are the bands that are shared among all operators. The interference in these bands will also be significant as in each cell all the operators share the same bands. On the other hand, the unshared frequency bands are exclusively allocated to one operator, and therefore reduces interference from other operators.

AFFR divides the total frequency, F, into two parts: shared frequency resources, F_s, and unshared frequency resources, F_u. Shard frequency bands are again divided into FR1 and FR3 resources. The unshared frequency bands is used to serve the users whose SINR is very low and those users are named as near outage or worst users. Thus, depending on the SINR values of users, they are classified into three groups, namely cell-center users, cell-edge users and the worst users. The cell-center users are the one whose SINR are high in F_s due to less interference from the other cells or being close to their serving eNodeB. Cell-edge users have low SINR in F_s either due to interference from the other cells or because they are far from their serving eNodeB. Worst users will have much lower SINR values F_s and they are served in F_u.

AFFR provides an attractive trade-off by exploiting the advantages of FR1-aided shared spectrum, FR3-aided shared spectrum and FR3-unshared spectrum, by relying on FR1-aided shared spectrum Fs for the cell-center users, FR3-aided Fs for the cell-edge users, and FR3-unshared spectrum F_u for the worst users as shown in Fig. 2.4. Note that the goal of FR1-aided shared spectrum, FR3-aided shared spectrum and FR3-unshared spectrum are to enhance both area-spectral efficiency and coverage probability.

As we are interested in the sectored antennas, two different frequency

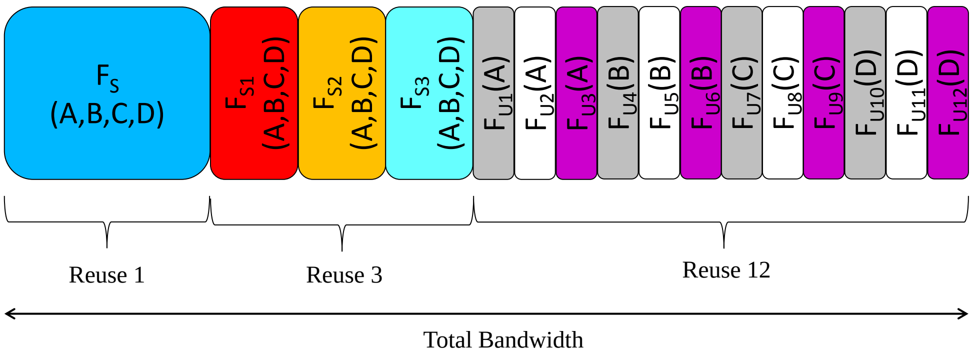


Fig. 2.4 Frequency plan(AFFR) for MOSSSAIC system(not to scale)

plans are possible as shown in Fig. 2.5. In Plan 1, FR3 is done across cells and all the sectors in a cell use same frequencies i.e, in this plan a UE in FR3 sees only interferers from second tier cells only. In Plan 2, FR3 is done across sectors i.e, different sectors in a cell have different bands. But note that in this plan there will an interfering sector in each cell of the entire network. For ease of implementation, we went for frequency Plan 2 in this work.

2.3 System Setup

A macrocell network relying on hexagonal tessellation and on an inter cell site distance of 1000m (R=500m) is realized using BWSim. From the cell centers with in a circle of raius R' four operators Base Stations (BS) are

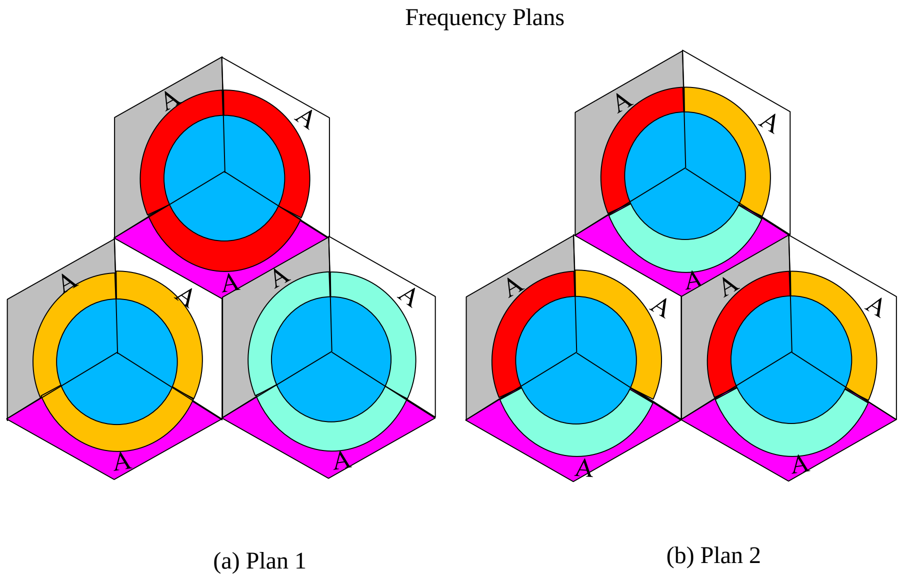


Fig. 2.5 Frequency plan across cells

randomly dropped. All the BSs are sectored into 3 each having a parabolic antenna type with a gain of 17dB, horizontal and vertical beam width being 70 and 15 respectively, Vertical Antenna tilt is varied. From each BS with in a circle of Radius R (500m) 100 UEs are dropped for an Operator. As the frequency of operation is 500MHz, Hata channel is used. All the enodeBs are at 46dBm transmit power and a noise of -90dBm power is taken. BWSim gives the path loss file which has Propagation loss from each enodeB to each and every UE in the entire network which is used to get to Rate results.

Rate calculations are done on center cell UEs only and can be approximated to any other cell with out any loss of generality. In level-0 each UE is connected to the strongest BS in terms of Received power of its own operator and in level-1, to the strongest of any operator. First assuming UE is in

FR1 SINR is calculated for each UE, where the interference comes from all the cells of the network. Now, ordering the UEs in the descending order of their SINR values, top 45 UEs are reserved for FR1, next 35 to FR3 where interference comes from only single sector of each cell of all the operators (Frequency Plan 2) and the bottom 20 UEs are given orthogonal spectrum i.e., interference comes from only one sector of each cell and that too from its own operator only. Rate of all the 100 UEs are calculated in each user drop and 10 such user droppings are done and Rate is averaged over all the 10 drops. Thus Average UE rate in AFFR network is calculated. Since there is no point of Orthogonal spectrum in single operator case, Spectral Utilization of MOSSSAIC in AFFR is compared with FFR in single operator system where half the UEs are in FR1 and the other half in FR3.

2.4 Impact of Cooperation Level on SINR

In level-0 a UE can attach only to the strongest of its own opearator while in level-1, UE can attach to the strongest enodeB of any operator. As in both the levels UE sees interference from all the cells of all the operators, intuitively SINR of each UE in level-1 will always be greater than or equal to that of in level-0 cooperation.

Now, we present the pre and post processing SINR cumulative distribution functions (CDF) of both single operator and multi-operator system. Here, the CDF $F(x)$ indicates the probability of number of users with SINR value less than x. The pre-processing SINR CDF and the post-processing SINR CDF are plotted. Both FFR and AFFR scenarios and also both Level-0 and Level-1, have been considered. In order to calculate the post-processing

SINR of the multi-operator system, it is assumed that the top 5 dominant interferers can be completely canceled by the receiver

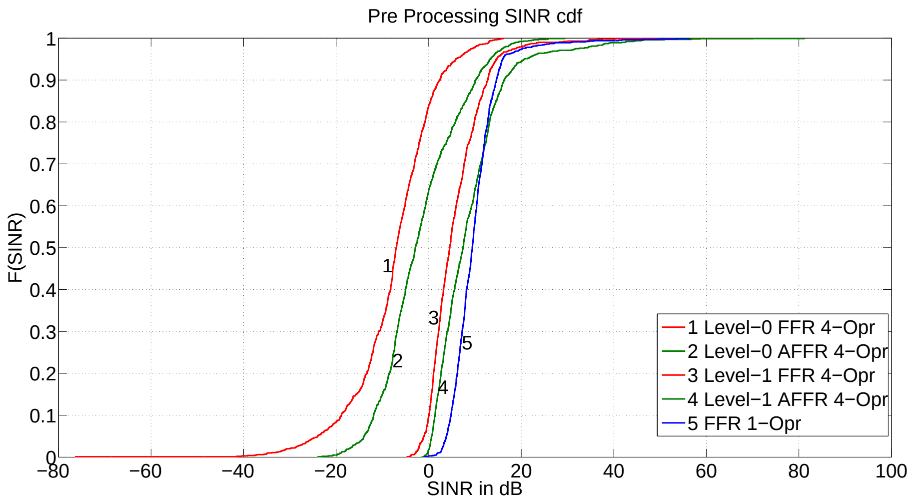


Fig. 2.6 Pre Processing SINR CDF for R'=350m

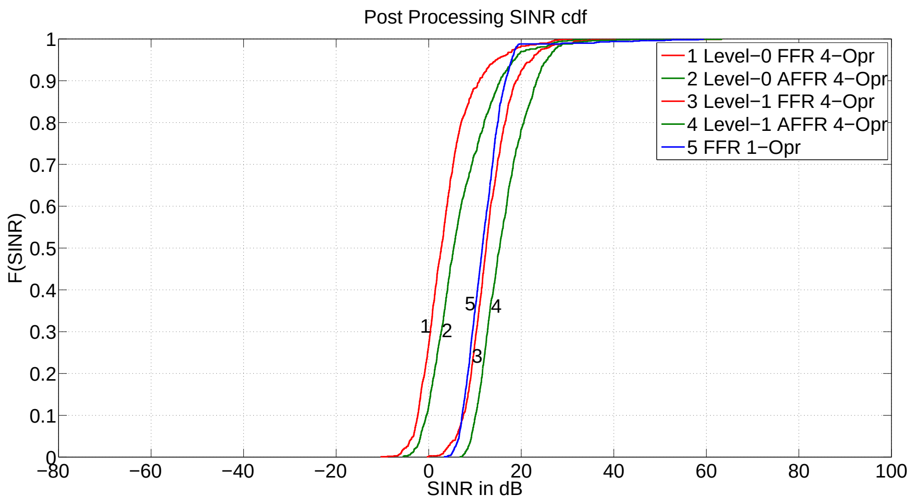


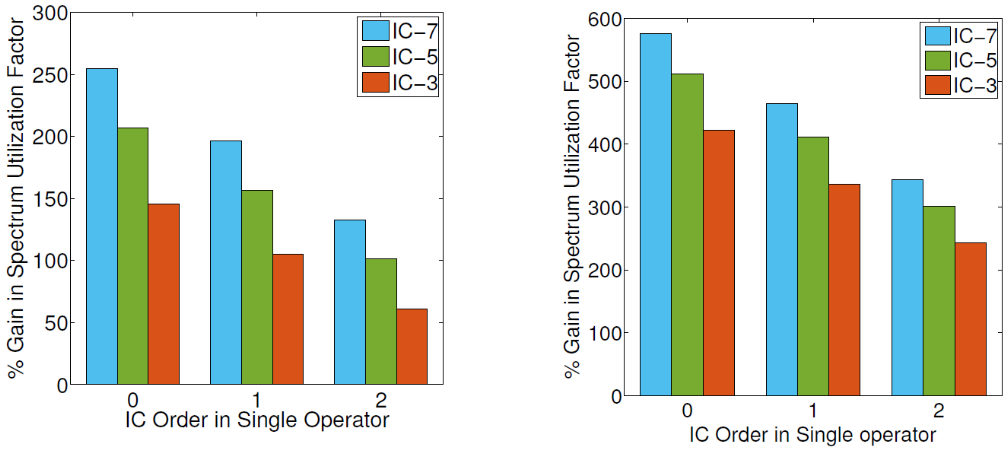
Fig. 2.7 Post Processing SINR CDF for R'=350m

Firstly, it can be observed from pre processing SINR cdf that AFFR and Level-1 systems provide better SINR compared to the FFR and Level-0 systems, respectively. Secondly, it can also be observed that the pre-processing

SINR CDF of Level-0 FFR system, Level-1 AFFR system, and Level-1 FFR system are to the left of FFR system with single operator. This is to be expected, since in multi-operator scenario, user experiences severe interference from the same cell, i,e., very strong interference. However, there is a crossover for the cases of Level-1 AFFR system and the FFR system with single operator. In particular, Level-1 AFFR system provides better SINR at 90 percentile point, and it is due to mainly AFFR. Interestingly, in the post-processing SINR CDF of both Level-1 FFR system and Level-1 AFFR system provides significantly high SINR compared to the FFR system with single operator. The reason for the significant gain is that we cancel the very strong interferers. This result also indicates the fact that with AFFR and Level 1 cooperation, not only will the DL sum rate be much higher, but even the coverage probability will be significantly higher for MOSSSAIC, when compared to the single operator network.

In the following figure the percentage gain with Level-0 and Level-1 cooperation on the spectral utilisation factor (SUF) is compared between the single-operator system FFR and 4-operator MOSSSAIC system AFFR. The SUF is measured by computing the sum-rate (for the same number of UEs per eNodeB in both single operator and in the MOSSSAIC systems).

The X-axis is the interference cancellation (IC) order in a single operator system. While the conventional single antenna UE with linear receiver cannot cancel any interference, here we consider the case where even the single-operator system gets upgraded to support a JD receiver which can detect and cancel 0, 1 or 2 interferers. When comparing MOSSSAIC employing 7 IC with this System for level-0 cooperation, we see only a modest gain (between 140% and 250%) in SUF, while the same system for level-1 cooperation gives



(a) Level 0 cooperation

(b) Level 1 cooperation

Fig. 2.8 % Gain in Spectral Utilization Factor

a huge gain (between 420% and 575%) in SUF.

2.5 Impact of Vertical Antenna Tilt on Rate

The vertical tilt of antennas plays a major role in the sum-rate. If the tilt is high, UE near to BS only get good SINR values while the cell-edge users do not get sufficient SINR i.e., coverge gets less. If the tilt is very low, the main beam has significant strength even in the neighboring cells and hence interference from neighboring cells increases which reduces the sum-rate.

In the MOSSSAIC system, with base station drop radius R'=200m is realized for various vertical antenna tilts. As we have seen already that level-1 cooperation gives best SINR values for all the UEs, we now compare SUF for different antenna tilts, canceling 5 dominant interferers.

From the table 2.1, it can be observed that as the vertical antenna tilt increases, SUF first increases till 12° and then starts decreasing. This is due

Vertical Antenna Tilt in degrees	SUF bits/sec/Hz
2.5	7.1644
5	7.9432
7.5	8.7128
10	9.3584
12	10.0008
15	9.9296
17.5	9.5936
20	8.6424

Table 2.1 SUF for different Antenna Tilts

to the fact that as the tilt is increasing the coverage of the cell is increasing till 12° and as tilt further increasing inter cell interference is dominating which reducing the SUF and also post processing SINR CDF cancelling 5 interferers in level-1 is plotted.

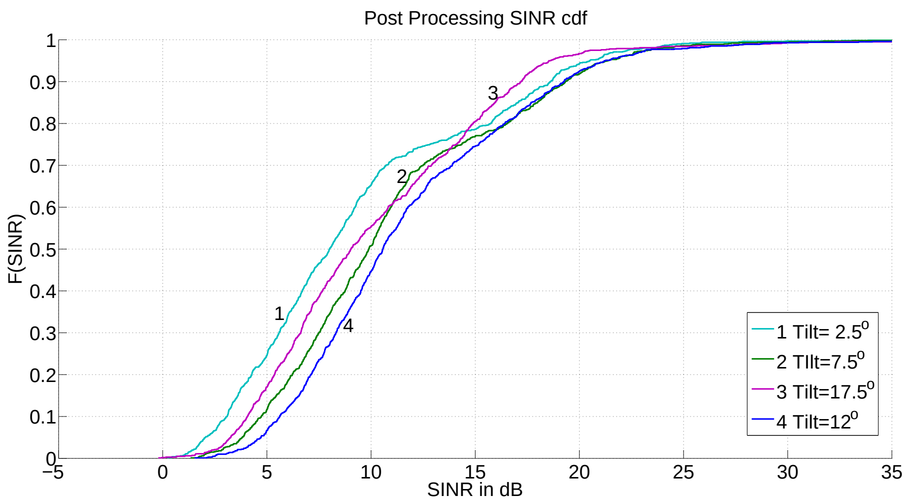


Fig. 2.9 Post Processing SINR CDF for different Antenna Tilts

For ease of understanding CDFs for only 4 antenna tilts are drawn. From the CDFs it can be observed that vertical Antenna Tilt of 12° gives the best performance compared to the other tilts and also we have seen the SUF value for antenna tilt of 12° is higher than the other. Thus Antenna tilt of 12° is chosen to be optimal for MOSSSAIC system.

2.6 Impact of BS drop Radius on Rate

As the tilt of the antenna is fixed to be 12°, Now we see the impact of radius R' in which all the four operators BSs are being dropped on the SUF.

Keeping the antenna tilt at 12°, MOSSSAIC system is being realized in BWSim for different R' values. In each of the realization, SUF of MOSSSAIC system with 5 dominant IC is calculated over single opearator system where only 1 top interferer being canceled.

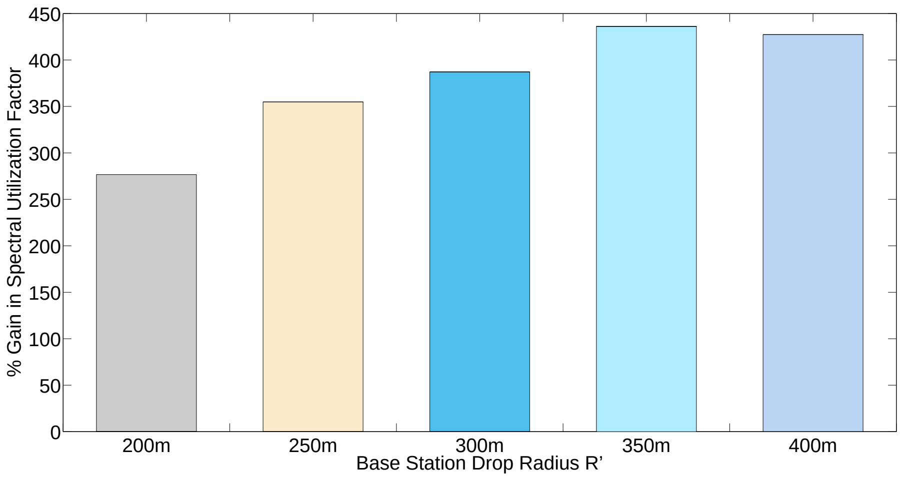


Fig. 2.10 %Gain in SUF for different R' values

From the figure 2.10, it is evident that as R' increases from 200 to 400m, %Gain in SUF of MOSSSAIC system over single operator system increased till 350m and started decreasing. It may be due to fact that as R' increases, the Base Stations are widely spread over the cell, covering entire cell so that all the UEs gets served better. But as R' keeps on increasing the cell-edge users start seeing more number of BSs dominantly and thereby increasing the interference which reduces the SUF.

Post processing SINR (considering 5 dominant interferers are being cancelled) is drawn for different base station drop radii R' in level-1 cooperation. From the CDF plots it is evident that as R' increases from 200m to 400m cdf is shifting right which means more number of users are seeing better SINR values. It can be observed that the plots 4 and 5 are very close to each other and very low and high SINR values 4 is slightly dominating 5 (The crossover can be observed from inner figure). And from SUF point of view we observed that $R' = 350$m gives the better performance than R' =400m and So, R' of 350m is chosen to be optimal for MOSSSAIC system.

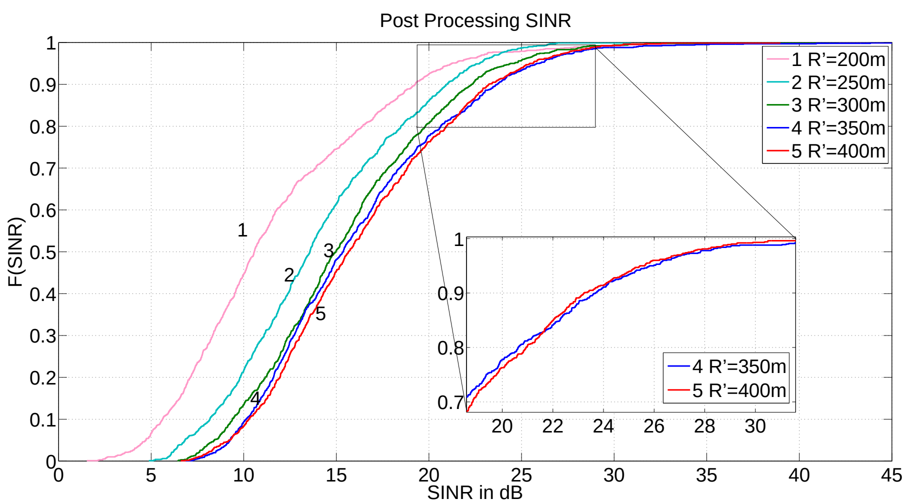


Fig. 2.11 Post processing SINR CDF for different R' values

2.7 Summary

By using non-orthogonal spectrum sharing techniques cost of the spectrum can be shared among operators and operation costs also can be greatly reduced. MOSSSAIC proposes a very simple yet powerful SISO-TDD based approach to simultaneous spectrum sharing, which not only provides this tremendous cost benefit, but also promises to deliver to each operator the same if not better sum-rate when compared to a (unshared) single operator deployment. These significant gains in simulation results can be attributed to a combination of interference cancellation (which becomes easier due to the frame structure of MOSSSAIC system and a JD receiver), level-1 cooperation and AFFR schemes.

From the above results and conclusions drawn, all the system parameters which seem ideal for MOSSSAIC are tabulated as follows:

Parameter	**value**
BS drop Radius R'	350m
Frequency	500MHz
Channel Model	Hata Model
Vertical tilt of Antenna	12°
Transmitter power	46dBm
Antenna Gain	17dBi
Noise Power	-90dBm

Table 2.2 System Parameters for MOSSSAIC

CHAPTER 3

VECTOR QUANTIZATION FOR COARSE RATE ADAPTATION

3.1 Motivation

The performance of cellular systems can be improved by adapting to the current channel conditions, referred to as link adaptation. Link adaptation allows a communication system to adapt its transmission modes according to channel conditions. Mutual Informatin(MI) based effective SINR metric (ESM) method is a widely used method for link abstraction and has been shown to provide good BLER prediction accuracy[2] [3]. Although a JD receiver provides optimal performance, getting to its MI is very complex. To reduce the computation complexity, we adopt the approach presented in [4] [5] where the MI for a JD receiver is computed based on the fact that it can be upper bounded by perfect interference cancellation receiver and lower bounded by Linear Minimum Mean Square Error(LMMSE) receiver and stored as the lookup table for each possible modulation schemes. But it took only one interferer into consideration. In order to proceed with the similar process in a more general way, we should have each and every possible interference profile for the system and have the corresponding MCS in a lookup table. As it is practically impossible to get every possible interference profile and to have a huge lookup table, by using vector quantization we can come up with a few clusters of vectors associated with a closest vector (interference profile) each. Thus the complexity and memory required for lookup table can be reduced drastically. Thus the idea of vector quantization is used in rate adaptation for nonlinear receivers

3.2 Introduction

Vector quantization (VQ) [6] is a generalization of scalar quantization to the quantization of a vector. A vector can be used to describe almost any type of pattern, such as a segment of a speech waveform or of an image, simply by forming a vector of samples from the waveform or image.

A vector quantizer Q of dimension k and size N is a mapping from a vector (or a "point") in k-dimensional Euclidean space, R^k, into a finite set C containing N output or reproduction points, called code vectors or codewords. Thus,

$$Q : R^k \longrightarrow C \tag{3.1}$$

Where, $C = \{Y_l, Y_2, \cdots, Y_N\}$ and $Y_i \in R^k$ for each $i \in J \equiv \{1, 2, \cdots, N\}$. The set C is called the code book or the code and has size N, meaning it has N distinct elements, each a vector in R^k

A vector quantizer can be decomposed into two component operations, the vector encoder and the vector decoder. The encoder is the mapping from R^k to the index set J, and the decoder D maps the index set J into the reproduction set C. Thus,

$$E : R^k \longrightarrow J \text{ and } D : J \longrightarrow R^k \tag{3.2}$$

It is important to note that a given partition of the space into cells fully

determines how the encoder will assign an index to a given input vector. On the other hand, a given codebook fully determines how the decoder will generate a decoded output vector from a given index.
The overall operation of VQ can be regarded as the cascade or composition of two operations:

$$Q(x) = D \cdot E(x) = D(E(x)) \tag{3.3}$$

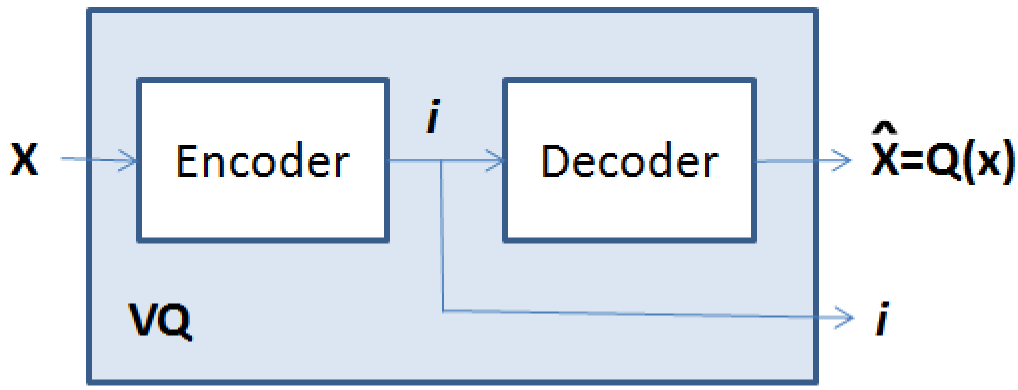


Fig. 3.1 VQ as Encoder and Decoder

3.2.1 Measuring VQ performance

The principal goal in design of vector quantizers is to find a codebook, specifying the decoder, and a partition or encoding rule, specifying the encoder that will maximize an overall measure of performance which can be assessed by either a statistical average of a suitable distortion measure or a worst case value of distortion.

A distortion measure 'd' is an assignment of a nonnegative cost $d(x, \hat{x})$ associated with quantizing any input vector x with a reproduction vector $\hat{x}$ Given such a measure we can quantify the performance of a system by an average distortion $D = E[d(X_i, \hat{X}_i)]$between the input and the final reproduction. Generally, the performance of a compression system will be good if the average distortion is small.Occasionally, it is preferable to use a worst-case distortion as a measure of performance rather than an average value. With respect to an arbitrary measure $d(x, y)$ of distortion, this is simply defined as the maximum attainable distortion for a given quantizer $D_{max} = \max_{x \in B} d(x, Q(x))$

The most convenient and widely used measure of distortion between an input vector X and a quantized vector X = Q(X), is the squared error or squared Euclidean distance between two vectors defined as.

$$\begin{aligned} d(X, \hat{X}) &= \parallel X - \hat{X} \parallel^2 \\ &\equiv (X - \hat{X})^*(X - \hat{X}) \\ &\equiv \sum_{i=1}^{k} |X_i, -\hat{X}_i|^2 \end{aligned} \tag{3.4}$$

The average squared error distortion or, more briefly, the average distortion is defined as

$$\begin{aligned} D &= Ed(X, \hat{X}) \\ &= E[\parallel X - \hat{X} \parallel^2] \end{aligned} \tag{3.5}$$

3.2.2 Encoder and Decoder

Encoder is completely specified by the partition of R^kinto the cells $R_1, R_2 \cdot \cdot \cdot R_N$. For a given codebook the optimal partition is one satisfying the

Nearest Neighbor (NN) condition. We define a Voronoi or nearest neighbor (NN) vector quantizer as one whose partition cells are given by,

$$R_i = \{x : d(x, y_i) \leq d(x, y_j);\ \text{for all } j\} \tag{3.6}$$

That is,

$$Q(x) = y_i \text{ only if } d(x, y_i) \leq d(x, y_j);\ \text{for all } j \tag{3.7}$$

In other words, with a nearest neighbor (NN) encoder, each cell Ri consists of all points x which have less distortion when reproduced with code vector Yi than with any other code vector.

Decoder is completely specified by the codebook, $C = \{y_1, y_2, \cdots, y_N\}$. For a given partition optimality of codebook follows centroid condition. Centroid $cent(R)$ of any set $R \in R^k$ as that vector which minimizes the distortion between a point X and y averaged over probability distribution of X given X lies in R

$$Cent(R) =_y^{argmin} E[d(X, y)|X \in R] \tag{3.8}$$

Thus the centroid is in some sense a natural representative or "central" vector for the set R and the associated probability distribution on R.For the squared error distortion measure, the centroid of a set R is simply the minimum mean squared estimate of X given that $X \in R$,

$$cent(R) = E(X|X \in R) \tag{3.9}$$

For a finite set $R \in R^k$, centroid can be found knowing the pmf for input distribution. If each point in R is equiprobable i.e., follows uniform distribution then, centroid reduces to arithmetic average

$$cent(R) = \frac{1}{\parallel R \parallel} \sum_{i=1}^{\|R\|} x_i \tag{3.10}$$

Where,$\parallel R \parallel$ is the cardinality of set R

3.2.3 Optimality conditions

Necessary conditions for a VQ to be optimal are

- Centroid condition
- Zero probability boundary condition

ZPBC is to require that the collection of points equidistant from at least two code vectors has zero probability, which means boundary points should occur with zero probability,

$$P(\bigcup_{j=1}^{N} B_j) = 0 \tag{3.11}$$

Where B_j has the boundary points of R_j

The quantizer is locally optimal if every small perturbation of the code vectors does not lead to a decrease in D. It is globally optimal if there exists no other codebook that gives a lower value of D.If we have a codebook that satisfies both necessary conditions of optimality, it is widely believed that it is indeed locally optimal since in the discrete input case, a slight perturbation of a code vector will not alter the partitioning of the (countable) set of input vectors as long as none of the input values lies on a partition boundary.

3.3 VQ Techniques

The necessary conditions for optimality provide the basis for iteratively improving a given vector quantizer. The iteration begins with a vector quantizer consisting of its codebook (initial codebook) and the corresponding optimal (NN) partition and then finds the new codebook which is optimal for that partition. This new codebook and its NN partition are then a new vector quantizer with average distortion no greater (and usually less) than the original quantizer.

3.3.1 Initial Codebook Design

Random Coding

It is the simplest approach toward filling a codebook of N code words by randomly selecting the code words according to source distribution or from a training set. Random coding means only that the codebook is selected at random, once selected it is used in a usual deterministic fashion.

Pruning

Pruning refers to the idea of starting with the training set and selectively eliminating (pruning) training vectors as candidate code vectors until a final set of training vectors remains as the codebook. A sequence of training vectors is used to populate a codebook recursively as follows:

- Put the first training vector in the codebook.
- With each new training vector find the nearest neighbor. If the resulting distortion is greater than threshold, add the new vector to the codebook

else continue to next training vector.

For a given set of training vectors, it is possible that the resultant code book may have fewer than the desired number of code words, if this happens the threshold value must be reduced and the process should be repeated.

Pairwise Nearest Neighbor Design

This is also a form of pruning as it begins with the entire training sequence of L vectors, and ends with a collection of N vectors. Unlike the previous design technique, however, the final vectors need not be in the training sequence. Suppose training set has L vectors, the partition is obtained as follows:

- First compute distortion between all pair of vectors
- The two training vectors having smallest distortion are combined into a single cluster and represented by their centroid. Now the training set is reduced to L-1 vectors, one is the centroid of two training vectors and remaining are original training vectors.
- Repeat the procedure until we end up with N centroids which form the codebook

Product codes

Initial codebook is obtained by Cartesian product of scalar quantizers. If $q(x)$ is scalar quantizer then

$$Q(x_0, \cdots, x_(k-1)) = (q(x_0), \cdots, q(x_{k-1})) \tag{3.12}$$

Or else one can build a two dimensional quantizer from one dimensional quantizer and so on recursively to k dimensional quantizer.

Splitting

This technique resembles the product code initialization in that it grows large codebooks from small ones. Codebook is obtained as follows:

- The globally optimal resolution 0 codebook of a training sequence which is the centroid of the entire sequence is calculated.
- The one code word, say Y_0, in this codebook can be "split" into two code words, Y_0 and $Y_0 + \epsilon$, where ϵ is a vector of small Euclidean norm. The iterative improvement algorithm can be run on this codebook to produce a good resolution 1 code.
- When complete, all of the code words in the new codebook can be split, forming an initial guess for a resolution 2 codebook.

One choice of ϵ is to make it proportional to the vector whose i^{th} component is the standard deviation of the i^{th} component of the set of training vectors. Another choice is to make it proportional to the Eigen vector corresponding to the largest Eigen value of the covariance matrix of training set.

3.3.2 The Generalized Lloyd Algorithm

It is an iterative codebook improvement algorithm based on the necessary conditions of optimality. GL is a descent algorithm, meaning that each iteration always reduces (or at least never increases) the average distortion. Any of the codebooks can be taken as the initial codebook for GLA. The Algorithm goes as follows:

- Begin with initial codebook, C_1. Set $m = 1$
- Given the codebook C_m, perform the Lloyd iteration to generate the improved codebook C_{m+1}
- Compute the average distortion for codebook C_{m+1}. If it has changed only by a small amount since the last iteration, stop. Otherwise $(m + 1) \longrightarrow m$ and go to step 2

Where the Lloyd iteration is done as:

- Given a codebook $C_m = \{y_i; i = 1, 2, , N\}$, find the optimal partition into quantization cells, that is use Nearest Neighbor condition to form the nearest neighbor cells:

  $$R_i = \{x : d(x, y_i) < d(x, y_j);\ \text{all } j \neq i\} \tag{3.13}$$

  If x yields a tie for distortion for one or more $j \neq i$, then assign x to R_j for which j is smallest.
- Using the centroid condition find $C_{m+1} = cent(R_i); i = 1, 2, , N,$ the optimal reproduction codebook for the cells just found.

Before terminating the algorithm, zero probability bound condition has to be checked. If this is not satisfied and the algorithm terminates then the resultant codebook can in principal be improved by re-assigning such a training vector to a different cell (i.e., one not consistent with tie breaking rule) and then perform an additional Lloyd iteration.

Furthermore each Lloyd iteration generally corresponds to a local change in codebook, that is, new codebook is not drastically different from the old codebook. This suggests that once initial codebook is chosen, algorithm will lead to nearest local optimal solution.

Stochastic relaxation

By introducing randomness into each iteration of the GL algorithm it becomes possible to evade local minima, reduce or eliminate the dependence of the solution on the initial codebook, and locate a solution that may actually be a global minimum of the average distortion as a function of the codebook.

Stochastic relaxation (SR) is characterized by the common feature that each iteration of a search for the minimizing average distortion consists of perturbing the state, the set of independent variables of the cost function (e.g., the codebook) in a random fashion. The magnitude of the perturbations generally decreases with time, so that convergence is achieved.A key feature of SR algorithm is that increase in the value of the cost function is also possible in iterations.

Important family of SR algorithms known as Simulated Annealing (SA) where noise is added to the training set prior to Lloyd iteration and the variance of noise is gradually reduced to zero.

3.4 Simulation Results

3.4.1 Setup

System level simulator (BWSim) is used to realize two tier hexagonal cell structure of ISD 1000m. From the cell centers with in a radius of 350m Base stations of four operators are dropped at random in each cell which share the same spectrum and 100 UEs are dropped in each cell for an operator. Each Base station is sectored into 3 and thus has 3 EnodeBs. In the downlink scenario, each UE sees interference from all the EnodeBs of all the operators (since all the operators share the spectrum). 10 such droppings were done and interference profiles of each UE in the center cell is collected and given to Vector Quantizer to get most prominent interference profiles. Interference profile is a vector where each dimension gives information about, how much interferer is stronger than noise power in dB.

3.4.2 Algorithm

Algorithm used for Vector Quantizer is as follows:

1. Fix number of clusters needed N.
2. Get the initial codebook using of the techniques mentioned of size N.
3. Perform GLA on the codebook. If the change in average distortion over iterations is less than a threshold δ STOP and get optimal codebook of size N.
4. Calculate the MSE of all the vectors from the cluster centers. If the MSE is higher than threshold ε, increase N by 1 i,e., N$\longrightarrow$N+1 and go to step 2 or else STOP

3.4.3 Parameters

Initial Codebook	Random Coding
Initial Codebook Size N	20
Threshold δ	10^{-10}
MSE threshold ε	7

Table 3.1 Simulation parameters for VQ

3.4.4 Results

Training set of 1000 interference profiles from MOSSSAIC system were given to Vector Quantizer. For visualization purposes only two dimensions of interference profiles were considered.

In the figure 3.2 we can observe that all the points are around y=x line. It is because top two interferers are considered and since interference profile is relative to noise power, both the coordinates are almost same. Hence all the points lie around y=x line. we started with 20 centroids and ended up by 24 satisfying MSE criteria.

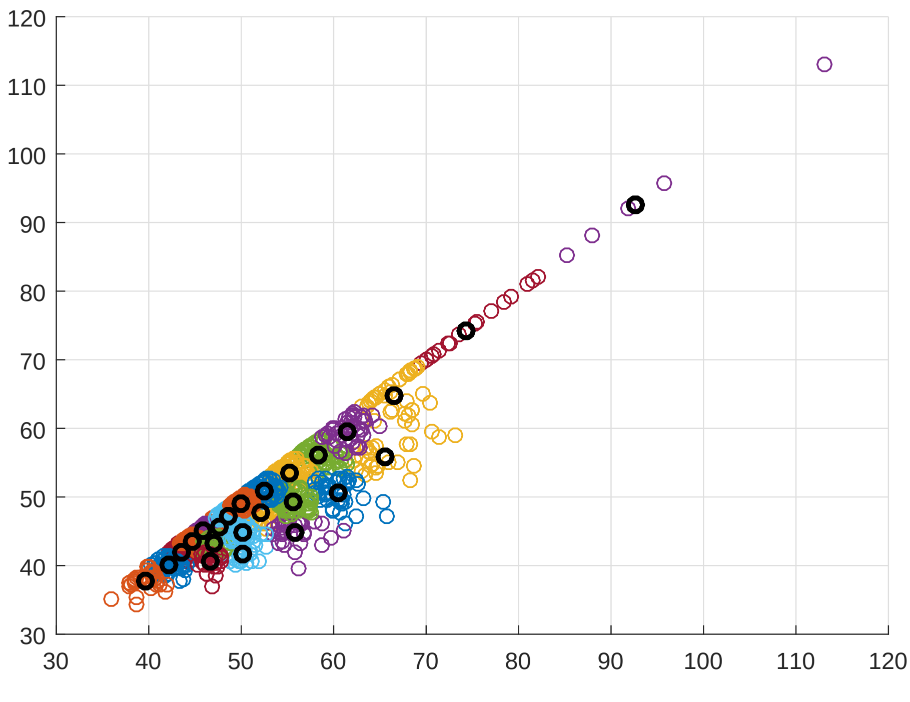


Fig. 3.2 VQ of top two interferers

If we can think of top 9 interferers which are very close and can be grouped into a vector and considering top and 10^{th} interferer which are sufficiently apart, then we can see points are spread enough and the clusters are also spread which is evident from fiure 3.3. In this case also we started with 20 clusters and ended up by 24 satisfying MSE criteria. The thick black circles denote the centroids of the clusters i.e, codewords.

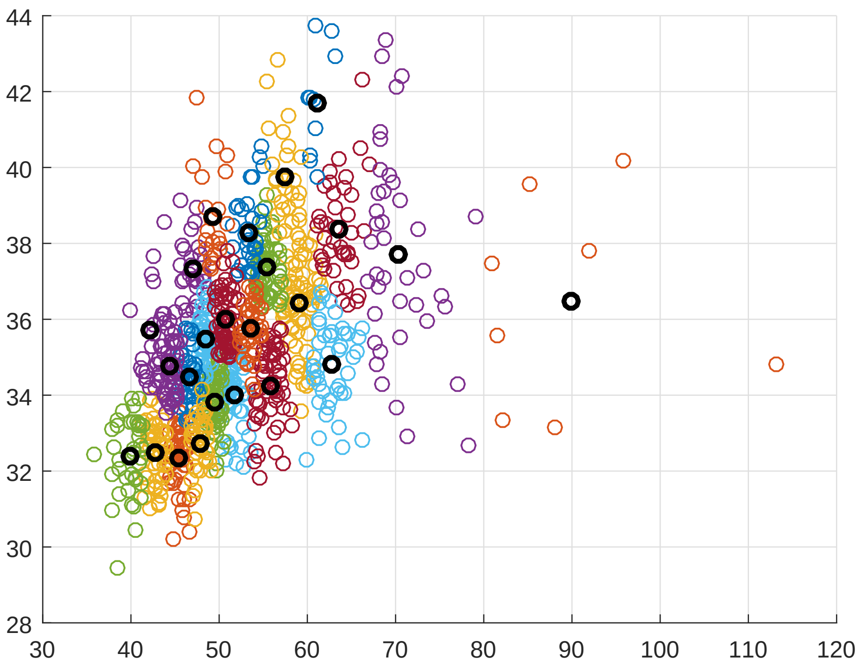


Fig. 3.3 VQ of $1^{st}, 10^{th}$ interferers

From these two figures it can be said that interference profiles in MOSS-SAIC system can be Quantized into finite codewords i.e, we can have a codebook containing interference profiles of finite size

3.5 Summary

As a UE in MOSSSAIC system will use a joint ML detector which is a Non-linear one, it is very complex to calculate the MI directly, making rate adaptation complex. One of the simplified approach needs the knowledge of every interference profile in the system. But Using Vector Quantization we showed that interference profiles in MOSSSAIC system can be quantized into a finite clusters i.e., each interference profile can be approximated to a closest codeword with minimum possible error. Thus we showed we can have only finite interference profiles in a lookup table, easing the process of rate adaptation. As quantization itself introduces error (quantization error) the rate obtained will not be exact one.

CHAPTER 4

CONCLUSION

Non-Orthogonal spectrum sharing techniques reduces the cost of spectrum and operation. MOSSSAIC is one such technique which also delivers the operators the same or better rate when compared to a single operator system. The improvement in sum-rate, SUF over single operator system can be because of the combination of interference cancellation, level-1 cooperation and AFFR and we came up with certain parameters like Antenna tilt, Base station drop radius R' that maximizes the performance of MOSSSAIC system.

Vector Quantization is a powerful tool to reduce the complexity by working only on quantized vectors rather than all the possible vectors. For example, in digital communication instead of transmitting the whole vector, encoder needs to send only the index of quantized vector where the decoder will have a look up table to reproduce the same, but it certainly introduces some quantization error. Using this VQ it is showed that the interference profiles in MOSSSAIC system can be quantized to a finite set of clusters thus reducing the complexity in rate adaptation in Non-linear receivers. Only the quantization of interference profile was presented, while the rate adaptation using those quantized interference profiles is yet to be done.

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