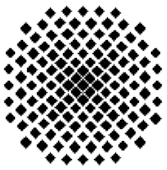
Designing a Frequency Selective Scheduler for WiMAX using Genetic Algorithms



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1 Introduction

1.1 Motivation

The massive usage of mobile communications, by 2006 41%[1] of the world population has a cell phone [1] and the increasing of internet usage (17% of penetration), as can be seen in figure 1.1. And more important, in less than a decade, broadband subscription worldwide has grown from virtually zero to over 200 million[1]. That allows technologies that gives users broadband connectivity at the same time are coming up to fill both issues up. The second generation of

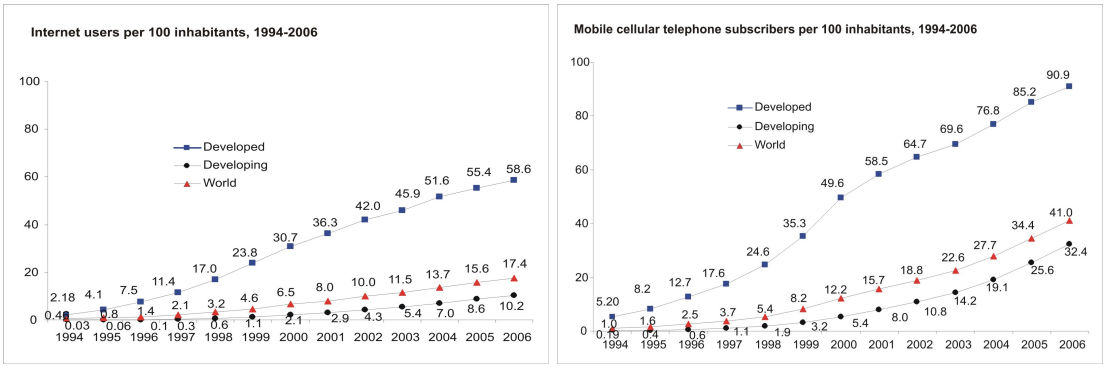

Figure 1.1: World internet and cell phone usage statistics, extracted from [1]

mobile communications was *global system for mobile communications* (GSM). This technology was used during the huge increase of cell phone subscribers, but it doesn't allow internet connection and data transference. Following evolutions in the mobile communications technologies tends to allow data transference, release 97 of the GSM standard added packet data capabilities with General Packet Radio Service. Later, with the release 99, higher speed data transmission by means of *enhanced data rates for GSM evolution* (EDGE).
Then, *universal mobile telecommunications system* UMTS, one of the third generation cell phone technologies, improved the downlink and uplink ratios of the communication, firstly with the *high speed downlink packet access* (HSDPA) protocol and later with the *high speed up-link packet access* (HSUPA).
The performance of these technologies are improved by WiMAX, IEEE 802.16 Standards, in some parameters. This technology multiplex users by splitting the band spectrum into subcarriers at different frequencies.
The aim of these project is to design a scheduler for WiMAX technology that optimizes the transference of data that users generate to one base station, taking into account that each subcarrier has a different channel condition.

1.2 Wireless communications environment

As is told in the previous section, in this project a design of a radiocommunications scheduler is done. The design is done into a radiocommunications environment.

[1]By November of 2007 is said that half of the world population is a cell phone subscriber[2]

A radiocommunications environment is characterized by a base station and multiple mobile stations in a cell.

- The cell is the portion of space that is served by one base station.
- The base station sends and receive data from all the mobile stations in a cell
- The mobile station is each one of the user equipments that sends its requests and receive the answers

1.2.1 Multipath propagation

Inside the cell, there can be obstacles. These obstacles makes transmissions between base and mobile stations not ideal. That's because these obstacles creates different paths between the base and one mobile station, this is the multipath propagation.
The multipath propagation means that a station will receive multiple copies of the same signal, but with differences in some parameters of the signal. These parameters are:

- Phase
- Time delay
- Power

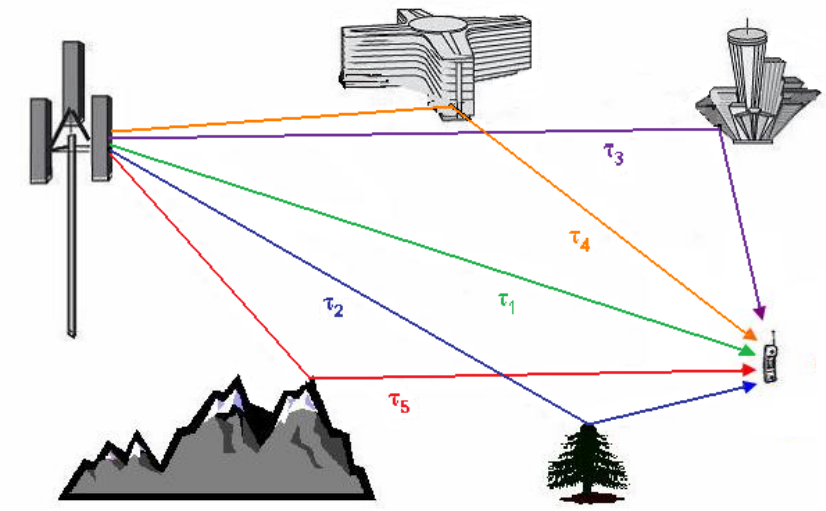

Figure 1.2: Multipath propagation, extracted from [3]

$$h(\tau, t) = \sum_{k} A_k(t)\delta(\tau - \tau_k(t)) \tag{1.1}$$

More details over multipath propagation can be consulted in [3].

1.2.2 Parameters of a wireless communications environment

The performance of the communications channel is modeled by taking into account the following parameters.

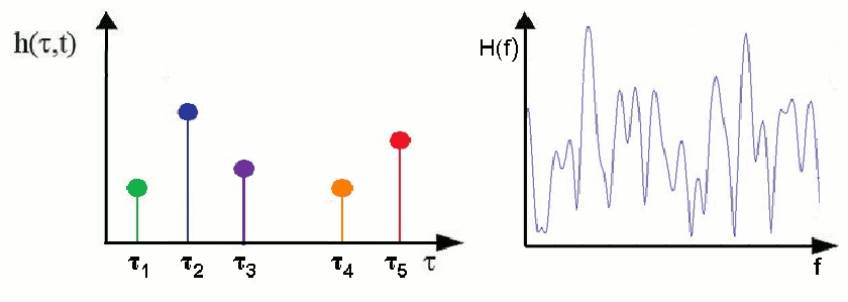

Figure 1.3: Effect of multiple signal arrivals with various delays

Delay spread

A mobile station receives various copies of the signal with different delays, see figure 1.2. The maximum time interval while the station receives signal with significant energy is the *delay spread*, so the difference between the LOS signal and last component.
The delay spread depends mainly on the terrain type, the environment (urban, suburban, rural). In urban environments this value can be around 10 μs, for further information consult [4].

$$B_c = \frac{1}{2\pi D_s} \tag{1.2}$$

Directly derived from the delay spread is the coherence bandwidth. In the equation 1.2 B_c is the coherence bandwidth and D_s is the delay spread. The coherence bandwidth is the band over which the channel transfer function remains virtually constant. So the criterion is satisfied if the transmission bandwidth does not exceed the coherence bandwidth of the channel. Therefore, if the transmission bandwidth doesn't exceed the coherence bandwidth of the channel, the transmission doesn't suffer distorsion.

Fading

In both directions, from base station to mobile station and vice-versa, as can be seen in figure 1.3, signal is received with variations of the presented before parameters. And this creates fading[2]. We have two types of fading; fast fading and slow fading.

- Slow fading is caused when shadowing occurs. The duration of the fading depends on the time that the mobile needs to be ahead of the shadow created by the obstacle. This variation follows a lognormal probability density function.

- Fast fading is caused directly by the multipath effect. Receiving the signals with delays that are fractions of λ, makes drastic change in the sum of the different signals, we can have constructive or destructive sums.
  In fact, there are two types of fast fading; it depends on how far is the echo created. If it's a nearly created echo, the delay between two signals is small related to the time of the symbol, there's a constructive or destructive sum, but there's not dispersion[3]. On the other hand, when the echo is further created, the delay between two signals is big related to the time of the symbol, there's dispersion.

[2]Fading refers to the distortion that a carrier-modulated telecommunication signal experiences over certain propagation media

[3]Is said that a channel is dispersive, when the module of transfer function is not constant and the phase is not linear

Path loss

The reduction in power density of an electormagnetic wave as it propagates is called path loss (or attenuation).
Path loss is produced by many effects like free-space loss, refraction, diffraction, reflection, difference between theoretical and practical antenna gain and absorption. Therefore, it's influenced by distance from the transmitter to the receiver, location of the antennas, terrain type, environment and weather.

$$L = 10n \log_{10}(d) \tag{1.3}$$

In the equation L is the path loss in dB, d is the distance between transmitter and receiver and n is the path loss exponent. The path loss exponent is a way to represent the path loss.
The value of the path loss exponent is from 2 to 4 outdoors. 2 is the value when propagation occurs in free space and 4 when it occurs in an environment with huge density of obstacles (urban). Indoors, the exponent varies from 4 to 6. But the calculation of the delay spread is, in fact, a prediction. An exact prediction is not allways possible, only for the simplest like free space propagation. For other cases empirical methods are used, these are based on averaged losses along typical radio links. Most commonly used methods are Okumura-Hata or COST-231 (Okumura-Hata extension). Hata model has three varieties of equation for urban, suburban and rural environments, and to calculate the path loss takes into account: distance, heights of the antennas and frequency of the transmission.

Part I

Background information

2 WiMAX (IEEE 802.16)

The technology which this thesis is based on is WiMAX, this chapter pretends to introduce into the key features of this technology that will be used to to face the scheduling problem.

2.1 Historic context

In this section WiMAX is located in its context into the broadband wireless communications history.

Broadband wireless

The history of broadband wireless remains in the desire of finding an alternative to wired access technologies.
Firstly, applications were oriented to cover voice telephony demand and were called *wireless local-loop* (WLL). These were successfull in countries with a developing economy, because the existing local loop infrastructure was not enable to serve the increasing demand. But in markets that had already good scaled local-loop infrastructure for voice telephony, WLL began to have sense with the start of the commercialization of Internet, in 1993.
Then with the tendency to broadband and thanks to *digital subscriber line* DSL[1] and cable,

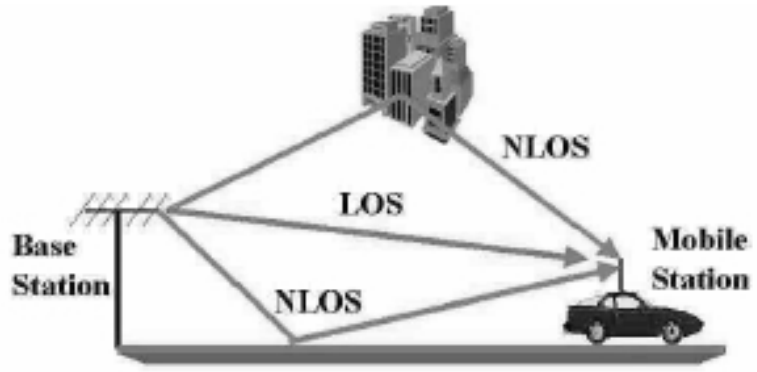

Figure 2.1: LOS and NLOS

wireless systems evolved to support higher speeds. In this way *line of sight* (LOS), see figure 2.1, systems were developed. Two type of systems were designed:

- *Local multipoint distribution systems* (LMDS) achieved high speed, working in the millimeter band (24 or 39 GHz). Its services were mainly targeted at business users and hat success in the late 1990's. But LOS requirements, involved installing antennas in rooftops, moreover the short range of the technology; stop the growth of this technology, by changing to other ones.
- *Multichannel multipoint distribution service* (MMDS), with a band between 2 and 3 GHz. This technology was mainly used to provide TV broadcasting in not cabled zones. In this

[1]DSL is a family of technologies that provide digital data transmission over the wires of a local telephone network

case the growth of satellite TV induced to a redefinition of the target, and the system was used to serve Internet access. Instead the coverage could be quite large, using tall base station antennas and high power transmitters, the capacity was too limited. This fact and the LOS requirements became on the main impediments to the higher success of this technology.

The next generation of broadband wireless systems overcome the LOS problem. This was done by tending to a cellular architecture and implementing a better signal processing techniques, these are *non line of sight* NLOS applications, more information can be found in [5]

WiMAX

With the aim of finding a interoperable solution for the emerging wireless broadband, the *Institute of Electronic and Electrical Engineers* (IEEE) created the 802.16 group. It was initially focused on developing a LOS broadband system, to operate in the 10 GHz to 66 GHz band. The standard developed, completed in December 2001, was based on a single carrier and time multiplexed (TDM)[2].
The next step was the 802.16a amendment that includes NLOS applications, working on the 2 GHz to 11 GHz band, and uses orthogonal frequency division multiplex technology (OFDM)[3] and OFDMA.
These revisions of the standard followed with the IEEE 802.16-2004 that replaced prior versions and focused on the fixed applications. One year later, the IEEE 802.16-2005 targeted on mobile applications, and called mobile WiMAX.[11]

2.2 Physical layer

The physical layer is the first of the seven layer OSI model. The physical layer provides an electrical and mechanical interface to the transmission medium.
As was said the WiMAX physical layer is based on OFDM and it's going to be presented in section 2.2.1. Further information that what are going to be presented in this section can be consulted in [5], [6], [8], [10] and [7].

2.2.1 OFDM

This technology is used in multiple types of communications. In wired communications; DSL, *power line communications* PLC[4] and in wireless communication; wireless LAN (802.11), terrestrial digital system *digital video broadcasting terrestrial* (DVB-T) or *digital video broadcasting - handheld* (DVB-H) amongst others. OFDM is a multicarrier modulation scheme utilized as a digital multicarrier modulation method. It's based on dividing a given high-rate data stream into several parallel smaller data streams or channel, and modulate each stream on separate carriers, called subcarriers.

The term orthogonal in OFDM refers to the fact that subcarriers are perfectly separable over the symbol duration. To ensure orthogonality; the frequency of the first subcarrier such that has an integer number of cycles during a symbol period has to be chosen. Also a space between subcarriers such that $B_{ISc} = \frac{B}{N_{sc}}$, where B is the total assigned bandwidth and N_{sc} is the number of subcarriers, has to be taken. This structure is quite easy to implement by directly

[2]With time multiplexing, all the users in a cell are using the same band, the resource is divide by giving each user a concrete time slot to transmit
[3]This technology uses time and frequency multiplexing at the same time. It will be deeply explain in subsection 2.2.1
[4]PLC is a system for carrying data on a conductor also used for electric power transmission

doing IFFT[5] and FFT in transmission and reception, respectively.

Multicarrier modulation minimize *intersymbol interference* (ISI)[6]. Splitting data stream into many parallel streams increases the symbol duration and makes symbol's time large enough over the delay spread of the channel. $\frac{T_s}{L} \gg \tau$, where T_s is the time of symbol, L is the number of streams and τ is the delay spread.

In order to keep each OFDM symbol independent among others over the channel, is necessary to introduce a guard time between symbols, introducing a larger guard band is possible to guarantee that there's no interference between OFDM symbols, further information can be consulted in [5] and [6].

A key feature of the OFDM is the synchronization in both dimensions:

- Timing synchronization: The margin of desychronization achievable is the difference between the delay spread and the duration of the cyclic prefix, $0 \leq \tau \leq (T_m - T_g)$. Where T_m is the maximum delay spread, T_g is the duration of the cyclic prefix and τ is the allowed error in synchronization.
- Frequency synchronization: This type of synchronization is not as relaxed as the timing, because the orthogonality of the data symbols is centered on their perceptible in the frequency domain. A small offset produces, *intercarrier interference* (ICI).

Advantages of OFDM

- Reduced computational complexity: OFDM can be implemented using *fast Fourier transform* (FFT) and *inverse Fourier transform* (IFFT).
- Slow degradation of performance under delay spread: Performance of an OFDM system degrades slowly as the delay spread grows over the maximum delay spread which was designed for optimal performance.
- Exploitation of frequency diversity: OFDM facilitates coding and interleaving subcarriers in the frequency domain, which provide robustness against burst errors, parts of the data that are transmitted into spectral bad channel conditions.
- Use as a multiaccess scheme: OFDM is also used as a multiaccess scheme, where the resource are partitioned among other users. This is called *Orthogonal frequency multiple access* OFDMA and is used in Mobile WiMAX.

Despite these, OFDM also have some problems. When there's a high *peak to average power ratio* (PAPR). OFDM have a higher PAPR than single carriers. That's because in the time domain, a multicarrier signal is the sum of the narrowband signals; this sum is very variable over the time, so the peak value of the signal is quite larger than the average. This fact brings to nonlinearities and clipping distortion[7]. It becomes a tradeoff between a reduction of efficiency and an increase of the cost of the RF power amplifier.

OFDMA

Orthogonal frequency division multiple access is a multiple access method based on OFDM that allows simultaneous transmissions to/from several users along with advantages of OFDM. It's

[5] FFT and IFFT are a relatively low computational load algorithms to compute the discrete Fourier transform and its inverse

[6] ISI is a form of distortion of a signal in which one symbol interferes with subsequent symbols

[7] Clipping distortion occurs when the receiver can't trace the signal, because its amplitude goes over the bounds that the receiver is able to manage

Parameters	Values			
System channel bandwidth (MHz)	1.25	5	10	20
FFT size (N_{FFT})	128	512	1024	2048
Subcarrier frequency spacing	10.94 kHz			
Useful symbol time ($T_b = 1/f$)	91.4 μs			
Guard time ($T_g = T_b/8$)	11.4 μs			
OFDMA symbol duration ($T_s = T_b + T_g$)	102.9 μs			

Table 2.1: OFDMA scalability parameters

essentially *frequency division multiple access* FDMA and *time division multiple access* TDMA at the same time. Users are dynamically assigned to subcarriers, like FDMA, in different time slots, like TDMA. While in fixed WiMAX, OFDM with 256 subcarriers is used; OFDMA permits a better mobile usage. Subcarriers are assigned to subchannels that can be allocated to different users, in this way high granularity from the spectrum point of view can be achieved, and permits various approaches on the subcarrier permutation as will be explained in subsection 2.2.4 that improves performances versus interference of other cells. Another advantage of OFDMA relative to OFDM is that manages better the PAPR problem. That's because when splitting the bandwidth among all the mobile stations of the cell, makes that one MS only manages a subset of the subcarriers, therefore each user transmits with smaller PAPR.

Scalable OFDMA

The design of OFDMA wireless systems deals with the choice of the number of subcarriers per channel bandwidth. This election is always a tradeoff between protection against multipath, Doppler shift and design complexity.
Increase the number of subcarriers means a better immunity to multipath propagation and ISI will be achieved. But on the other hand it means the complexity, and cost, of the system and also leads to a narrower subcarrier spacing. And this makes the system more sensitive to Doppler shift and phase noise.
In order to keep a suitable subcarrier spacing, in OFDMA, the FFT size is scaled by adjusting the FFT size while fixing the sub-carrier frequency spacing at 10.94 kHz. The unit sub-carrier bandwidth and symbol duration is fixed, so the impact on higher layers is minimal when scaling the bandwidth, parameters that can be seen in table 2.1. It has to be said that in order to reduce complexity, the profile was limited to FFT sizes of 512 and 1024.

2.2.2 Channel coding

Channel coding in WiMAX is based on FEC.
Forward error correction (FEC) is an control system for errors in data transmission, where the sender adds redundant data to its messages. This allows the receiver to detect and correct errors without asking more data to be sent. More information than it's going to be presented in this chapter can be consulted in [5] and [7].
Data is divided into FEC blocks, and these blocks are placed into an entire number of subchannels[8].
The mandatory channel coding scheme in mobile WiMAX is based on binary nonrecursive convolutional coding.
Mobile WiMAX permits various types of coding to correct data; *convolutional coding* (CC), *convolutional turbo code* (CTC), *block turbo code* (BTC) and *low density parity check code* (LDPC),

[8]Subchannel are the granularity in the time/frequency resource

but the WiMAX Forum profile[12] only defines as mandatory CC and CTC.

Convolutional coding

In convolutional coding, a symbol of m length is converted to a n length symbol, where m/n is the code rate and $(m \geq n)$. The transformation is a function of the last k information symbols, where k is the constraint length of the code, there are k memory registers, each holding one input bit. All memory registers start with a 0. Bits enter from the first register on the left side and using the existing values in the remaining registers the output gets n bits, then all register values are shifted to the right and the next bit is expected. When there are not more bits going in, the encoder output continues until all registers returns to zero state.
CTC in WiMAX uses duo binary turbo codes. In duo binary turbo codes the encoder sends three

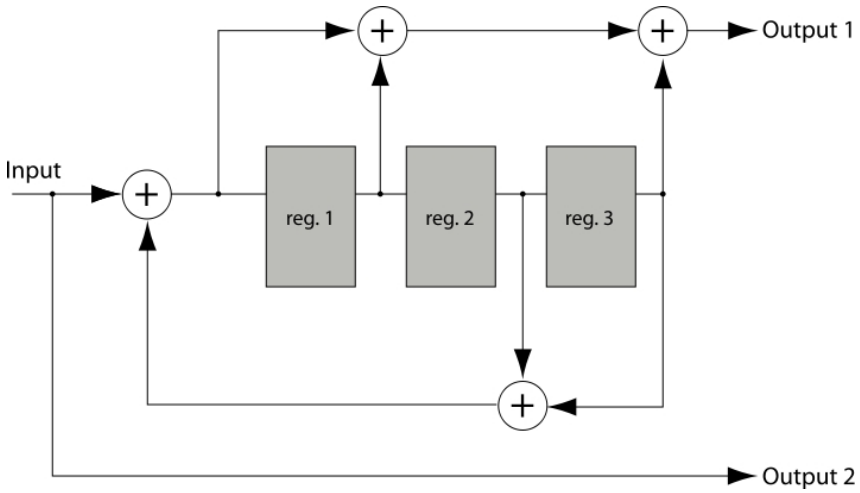

Figure 2.2: Recursive convolutional code scheme with 1/2 rate and constraint length 4

sub-blocks of bits. The first sub-block is the m-bit block of payload data, the second sub-block is n/2 parity bits for the payload data, computed using a *recursive systematic convolutional* code (RSC code), the third sub-block is n/2 parity bits for a known permutation of the payload data, again computed using an RSC convolutional code. That's, two redundant but different sub-blocks of parity bits for the sent payload. The complete block has m+n bits of data with a code rate of $\frac{m}{(m+n)}$. The permutation of the payload data is carried out by a device called interleaver.

Interleaving

Interleaving is used in digital data transmission technology to protect the transmission against burst errors. These errors overwrite a lot of bits in a row, and an error correction scheme expects errors to be more uniformly distribute. Therefore interleaving is used to overcome this from happening.
The encoded bits are interleaved by two steps and is done independently on each FEC block. Firstly adjacent coded bits are not mapped on adjacent subcarriers (more frequency diversity is achieved), and then is ensured that adjacent bits are alternately mapped to less and more significant bits of the modulation constellation.

2.2.3 Symbol structure

During the symbol mapping stage, the sequence of binary bits is converted to a sequence of complex valued symbols.

Mandatory constellations in WiMAX are QPSK and 16 QAM (see figure 2.3), 64 QAM is also defined in the standard as optional to transmit data, and BPSK can be used for broadcast control messages. Then, the constellation used, the coding type and rate, together, are the burst profile.

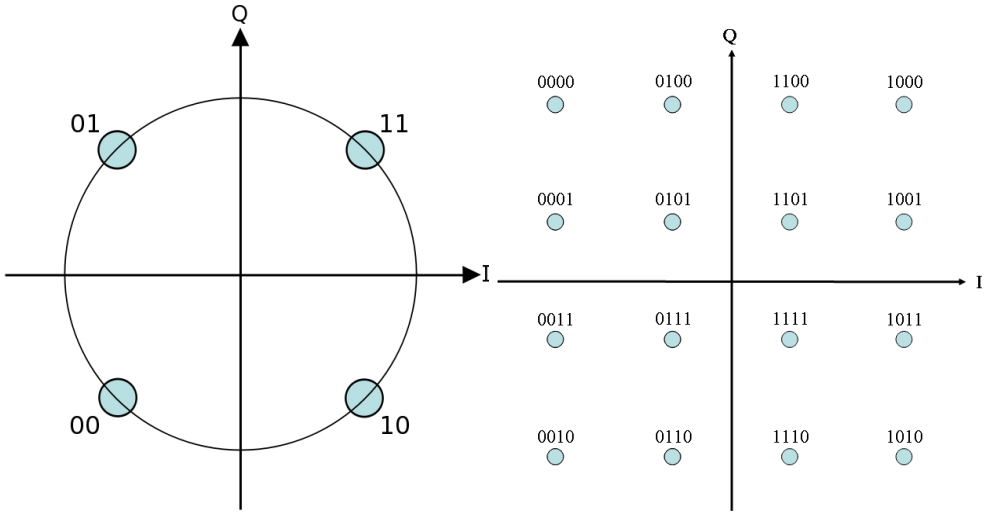

Figure 2.3: QPSK and 16QAM constellation

Each modulation is scaled by a constant, because the average transmitted power is unity.
As we commented in section 2.2.1, a data rate sequence of symbols is split into multiple parallel low data rate sequences, each of which is used to modulate an orthogonal subcarrier.
In the frequency domain each OFDM symbol is created by mapping the sequence of symbols. WiMAX has three classes of subcarriers, distribution can be seen in 2.2.4:

- Data subcarriers are used for carrying data symbols.
- Pilot subcarriers that transmit pilot symbols, which are known a priory and are used to estimate the channel.
- Null subcarriers have no power allocated and are used to save the guard subcarriers, this reduce the interference between adjacent channels.

Further information about the symbol structure can be obtained in [5].

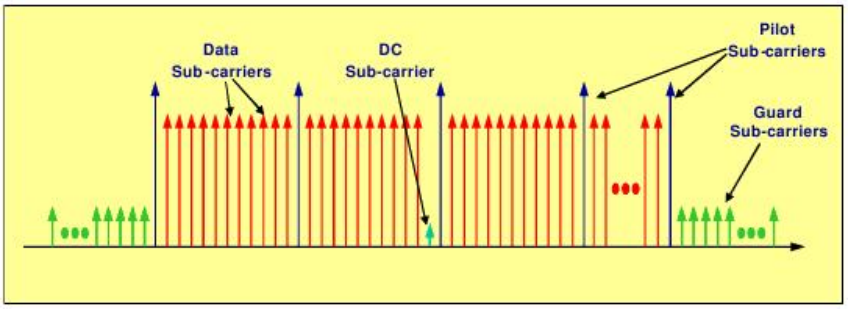

Figure 2.4: OFDMA sub-carrier structure, extracted from [10]

2.2.4 Subchannel and subcarrier permutation

To create the OFDM symbol in the frequency domain, the modulated symbols are mapped on to the subchannels to transmit the data block.

In WiMAX subcarriers can be continuously mapped, one adjacent to the next one, or distributed through the whole band. When distributing subcarriers through the whole band, OFDMA symbols are transmitted at the same time in different regions of the band. Therefore, there are subcarriers that have an SINR over the mean and others that are under the mean, so there's an averaging of the channel. In this way frequency diversity is ensured.
The other option is to map the subcarriers continuously. In this way, whole OFDMA symbols are transmitted in the same region of the band, there's no averaging of the channel, then some symbols has a better SINR than others. With this approach the system can take advantage of the fluctuations of the channel. The idea is transmit as high a data rate is possible when the channel is good and reduce the rate when the channel is poor, by using smaller constellations, to avoid an increase of packets dropped.

Full usage of subcarriers

In *full usage of subcarriers* (FUSC), all data subcarriers are used. Each subchannel is made up of 48 data subcarriers, which are randomly distributed through the whole frequency band. Pilot subcarriers are first allocated and the remaining subcarriers are permutated on the various subchannels. That allows to average the channel response for all symbols.

Partial usage of subcarriers

The difference between *partial usage of subcarriers* PUSC and FUSC, is that PUSC subcarriers are firstly divided into six groups. Then, permutation of subcarriers to create subchannels is done separately for each group.
All subcarriers except the null ones are arranged in clusters, each cluster consists of 14 adjacent subcarriers over two OFDM symbols. Inside the clusters; 24 subcarriers are used to transmit data and 4 are pilot subcarriers. The clusters are then renumbered, which makes a redistribution of the clusters.
Once clusters are renumbered, six groups are made taking a part of the total number of clusters, and a subchannel is the union of two clusters of the same group.
With PUSC is possible to assign a set of the group of carriers to a base station, by doing sectorisation[9] or leave a group of clusters without using and assign when necessary.
In the uplink mode, the distribution is almost the same, but pilot over data subcarriers ratio is higher.
Both distributed options, FUSC and PUSC, are better for mobile environments, where channel conditions change fast.

Adaptive modulation and coding

In *adaptive modulation and coding* (AMC) subcarriers are continuously mapped to create subchannels. The channel response will affect the transmission dependending on the group of subcarriers that is used, then frequency diversity is lost, but exploitation of multiuser diversity can be used. This approach is better when the environment of the channel doesn't change fast
Within this subcarrier permutation, 9 contiguous subcarriers with 8 data subcarriers and 1 pilot subcarriers creates a bin.
One subchannel is created on AMC mode by using six consecutive frequency bins, the IEEE Mobile WiMAX amendment permits the following associations of frequency bins and consecutive symbols in time:

- 1 bin and 6 symbols

[9]By sectorisation, the cell is divided into different zones, and different subcarriers are assigned to each sector. This method reduces the interference inside the cells.

- 2 bins and 3 symbols.
- 3 bins and 2 symbols.

But as can be seen in [12], 2 frequency bins and 3 consecutive symbols is the option that vendors associated in WiMAX Forum decided to define as mandatory.
This approach is better for more stable conditions than randomly distributed allocations. A less variable channel condition is needed, in order to let the feedback between mobile and base station be fast enough to adapt the transport format to the instantaneous conditions of the channel.

2.3 MAC layer

The *media access control* (MAC) data communication sub-layer is the second layer of the seven layer OSI model. It provides addressing and channel access control mechanisms. This sub-layer is responsible of controlling and multiplexing various links over the same physical medium. The most important functions of the MAC layer in WiMAX are:

- Select the appropriate burst profile and power level.
- Retransmission of packets when ARQ is used and the packet was received erroneously.
- Provide QoS or handle priority.

Following subsections are extensively explained in [9].

2.3.1 MAC PDU

Each MAC *protocol data unit* PDU[10] consists of a header, a data payload and CRC[11]. WiMAX has two types of PDU's, one is generic and used for data transmission and another one is used to transmit bandwidth requirements.
Once a PDU is built, it's given to the scheduler that schedules it over the physical resources available.
The scheduling procedure is not in the WiMAX standard and is left to the manufacturers to implement. The scheduling algorithm has a huge effect on the capacity and performance of the system.

2.3.2 ARQ

Hybrid automatic repeat request (HARQ) is a type of error control method for data transmission which uses acknowledgments and timeouts to achieve reliable communication.
ARQ uses acknowledgment packet sent by the receiver to the transmitter to indicate that it has correctly received the data frame. A timeout is a reasonable amount of time after the packet was sent by the transmitter. If the transmitter doesn't receive an acknowledgment before the timeout, it re-transmits the packet until receiving an acknowledgment or exceeding a predefined number of re-transmissions.

[10] Is a unit of information delivered through a network layer
[11] *Cyclic redundancy check* (CRC) is a function that takes as input a data stream and produces a value as output. This value is used check that there was no alteration during the transmission of the packet.

HARQ

The H in front of ARQ means that it's hybrid, means that amount of redundancy is managed over retransmissions. So part of the physical layer is implemented. To ensure that following retransmissions have more possibilities to be correctly received, more redundancy is added for each new retransmission. Some feedback is added in the process of making the transmission stronger.

2.3.3 Quality of service

One of the key functions of the MAC layer is ensure to get the *quality of service* QoS requirements. This implies that various negotiated performance indicators such; latency[12], jitter[13], data rate, packet error rate and system availability, must be met for each connection. WiMAX has 5 different scheduling services to deliver and handle packets with different QoS:

- *Unsolicited grant service* manages real time flows that generates packets periodically with the same size. It's ideal for services like VoIP.
- *Real time polling services* manages real time services that generates packets periodically but with different size, like MPEG video transmissions. In this case the base station polls regularly to the mobile station, asking for the bandwidth required.
- *Extended real time polling service* is a mix between *unsolicited grant service* and *real time polling service*. In this case periodic uplink packets can be used either to transmit data or to request additional bandwith.
- *Non real time polling service* is very similar to the service explained before with the difference that in this case the polling is contention based, so there's a time of security to avoid collisions. The difference between two opportunities of unicast polling is in the order of few seconds.
- *Best effort service* is suitable for services that have not strict QoS requirements. When resources are not requested by other service classes best effort data is sent. The mobile station requests to the base station are also contention based.

Other important functions of MAC layer such power management or mobility management are far away from the aim of this thesis.

2.4 Frame structure

The Mobile WiMAX physical layer supports both TDD and Full and Half-Duplex FDD mode, but initial releases from WiMAX Forum only includes TDD, as is explained in [10].
TDD is preferred as FDD mode for the following reasons:

- Enables regular adjustment of the DL/UL ratio, and supports asymmetric traffic, while FDD doesn't permits negotiation of the DL/UL ratio and generally UL has the same bandwidth as DL.
- Channel response is the same in the UL than in the DL, and that allows a better link adaption[14].

[12]Latency is a time delay between the moment something is initiated, and the moment one of its effects begins or becomes detectable

[13]Jitter is the variation of the parameters of the transmission: phase, delay...

[14]Receiver and transmitter can take on smart antenna technologies like *multiple input multiple output*, throughput is increased without increasing bandwidth or power of transmission

- TDD requires a single channel, which provides more flexibility than FDD, because of the spectrum allocation restrictions.
- TDD implementation is less complex than FDD, therefore cheaper.

The frame structure for a TDD implementation, as illustrates figure 2.5, is divided into a DL subframe and a UL subframe separated by a gap to avoid collisions. In a frame, as well as data bursts, there is the following control information.

- Preamble: Is used for synchronization and is the the first OFDM symbol of the frame.
- *Frame control header* (FCH): FCH follows the preamble. It provides system control information such as subcarriers used (in case of segmentation), the usable subchannels and the length of the DL-MAP message. This header is always code with BPSK R 1/2 to ensure maximum robustness and reliability.
- DL-MAP and UL-MAP: It provides sub-channel allocation for the users in the current frame for DL and UL sub-frames.
- UL ranging: The UL ranging sub-channel is used for the MS to do frequency, power adjustments and bandwidth requests.
- UL *channel quality indicator channel* CQICH: The UL CQICH channel is allocated for the MS for channel feedback information.
- UL ACK: The UL ACK is used for the MS as feedback for the DL *hybrid automatic request* HARQ.

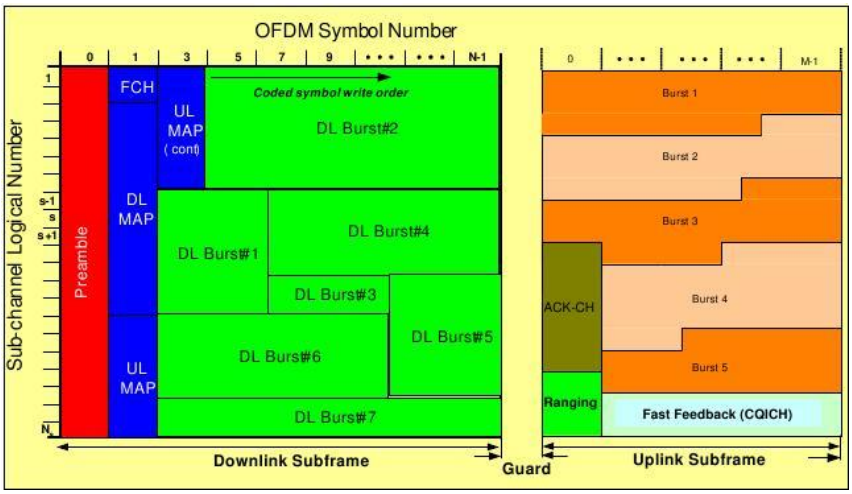

Figure 2.5: Frame structure, extracted from [10]

The amendment permits various lengths of the frame (in ms): 20, 12.5, 10, 8, 5, 4, 2.5 and 2. But the WiMAX Forum profile[12] only defines 5 ms as the mandatory frame length.
The default number of symbols per WiMAX frame is 48.

3 Packing problems

3.1 Overview

The WiMAX scheduler has a 2 dimensions resource (time and frequency) to pack coded data. Therefore, a packing problem is faced. The optimization of the resources used to pack data is a key point.
In a packing problem is given a resource (one or more dimensions, usually two or three), and an amount of items that have to be placed within the available resource. So, there are two possibilities that all the items are packet into the resource or that only a subset of the items are indeed packed. There exists different types of packing problems, two of the most used are:

- Bin Packing: In this type of problem a number of elements with different sizes have to be packed into a finite number of bins with different size and forms. The objective is to minimize the number of bins used or the total height used.
- Knapsack problems: Its name is derived from the problem that tries to maximize the valuables that fits into a bag, or knapsack. Each valuable has a weight and a value; the objective is to maximize the value of the items inside the bag, taking account the limit weight or capacity of the "bag".

3.2 Bin packing problems

The study of this problem was started in the early 70's, when computer science was still forming A sequence of items are received to be packed $i_1, i_2, i_3, ..., i_n$ and there's a bin with finite or infinite size, with the first option the objective is to place as many items in the bin as possible and with the second option minimize size of the bin used. The second option can be formuled as follows:

$$\sum_{j=0}^{j=n} s(i_j) \leq C \tag{3.1}$$

Where C is the maximum capacity of the bin and i_j are all the items that can be placeable. If the previous statement is verified, all the items will be placeable, if not, only a subset will be placed. While the first option can be exemplified by taking a bin with a stated width and an infinite height, as can be seen in 3.1, and then improved by allowing less unused capacity in between the items without changing its shape.

3.2.1 Solving

Bin packing problems are NP-hard. This is a type of computational complexity and is the acronym of *nondeterministic polynomial-time hard*. This means that can't be ensured that the problem can solved in polynomial time[1].
When solving, a clear separation can be done in the way to manage the items that are going to be placed:

[1]Solve a problem in polynomial time, means that the CPU time to solve the problem is a polynomial function of the size of the problem

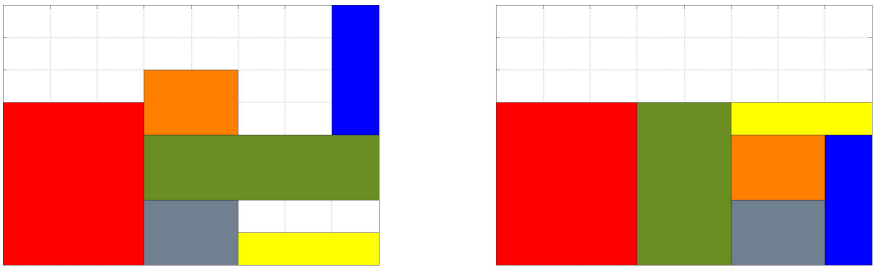

Figure 3.1: Bin packing

- Online: Items are placed with the order they are in the queue, so there's no sorting. The placement algorithm doesn't know how will be the items that are coming next, only knows the actual one and the ones that have been already placed.
- Offline: In this way, the placement algorithm knows all the elements that should be placed before starting the placement itself, sorting is allowed.

To solve bin packing problems various algorithms are defined:

- *Next fit* (NF): Items are placed in the current level, if fits. If doesn't a new level is started and becomes the current one.
- *First fit* (FF): Items are placed into the lowest indexed initialized level (levels are indexed increasingly as they are initialized), when an item doesn't fit in any of the existing levels, a new level is created.
- *Best fit* (BF): It's similar to the FF approach, the difference is that here an item is always placed into the level with lowest residual capacity (when it fits). In case of a tie the item is placed into the level with the lowest index.

An evolution of these algorithms is the decreasing height option. Items are sorted in a decreasing height way[2], then it's an offline method.

3.3 Knapsack problems

The main difference between knapsack and bin packing problems is that knapsack problems have another parameter, it's the value of each element that's packed in the bin.
There exists two types of knapsack problems bounded or unbounded. Bounded problems restrict the number of each element to a maximum value and unbounded problems doesn't have a limit on the number of elements to be placed. There's a variation from the bounded problem, this is the 0-1 knapsack problem, where the bound is 1. It can be formuled in this way:

$$\sum_{j=1}^{n} w_j x_j \leq c \tag{3.2}$$

$$\sum_{j=1}^{n} p_j x_j \tag{3.3}$$

Where x_j shows if the object j is selected, and how much of this elements are selected. The knapsack problem must accomplish the equation 3.2 and also try to maximize the equation

[2]The first to be placed is the highest, then the second highest, and so on.

3.3, where p_j is the value of the element.

3.3.1 Solving

To solve knapsack 0-1 problems, there are different types of algorithms to apply.

- Greedy algorithm: Tries to optimize the solution by sorting the values from the greatest to the lowest, and then placing them in the knapsack. It has low computational complexity, but with this method only can be ensured that half of the values that fits in the optimal solution will be placed.
- Branch and bonus: This approach is done like an inverse a tree. First is tried to place as many elements as possible in a greedy way and the backtracking is done, going back in the tree and looking for the points that can be improved. This is done successively in all the branches; and at the end all branches are analyzed to look for the one that results in a higher sum of values of the items placed.
- Dynamic programming: This approach divides the optimization problem into smaller problems, and attack them separately.
- Reduction algorithm: Reduce the size of the problem by fixing optimal values to as many variables as possible. If placing of not placing an element produces that a solution is worse that another existing one, then the placement or not of this element will be fixed in all new possible solutions.

In [13] algorithms are deeply explained and its computational complexity is discussed.

4 Evolutionary algorithms

Since packing problems are NP-hard, an heuristic approach is suitable to solve them, and a possible approach is with *evolutionary algorithms* (EA).
With evolutionary algorithms can't be ensured that a unique optimal solution will be find, but as more time runs the algorithm a more optimal solution will be the result.

4.1 Overview of evolutionary algorithms

An evolutionary algorithm (EA) uses mechanisms inspired by biological evolution; like reproduction, mutation, recombination and selection.

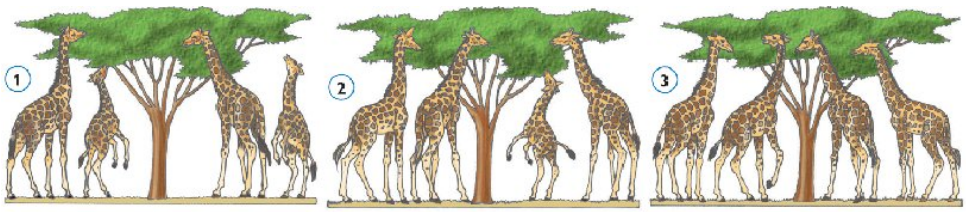

Figure 4.1: EA mimics on biological evolution

In figure 4.1, a biological of evolution of giraffes can be seen. Candidate solutions play the role of the individuals in a population (in the example of the figure giraffes).
EA rank the kindness of solutions with an objective cost, drawing a parallelism between EA and biological evolution of the figure, the objective function plays the role of the environment, in this case the high trees, this is decide which solutions "survive" and which don't.
The evolution of the population occur with the application of the mutation and recombination. Recombination is inspired on a sexual reproduction, so the combination of two individuals of the population. After evolution fittest solutions remains, like with the giraffes where the long necked giraffes remain.
The power of EA have been demonstrated by solving many problems, some examples are presented:

- Dr Adrian Thompson[19] used EA to produce a voice recognition circuit that can distinguish between and response to spoken commands using in a FPGA. A random bit string was generated and then evolved to get a solution that can distinguish between the spoken words "go" and "stop". This was done by using only 37 logic gates and without a clock, something that could not be possible by direct human design. Dr Thompson doesn't know how it works, it seems that evolution take advantage of some electromagnetic effects of the FPGA cells, moreover if we take into account that 5 logic gates are not connected to the rest of the circuit.

- Sato *et al.*[18] used EA to design a concert hall with optimal acoustic properties; maximizing the sound quality for the audience, the conductor and for the musicians. Beginning with completely rectangular hall, they a leaf-shaped hall as a result. Authors declared

that the solution have similar proportions similar to the *Wiener Groβer Musikvereinsaal*, considered by experts one of the three finest concert halls in the world.

- He and Mort[20] applied genetic algorithms to find optimal routing paths in telecommunication networks. There were multiple parameters to maximize data throughput, minimizing transmission delay, finding low-cost paths and distributing load among routers or switches of the network. In the authors solution the population is initialized with shortest path solution, which minimizes the number of "hops", and congestion or failure was left to the algorithm. The algorithm was found able to efficiently route around congested links, balancing traffic load and maximizing the total throughput.

There exist various types of evolutionary algorithms, the main differences between them are here presented:

- Genetic algorithm. This is the most popular type of EA. Seeks for the solution of a problem in the form of a string of numbers and applying recombination operators in addition to selection and mutation.
- Genetic programming. Here solutions are in the form of computer programs, and their fitness is determined by the ability of the program to solve a computational problem.
- Evolutionary programming. It's like genetic programming with the difference that the structure of the program is fixed and the numerical parameters are allowed to evolve.
- Evolution strategy. It works with vectors of real numbers as representations of solutions, typically uses self-adaptive mutation rates.

This thesis will be focused on GA, as is the most commonly used approach and is told as suitable to solve NP-hard problems like packing problems.

4.2 Genetic algorithms

As was told *Genetic algorithms* (GA) mimics biological evolution. Given a specific problem to solve, the input of the GA is a set of potential solutions to the problem (population), encoded in some way. These candidates can be randomly generated and delivered or after searching a certain number of solutions. Following, the GA evaluates the solution with a fitness function. The fitness is a quantitative value to the solutions. Best candidates are allowed to continue to the next generation and reproduce themselves. Reproduction is both asexual; when the individual is copied but introducing random changes (mutation), or sexual when two individuals are crossed to create new ones (crossover). By repeating this process is expected that the average value of applying the fitness function to all individuals will increase, and better solutions can be discovered. In the figure 4.2 are represented which are the steps of a genetic algorithm.

4.2.1 Representation of the solutions

In biological evolution the nature of each individual in a species is coded in its DNA. Each variation in the essence of an individual is coded as a change in the DNA chain. Genetic algorithms refers to each solution as a genome, and each one of the elements that codes the solution are genes. There are various ways to encode solutions in genetic algorithms.

- Numeric representation: This is the most typical approach. Solutions can be coded as a binary string, where the digit at each position represents a value of some aspect of the solution. Another approach is to code solutions as arrays of integers or decimal numbers, this approach allows greater precision and complexity.

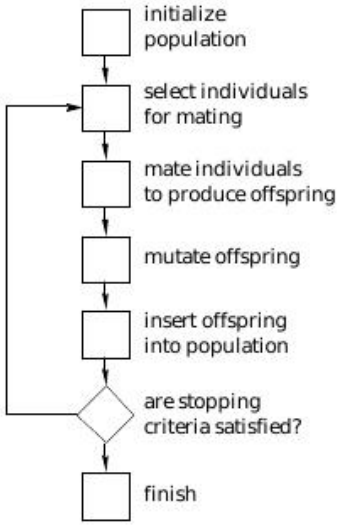

Figure 4.2: Genetic algorithm steps

- List: The coding of the solution is done by a list of objects, the position inside the list of each object represents some aspect in the solution. This possibility is particularly suitable for packing problems, because we can define items to place as objects and define the order with are going to be placed as the position in the list.

- Tree structure: Also suitable for packing problems. This is like a list oriented structure, but also using nodes of the tree to define how are the items placed, this structure is defined in [22].

Representation is a key factor in GA. That's because inside an individual there should only be coded the information of the solution that can improve the solution when changed.
A problem in the representation could be the introduction of redundancy into the codification of the individual. That becomes into an addition of noise when genetic operators are applied, this is because applying a genetic operator will have different effect to characteristics that are redundant in the code to others that are not.

4.2.2 Evolution strategies

Evolution of the population can be done in multiple ways as is done in nature, the most important ones are here presented:

Simple

With this approach, every generation a completely new population. Therefore, all individuals of the old generation are replaced by new ones. Drawing a parallelism, this would be like in annual plants or animal species where only the eggs survives the winter.

Steady-state

Generations are progressively renewed. A temporary new generation is created from the old one, the size of the temporary population is defined as a parameter of the genetic algorithm, this population is crossovered and mutated and then joined with the old population. Finally the size of the population is fixed to its initial value.

Niche technique

This technique avoids the existence of too many equal individuals in a population to maintain the genetic diversity of the population. There are various methods defined for this technique (as can be seen in[21]), the most common are:

- **Sharing methods**. The fitness value is reduced depending on the. This is done by defining a function that given two individuals returns a value proportional to its likeness[1]. The degree to which to individuals are considered to be of the same species is controlled by the sharing radius; if the distance between to individuals is greater than the sharing radius, they are not occupying the same niche.

- **Crowding methods**. This method also uses a function that measures the likeness between two genomes individuals, but no radius is defined. An offspring is created from two individuals of the population. If the offspring fitness is better that its closest parent, the new individual replaces the old one.

4.2.3 Genetic operators

To maintain diversity into a population of solutions is necessary to create new solutions from the old ones. In genetic algorithms, this is done by mutation and crossover.
Further information of the elements presented i this subsection can be found in [14], [15] and [16].

Mutation

Mutation changes one solution individually at a time. A solution is selected randomly applying a mutation rate, the mutation rate is the probability of one solution to be mutated.
Depending on the type of problem, the mutation applied is customized to the individuals of the space of solutions. For example in packing of rectangular elements problems, there are the following types of mutators (see [22]).

- Swap mutator: This mutation operator takes two elements of the list and exchange its position each other.

- Change mutator: This operator takes one element and maintaining the same area, the mutator change its shape. Rectangles can be changed by rotating them, increasing one dimension (and decrease the other one) or randomly change one dimension (and adjust the other one).

- Swap and change mutator: It's a combination of the two operators presented before. Two genes of the genome are selected, swapped and finally mutated.

Both mutation operators can be combined into one operator that does both actions, this is the swap and change mutator.

Crossover

Crossover is a genetic operator inspired in biological sexual reproduction. It takes two individuals of the solution space and combines themselves to create two new solutions that are a mix of the first two individuals.
For crossover in bin packing, only crossover types that mantains the length of the individuals does makes sense, here some types of crossover are presented:

[1]The likeness is calculated by comparing gene per gene

- N-Point Crossover: With this type of crossover, n points are placed along two encoded solution (the points are placed in the same position in both solutions), and n+1 sections are created. Sections between the points selected are alternately exchanged from one solution to the other to create two new solutions from the first two ones.
- Partial match crossover: In partial match crossover, two points are selected into the solution. Then, the encoded solution that's inside the two points are exchanged between the two solutions, and the elements that because of the exchange are repeated inside solutions are changed for the elements that have been lost because of the exchange in its position.

4.2.4 Selection

Fitness function is what provides a measure to realize a selection between the individuals of the population.
The first step to obtain the fitness function is by defining an objective function. This function returns a score that evaluates how good is a concrete solution from the point of view of the designer of the GA.
Selection is deeply explained in [17].

Truncation selection

In truncation selection the candidate solutions are ordered by fitness. Then, some proportion p, of the fittest individuals are selected and extended 1/p times to cover the number of individuals of the population.

Roulette wheel selection

In fitness proportionate selection, the fitness function assgins a fitness to possible solutions. The fitness value is used to associate a probability of selection with each individual chromosome, as can be seen in equation 4.1, where p_i is the probability of being selected, f_i is the fitness of individual i in the population and N is the total number of individuals in the population.

$$p_i = \frac{f_i}{\Sigma_{j=1}^{N} f_j} \tag{4.1}$$

Therefore, fitter individuals are more likely to be selected, but there's still a chance fore some weaker solution to survive the selection process. Another important point for this approach is that individuals can be selected more than once.
It's called roulette-wheel because it can be conceptually represented as a game of roulette, where each individual gets a slice of the wheel, but fitter ones get larger slices than less fit ones.

Rank selection

In this approach each individual in the population is assigned a numerical rank based on fitness, and selection is based on this ranking rather than absolute differences in fitness. The probability of being selected depends on the position of the individual in the ranking.
The advantage of this method is that it can prevent very fit individuals from gaining dominance early at the expense of less fit ones, which would reduce the genetic diversity of the population.

Tournament selection

This type of selection behaves like roulette wheel, but with a defined number (usually 2) individuals of the population. Subgroups of individuals are chosen from the larger population, and the fittest individual remains "competes" like in *roulette wheel* versus the others. Therefore,

with this selection is more likely than fittest solutions remain and population diversity tends to reduce.

4.2.5 Termination Criteria

- The fitness of a solution reaches a minimum stated value.
- A certain number of generations is reached.
- Planned time (budget) is reached.
- The highest ranking solution fitness has reached a value that successive iterations are not able to increase significantly. The value that measures how is the fitness of solutions increasing along iterations is convergence.

Part II

Design and simulation

5 Description of the problem

As was introduced in section 1.1, the aim of this project is to design a scheduler that tries to optimize the traffic inside a cell using mobile WiMAX technology.
Assuming that a certain amount of users are inside a cell and these users pretend to receive data by using WiMAX technology. These users have a common resource to share. Concretely a 2 dimensions resource, frequency and time. Therefore the problem is how to pack data from all users in rectangles within the resource. It's assumed that there's only one cell (there's no interference) and only one frame is taken into account (retransmissions are not managed).
To pack data into a time-frequency rectangle, the first step is to select the transport format for the codification.
As it's explained in 2.2.3 there are various possible constellations to manage the raw of bits of data that a user wants to transmit, choosing the constellation and also the various options of code rate (that can be seen in 2.2.2), together transport format. From this election depends the number of necessary blocks to pack data[1] and the *block error rate* (BLER) for transmitted blocs would also be affected.
This master thesis is focused on the AMC subcarrier and subchannel permutation. Subcarriers are continuously mapped and therefore frequency diversity is lost, as is told in 2.2.4, so the scheduler has to take profit of the frequency bins channel variation of conditions. That means that depending on the frequency bins that are being used for a user, this user will have a concrete effective SINR to transmit its packets. Then, BLER is affected also by the frequency bin where user's data is going to be packed. Because of that, selecting the transport format is not trivial, because changing the transport format also affects the number of necessary bins, and both parameters affects a key factor of the transmission, BLER. Overlapping the *target BLER* of the system can produce a dramatically decrease in the overall effective throughput of the system[2].
The problem becomes in a packing problem, without knowing the size, a priory, of the rectangles that are going to be packed.
As is told in 3.2.1 it's not possible to solve packing problems linearly, and heuristics have to be used to solve such type of problems. In this case, the space of solutions will be possible placements.
Coding how are the rectangles into individuals of a population in a genetic evolution is also a key point. Genetic operators will be customized to affect the parameters of the placement that can improve performance. To measure this improvement, the objective function also has to be customized.
And together with the the genetic algorithm elements described; a placement algorithm is necessary to get the placement parameters from the coded solution in the genetic algorithm population[3].
The problem is done assuming a 10 MHz channel with a consecutive 2 frequency bins and 3 symbols association[4] and the length of the frame is 5 ms. We assume also a downlink situation, the base station transmits to various mobile stations.

[1] Logically, as more bits per symbol are coded less resources to transmit the coded will be needed
[2] The target BLER is a parameter that depends on the application and affects the probability of packets dropped
[3] Placement parameters are the values used to calculate the objective functions. Parameters that measures the goodness of a solution
[4] That's the mandatory association for AMC defined in the profile, as can be seen in 2.2.4

6 Problem modelling

This chapter has two differentiated parts. The first one is focused on how the problem is modelled, and the second part concretes more about the details of the software implementation.

6.1 Non-selective approach

Before dealing with the frequency selective approach, a non selective approach was done.
The main difference between selective and non-selective approach is that the frequency variation is not managed and then a flat the channel response on all subchannels is assumed. This means that a user would use the same codification while transmitting in all frequency bins and also the same *bit error rate*. So the description of the problem doesn't fit within the restrictions of the problem description, but this approach was used for involving into the packing problems with genetic algorithms, before dealing with the topic of the master thesis.

6.1.1 Common resource

The common resource for all users is the two dimension space where data is packed. The size of the resource has to be stated in some way.
The subchannel distribution fixed on AMC profile[1] is 2 frequency bins and 3 consecutive symbols (see section 2.2.4), and the number of subcarriers per subchannel is 9, reserving 1 as a pilot subcarrier and the other ones for data. Assuming a 10 MHz channel and a FFT size of 1024, where 768 are usefull subcarriers. It means that there should be 48 frequency frequency bins.
In the time dimension, knowing that the standard number of symbols per WiMAX frame is 48, and an AMC subchannel is created with three consecutive symbols, it means that there are 16 time divisions in the frame. But it has to be considered that some symbols are reserved for different reasons than placing usefull data. For this approach round numbers near AMC values are taken, 50 frequency subchannels and 10 time slots.

6.1.2 Users

With this approach is assumed that there's not frequency variation, therefore it's not necessary that users demand a certain amount of data, they ask directly for the size of the resource that need.

6.1.3 Representation of the solutions

The genome is a list of pairs of data. There's a pointer to the object that is going to be placed (that gives the information about the am mount of subchannnels needed per user) and the width that will have each rectangle in the solution. The position of each pair of data into list is the order which objects are placed.

6.1.4 Initialization

The first step for the initialization is to generate the resource demand of each user. This value is assigned by calculating a random (uniformly distributed) integer number between two prefixed

[1] The non selective approach is done assuming any subcarrier permutation zone. But AMC will be applied in the selective approach, therefore near values of this approach are applied here.

bounds. After that, a width value is generated from 1 to either the resource demand of the user or the width of the common resource (the maximum of two values). But some restrictions are applied, a maximum number of unused subchannels per data pack are allowed, this parameter adjust how much flexibility is given to the creation of rectangles. For example; assume a pack of 7 subchannels, if the parameter is fixed to 0, there are only 2 possibilities of packing; setting the height to 7 or 1 and the width to 1 or 7 respectively. But changing the number of allowed unused subchannels parameter to 1, the use of 7 or 8 subchannels are allowed to pack data and therefore more possibilities are allowed: the width to 1, 2, 4, 7 or 8 and the inverse values for the height.

6.1.5 Genetic algorithm

The genetic algorithm selected for this approach is the steady state algorithm. It permits that good solutions from old generation remains.
Two objective functions are designed to score solutions, depending on the relation between the total number of subchannels that users ask for and the subchannels available:

- The total number of subchannels required are more than the available ones. In this case the objective function takes into account the density of the packing. This is the number of usefull subchannels (total number of subchannels - unused subchannels) divided for the total number of subchannels.

- The total number of subchannels required are less than the available ones. With this supposition the objective function measures the total height of the placement. For the same packets placed, the one using less frequency bins, would use resources in a more optimal way.

The selection done after scoring solutions is the roulette wheel method, best solutions have more possibilities to go ahead generations but there are some options for the worse ones, as it's not a deterministic selection.

6.1.6 Genetic operators

The genetic operators applied are swap and change mutator and partial match crossover.

- Swap and change mutator. With this mutator operator the first step is to select a gene of the genome, each gene of the genome can be selected by a rate, the *mutation rate* M_r. If a gene is selected then it's swapped[2] by another randomly selected gene in the genome[3]. Various change mutator possibilities are designed: rotate rectangles, increase a dimension or randomly change a dimension.

- Partial match crossover. Two genomes are selected with the probability fixed by the *crossover rate* C_r. After that, the two genomes are mixed to create two new offsprings with the system described on subsection 4.2.3.

6.1.7 Placement algorithm

The placement algorithm takes each pair of data in the order that are listed in the genome. For one side takes the width of the rectangle and for the other side the total number of subchannels needed. Once taken the information, the data rectangle is packed from the bottom to the top of the shared resource with a *next fit* (see subsection 3.2) algorithm variation. Objects are not

[2]Swapping two elements means that their positions are exchanged
[3]The probability of a gene to be mutated is the mutation rate, but the mutation rate applied gene per gene is the half of the mutation rate. That's because the mutation process implies two genes

presorted, it's an online algorithm. But a kind of *decreasing height* is also applied. Rectangles are placed in levels and a new levels are started in these two cases:

- The width of the actual rectangle exceeds the remaining width of the level.
- The height of the actual rectangle exceeds the height of the last rectangle that was placed.

The election of *next fit*, instead of more optimal procedures, like *first fit* or *best fit*, is because the aim of the non-selective approach is to be more familiar to packing and genetic algorithm problems. Applying these other procedures would lead to a more complex implementation.
The algorithm is done online because a pre-sorting clips a part of the genetic algorithm. If rectangles are always decreasing height ordered, the only element left to the genetic algorithm to optimize the solution is the width of the rectangles, what reduces the power of genetic algorithms.

6.2 Frequency selective approach

This approach deals with the topic of the master thesis. The design of a frequency selective scheduler.
With this approach the frequency variation is taken into account. Each user "see" a different channel that's better in some subcarriers than in another ones. Therefore the effective SINR[4] is different depending on the subcarrier. Subcarrier permutations like FUSC or PUSC average the SINR of the whole channel by randomly distributing subcarriers through the channel. AMC maps subcarriers continuously, this fact makes that the transport format selected depends on which frequency bins are going to be used to transmit the data packets and therefore the number of channels that a user needs are not known a priory. With this approach packets are differentiated between priority and non-priority. Let's see how this fact affect the modeling.

6.2.1 Common resource

In this approach AMC values are taken into account. The number of frequency bins is 48 (as is explained in subsection 6.1.1). In the time dimension, the number of time slots is 10 (the maximum allowed in a bin is 16). Thereby the shared resource for all users transmitting to a cell are 480 subchannels, as can be seen in figure 6.1.

6.2.2 Users

In this case users has to provide more data to the system that in the non-selective approach.

User type

Users can receive priority packets or not priority packets. Priority packets represent data of real time applications (VoIP, video streaming ...) and non priority packets represent bulk traffic.

Data size

The data size is generated by a randomly distributed function delimited by a lower and an upper bound. These bounds are different depending on the type of data that's going to be transmitted. Bounds for the real time applications will be lower than ones for bulk applications. That's because real time applications require a continuous transmission with critical time restrictions (restrictions are explained in subsection 2.3.3) and bulk traffic transmit a certain amount of data, but without time restrictions.

[4]The effective SINR is the calculated mean of the SINR in various subcarriers

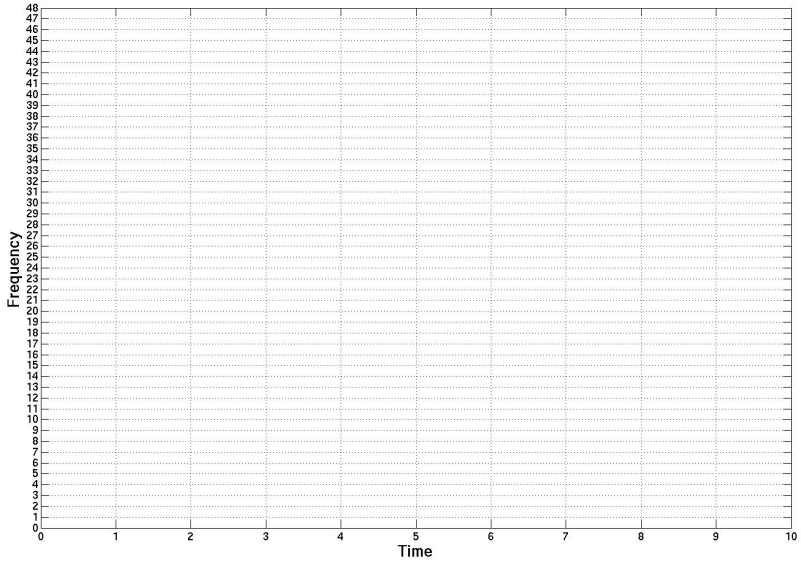

Figure 6.1: Common resource of 480 subchannels

Coding data

Data is coded with FEC blocks, the size of an FEC block depends on the transport used, it can be consulted in table 6.1. Select the transport format necessary is not a direct procedure instead of a feedback one.

Transport format	Block size (bits)	Beta
QPSK 1/2	48	1.57
QPSK 3/4	72	1.69
16 QAM 1/2	96	4.56
16 QAM 3/4	144	7.33
64 QAM 2/3	192	23
64 QAM 3/4	216	42

Table 6.1: β and FEC block length depending on transport format.

Channel conditions

Each user transmits on a different channel. The channel response for each user is modeled as 768 values (one for each subcarrier), calculated in two steps: fast fading simulation for one side and slow fading and propagation for the other side.
The fast fading simulation is done using NLOS empiric outdoor model. To model the slow fading and propagation a lognormal function is used. Thereafter the two values are multiplied to provide the SINR of a single subcarrier.

6.2.3 Placement algorithm

The placement algorithm is introduced before the representation, because in this case the representation depends strongly on the election of the placement algorithm. The process is done for each frequency bin of the resource and for each width possible into the frequency bin (from 1 to 10), it's 480 times per user. It starts by trying the transport format that allows more bits per symbol, then data is splitted into blocks. And when the hypothetical number of subchan-

nels that are going to be used are known, an hypothetical height of the rectangle is taken and therefore the frequency bins that are going to be used. Once this is known the SINR for the transmission is calculated. To calculate the SINR is necessary to average the channel response of the subcarriers that are going to be used to transmit each FEC block. To calculate this value *exponential effective signal to noise ratio mapping* (EESM) is used.

$$\gamma_{eff} = -\beta \ln(\frac{1}{N}\sum_{i=1}^{N} e^{-\gamma_i/\beta}) \tag{6.1}$$

EESM is presented in equation 6.1, where β is a constant value that depends on the transport format (can be consulted in table 6.1), N is the number of subcarriers to average, γ_i is the SINR of each one of the N subcarriers and γ_{eff}.
With the SINR, the BLER of each FEC block can be mapped using BLER tables (detailed on appendix B). Therefore the error rate of the whole data packet. If the error rate of the whole packet is bigger than the maximum error rate allowed, the procedure is repeated with the following stronger transport code; and so on until there's a transport format that achieves a lower (or equal) BLER. If there's not a possible transport format for the user with the width defined, then it's not possible to place the user in the actual frequency bin and the concrete width. Thereafter the process is repeated with the following width. The maximum error rate allowed is the target BLER and is fixed for each type of data. The target BLER for priority data will be lower than for non-priority data. Instead only one frame is simulated, and therefore no retransmissions are managed, non-priority data is not as critical as priority data. Because of that a bigger probability of retransmission is allowed for not real time applications.
Overhead is not taken into account, only usefull data.

Position management

At a first sight the placement designed for the non-selective approach could seem also suitable for the selective approach. But this approach has to deal with the another problem, ensure the locality of a change in the solution. For a suitable performance of the genetic algorithm is necessary that a changing a part of the solution (by swapping two elements, for example) only affects the zone of the change. If it affects the whole solution, noise is introduced into the genetic algorithm and it makes more difficult to improve solutions. By placing from bottom to the top a swap between elements produce that an element can changes its size because of the change of channel characteristics, and therefore the transport format (to keep the maximum block error rate allowed). This effect causes that elements placed above the swapped element, also changes its position and its size. To reduce this effect another placement algorithm is designed.
With this new placement algorithm, diagram of the algorithm modelled can be seen in figure 6.2, data is not placed from bottom to the top, it's placed in a frequency bin depending on the position that's code in the genome (described in next subsection). Elements are placed on levels and the procedure of placing data is different if the element that's going to be placed if it's the first on a level or it's not. Notice that the level where the element is going to be packed depends on the position code in the gene and if there's free space in this position, if not placement in the following upper frequency bin is tried.

- First in the level: In this case the packet is tried to be placed by first minimizing the height of the rectangle. This is, starting with the maximal width of the resource. If it's possible to be placed, the width is decreased by one until the height needed for placing the element is increased; then the following bigger width is selected. In case the element can't be placed with maximal width. Placing in the following upper frequency bin is tried.

- Not first in the level: In this case, the process is trying to minimize the width in front of minimizing the height. Starting with width=1 if the height necessary is lower than the

height of the first element, data is packed; if not width is incremented until the height doesn't overlap the height of the first element of the level or the amount of free width in the level is reached. Then placing in the following upper frequency bin is tried.

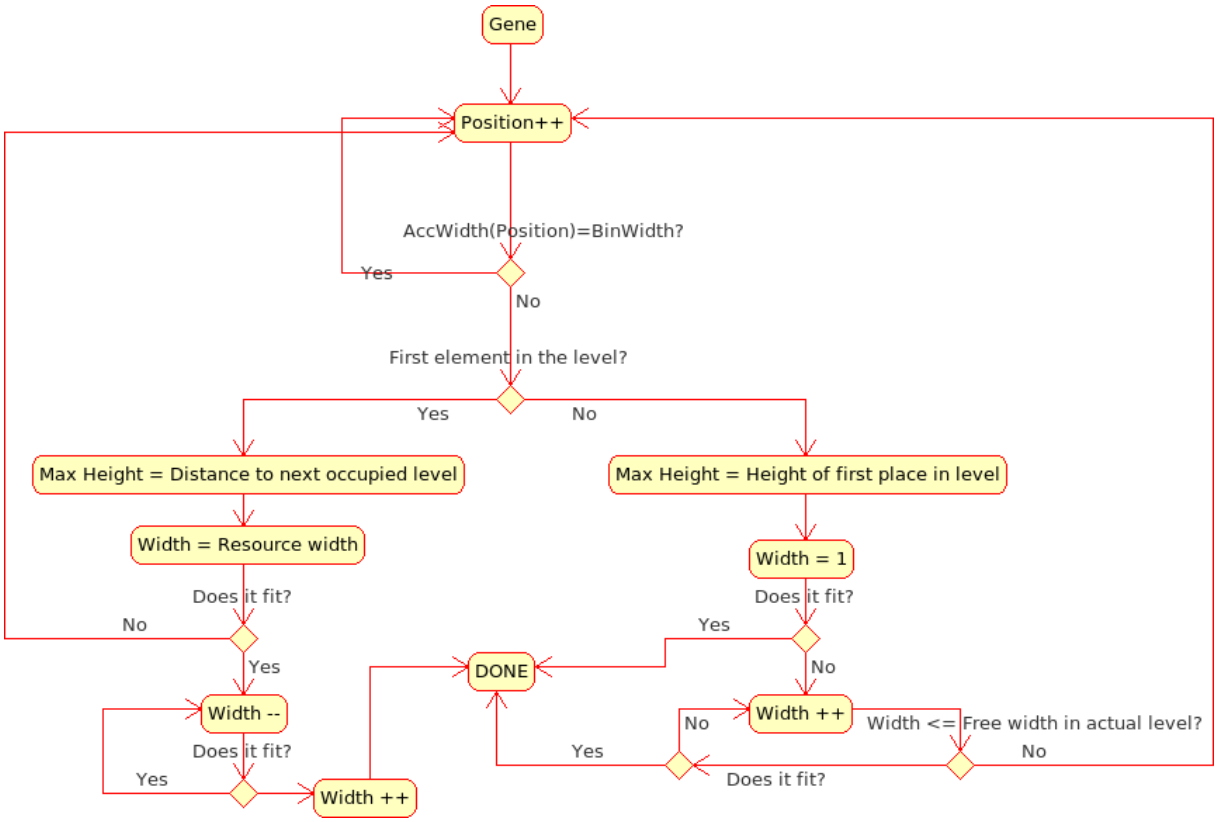

Figure 6.2: Diagram of the position management algorithm modelled

The strategy of trying to minimize the height of the firsts of the row is token because provides better frequency selectivity to the packing process. Minimizing the number of frequency bins used per user, means reducing the averaging of the channel response and give more freedom to the genetic algorithm to improve solutions. An alternative to this strategy is try to minimize the total number of subchannels used on the packing processes of the firsts of the row, in this way the strategy is lost but firsts on the row are tried to be placed minimizing number of subchannels.
The way how elements are placed in the shared resource also takes into account the order of the genes inside the genome. That's because the position defined for an element to be placed can be already occupied for another element (that was code firstly in the gene's list), then the element is tried to be placed in the upper frequency bins and if the placement algorithm arrives to the top of the common resource it continues from the bottom; and if it gets another the initial position, the packet is discarded.

6.2.4 Representation of the solution

As is told in the last subsection, the representation change from the non-selective approach is necessary to afford the changes in the placement algorithm. Each gene of the genome has a reference to the user information (presented on subsection 6.2.2) and the position where the data will try to pack, concretely where the placement algorithm will start the process.
Representation can be seen in figure 6.3, where each colour represents a genome with a reference to the user (represented for the big number, it's the user's identifier), and the little number represents the position assigned.

Figure 6.3: Solution representation

6.2.5 Initialization

The first step is the initialization of the users. Assign the channel conditions to the user (an array of 768 values, one for each subcarrier), create the number of priority and non-priority users required and depending on the type randomize the number of bits that will be transmitted. Then, a gene is created with a reference to the user and a random position into the 48 frequency bins is assigned.

6.2.6 Genetic algorithm

In this approach both steady state and deterministic crowding strategies are applied. Both strategies will be compared in terms of results achieved and time of execution in chapter 7. The objective function in this case takes into account the difference between placing priority or not priority packets, ranking solutions in the following way:

1. Number of priority packets: A placement with more priority packets is better than another with less.

2. Percentage of data placed: With the same number of priority packets placed. The percentage of the total amount of priority and non-priority data placed is taken into account with a weighted sum, giving more importance to the percentage of priority than to the non-priority. Consider that two placements can pack the same number of priority packets, but placing different packets.

$$Score = N_{pr} + W_{pr}R_{pr} + W_{nopr}R_{nopr} \tag{6.2}$$

Objective function is presented in equation 6.2, where N_{pr} is the number of priority packets placed, W_{pr} is the weight given to priority data, W_{nopr} the weight for non-priority (W_{pr}+W_{nopr}=1), R_{pr} the fraction of priority packets placed and R_{nopr} the fraction of non-priority packets placed. Roulette wheel selection is applied.

6.2.7 Genetic operators

Swap, change and swap & change are modelled. Swap mutator behaves in the same way that the non-selective approach. But, the change operator, changes the frequency bin value for the gene (the frequency bin where the packing algorithm starts the process).
In figure 6.4 it can be seen an example of how swap is applied (on the right of the figure) between genes 1 and 4, and thereafter change of the genes is applied. It can be seen for the change on the colour, but also the position is changed. In gene 4 position is changed from 12 to 19 and in gene 1, position is changed from 22 to 34.
Swap & change can be done in two ways: change the two elements that have been swapped or swap two elements and then mutate an element. Taking into account that the rate applied when swapping and mutating two elements is the half of the mutation probability required (by swapping one gene, two genes are affected), and when mutating a single element, the mutation

rate applied is directly the mutation probability. The first option is the same that was applied in the non-selective approach and will be called swap & change mutation I and the second option will be called swap & change II.

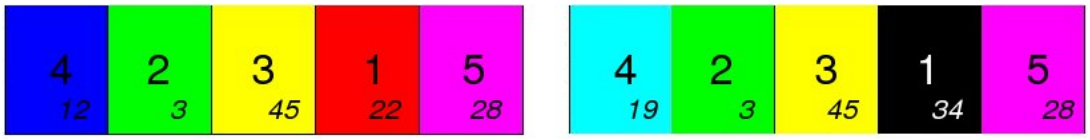

Figure 6.4: Swap & change I. Swap is applied on the left and change on the right of the figure

To apply the change on the position, two possibilities are modelled and will be compared in results. The new position is extracted randomly from:

- Uniform distributed mutation.
- Normal distributed mutation. The value is extracted from a normal deviation centered in the old position bin of the gene, the deviation of the normal distribution is a parameter that must be selected.

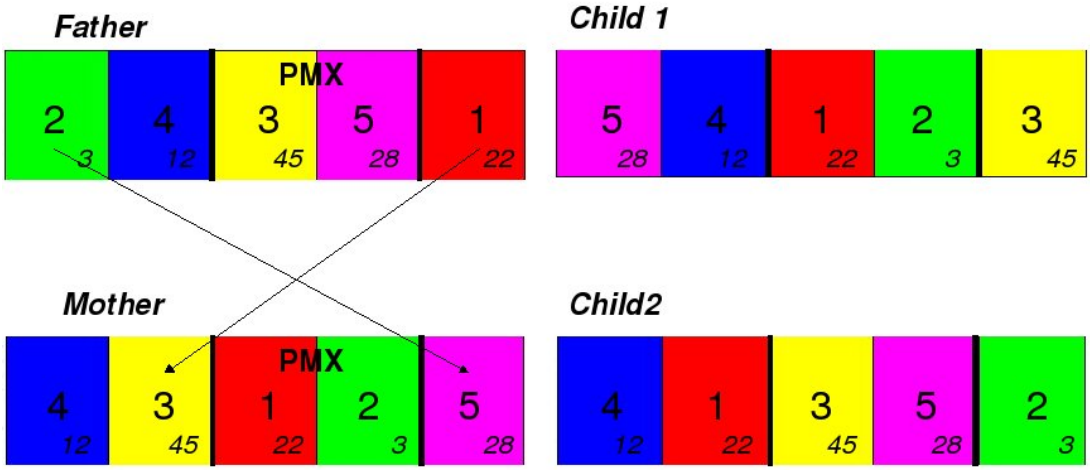

Figure 6.5: Partial match crossover

The crossover method used is partial match crossover, this method was explained in subsection 4.2.3. In figure 6.5 can be observed how this crossover method is done. Looking at the left part of the figure, two points are selected in both parents, in this case between 3rd and 4th genes are selected, then positions of genomes are related; in the figure gene of user 2 in the father is related to gene of user 5 in the mother, that's because they are the genomes placed in the 4th position of the other parent. The same happens with the third position, gene of the 1st user of the father is related to gene of the 3rd user of the mother. Once relations are done the right part of the figure can be observed, 3rd and 4th gene are exchanged between individuals and to get the genes that have been lost in the exchange, these are placed in the position where relation was established, as it was seen in the left part of the figure.

6.2.8 Parameters of the simulation

- Number of users. Total number of users, priority and non priority.
- Number of priority users.

- Lower and upper bounds for non-priority data.
- Lower and upper bounds for priority data.
- Target BLER. Different target BLER for priority and non-priority data are allowed.
- Mean and deviation values for the lognormal distribution of the slow fading model.
- Number of generations.
- Size of the population.
- Regeneration value in steady state algorithms.
- Mutation ratio.
- Crossover ratio.
- Deviation of the normal distribution in mutation.
- Weights for the priority and non priority data transmitted in the objective function.

6.3 Implementation

In this section the implementation of the frequency selective model is explained.
As was explained previously it's not possible to calculate an exact solution in a deterministic way. Therefore *Monte Carlo methods*[5] are applied to get reliability of the results.
To implement the model C++ language is used and to make the application and get the results some libraries that will be introduced in section 6.3.2.

6.3.1 Program structure

As was seen in subsection 6.2.3, the program requires the calculation of the suitable transport format when a packet is going to placed in the common resource to know which dimensions will have the packet. This process has to be done for each packet and repeated until the packet can be placed in a subset of frequency bins. But not only this, the process has to be done for each genome of the population, repeated for each generation in the evolution of the genetic algorithm and if we take into account that the algorithm has to be run many times when applying Monte Carlo methods, another step of repetition is added. This induces to think that one concrete calculation of the transport format and the size of the packet in the time/frequency resource will be done more than once, therefore CPU time could be wasted. For one user the total number of placing possibilities are:

$$N_p = \sum_{i=0}^{i=47} 48 - i = 1152 \tag{6.3}$$

As there are 48 frequency bins (see subsection 6.2.1) in the common resource, and the packet can be placed from the bottom to the top, there are 48 possibilities of taking frequency bins together from the frequency bin 1, 47 from the frequency bin 2, and so on. This number is clearly overlapped by the number of times that the the calculation of the transport format and the size of the packet from one user will be calculated. Typical numbers for number of generations and size[6] of the population are over 100, in the best case 10000 calculations of the

[5] Monte Carlo methods consists on running an algorithm various times and then compute the solutions together to get a mean and a confidence margin of the solutions

[6] Selection of number of generations and size of the population is a tradeoff between results and time of computation, in chapter 7 is this tradeoff discussed

size will be done (assuming that all packets can be directly placed, and the algorithm doesn't have to go ahead the shared resource) without taking into account the Monte Carlo repetitions. Then, it was seen that's more optimal to precalculate all the possible placements before the placing algorithm, to make the placement algorithm faster. But there's another factor to take into account, the memory management.
Going deep into the placement process. Only 10 possibilities of placement when starting on a concrete frequency bin have to be saved for the placement process, that's one placement possibility for each width possible of the rectangle (see subsection 6.2.1). With a certain width it's only interesting to save the possibility that uses less frequency subchannels. Therefore, number of elements that have to be saved per user is reduced to 480, ten values per frequency bin. The intention of the simulation is to evaluate the goodness of the algorithm with various parameters and not to physically transmit the data packet, because of that the only value that has to be saved for the placement process would be the hypothetical number frequency bins necessary when a certain width is fixed and also a starting position, therefore an integer. What means that 480 bytes for user are necessary to be saved. Assuming a number of users of 50, 24 KB of memory would be needed.
After these paragraphs, it has been seen that it's more optimal to precalculate the transport formats and the sizes of the data packets, and after apply this information in the placement. Assuming this, the implementation of the precalculation is separated from the placement.
Before the startup phase itself, a model of the fast fading channel is done in Matlab using the Winner Project channel models[25]. Winner model is a geometry based stochastic model. Model radio channels based on geometry enables separation of the propagation and anthenna parameters. The channel parameters are based on statistical distributions extracted from channel measurement in different scenarios.
Winner models permits modelling diverse types of scenarios by changing some parameters. An array of 768 columns (one per each subcarrier) and 2^{14} rows is created to be used in the startup phase.

Startup phase

To initialize users, data size is randomized and one of the $2^{14 channels}$ created with the Winner model is selected by each user.
In the startup phase the height that would need a packet to be placed, starting in an hypothetical frequency bin and using a concrete width is calculated. To do this for each of the 480 possibilities, the transport formats are iterated, from the one that permits more bits per symbol to the strongest one. Taking advantage of this process, the best possibility of placing is saved (the placement that requires less subchannels). With this values a maximum amount of data that can be placed in the common resource can be calculated, to compare a placement process with the best possible placement.
Another parameter that's saved during this phase is the relation between the SINR of the frequency bins that are used to transmit data over the average SINR of the channel. With this information it can be calculate the improve we get in the channel response with AMC in relation to randomly distributed subcarriers (like PUSC or FUSC), in this case a a 32 bits float is used (assuming 50 users, it's 96 KB of memory).
All the information calculated in the startup phase is saved on files, then will be used in the placement phase. Diagram of how is the calculation done in the startup phase can be consulted in 6.6.

Placement phase

This part of the implementation has two parts; the genetic algorithm and placement algorithm. The placement algorithm is used to score the results in the objective function of the genetic algorithm.
As was told in this section before Monte Carlo methods are used, working in the following way. The genetic algorithm is ran a certain amount of times, calls, and with the average of the result of the best solution in the last generation we get a batch. By repeating the process o running the algorithm the number of calls required, we get various batches. The final result is calculated by doing the mean of all batches, and also with the different values of the batches, a confidence margin is calculated.
But for the result another value than the score of the objective function presented in subsection 6.2.3 is used and it's calculated in the following way.
When initializing the algorithm the best placement for each user calculated in the startup phase is used. To calculate a maximum bound of data placeable in the common resource, users are ranked taking into account:

- User type: Priority packets are ranked in front of non-priority packets.
- Data/subchannels ratio: Inside each type division, packets are ranked depending on how many data is placed in each subchannel. Therefore, the first packets the ones that can coded with a transport format that allows more bits per symbol.

With this ranking, packets are selected for this maximum bound placement, until the total number of used subchannels is lower than 480. Notice that it's not a real placement, because the positions of the packets are not taken into account, only the value of subchannels. Then, it's not ensured that two packets are placed in the same subchannels. It's a maximum bound, but not reachable in a real placement. This value is used as a reference.
Results are presented as a percentage relation with the data placed in the maximum bound and the data placed in each result. Notice that this value is only necessary for the best solution of the last generation in the genetic algorithm. This is the value managed as result.

$$R_{100} = 100\frac{Max}{Res} \tag{6.4}$$

The 100% mark is then a non-realistic placement and all results will be over this value, the best values will be the nearest values to the 100% mark.
Also, when the best solution of the last generation in the genetic algorithm is reached, the mean SINR in the AMC placement over average placement is calculated. It's done by using the values saved for each packet in the startup phase, a geometric mean is calculated with all the packets packed in a placement.[7].
In figure 6.7 how a placement looks into the common resource look. This placement has been done with 20 priority users and 10 non-priority users. The bigger rectangles are non-priority users (that transmit bigger amounts of data) packets. Also it's noticed that there are not all 30 packets, that's because some packets where not able to be packed and are discarded for the frame

6.3.2 Libraries used

To implement the model, two libraries are used. GAlib from the *Massachusetts Institute of Technology* (MIT) and SimLib of the *Institute of Communication Networks and Computer Engineering* (IKR) of the University of Stuttgart.

[7]In appendix A the class diagrams of both program phase implementation can be consulted

GAlib

GAlib (genetic algorithms library) is used to implement the genetic algorithm. GAlib provides most of the possibilities presented on the section 4.2, and also permits an easy customization of the elements, to achieve the performance of the genetic algorithm for the implementation wanted. In case of the simulation done in this master thesis, the customization has been mainly done with the representation, the initialization and the genetic operators.
More information about GAlib can be found in [23].

IKR Simlib

The simulation control and the management of the statistics has been done with the help of the IKR Simlib. Simlib provides many functionalities to manage simulations, like event handling. With this implementation, it has taken advantage of the simulation control to use Monte Carlo methods, the statistical tool to measure values and the functionalities to parse parameters[8] to the simulation. More information about IKR Simlib can be found in [24].

[8] Parsing parameters, permits to run a simulation with different parameters automatically, and therefore saving time

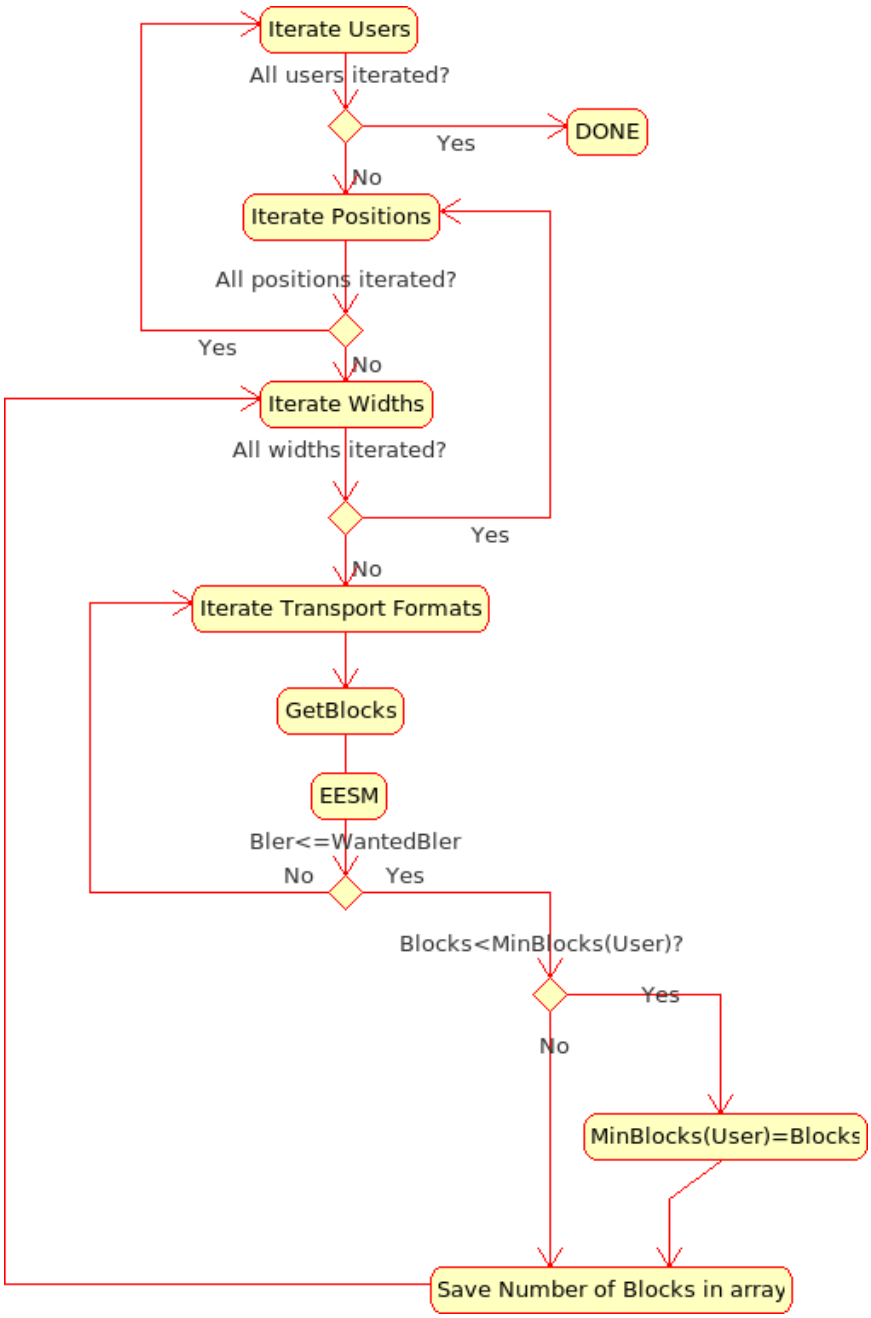

Figure 6.6: Diagram of the startup phase

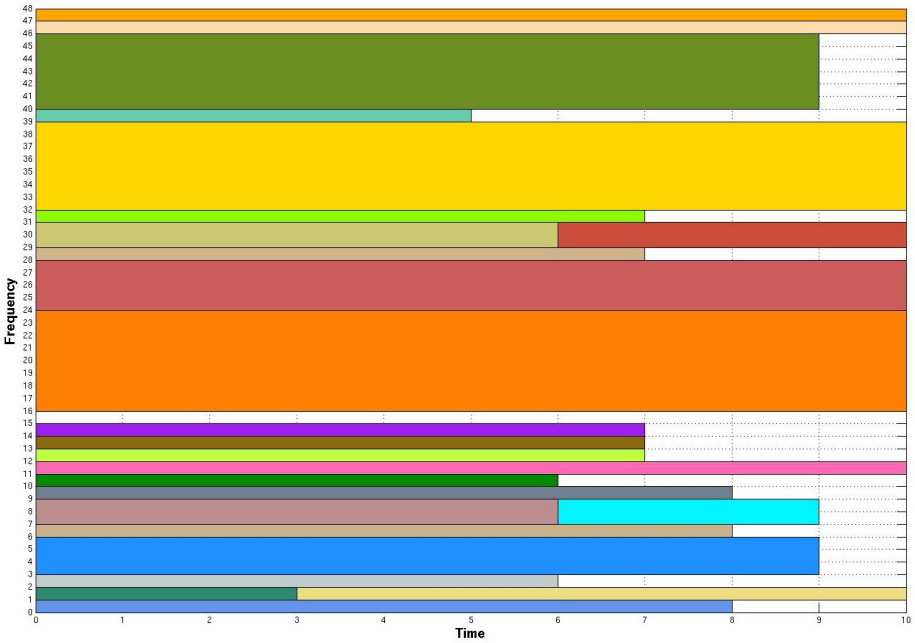

Figure 6.7: Data placement

7 Results of the simulation

In this chapter, results of simulation model explained in chapter 6 are presented, and different variants are compared.

- Different implementations of genetic operators and evolution strategies introduced in subsection 6.2.7.
- Parameters of the genetic algorithm.
- Different scenarios, this is different number of priority users and bounds for the randomization of the size of the data packets for each type of users (priority and non-priority)

Scenario

For all simulations, if anything else is said, following parameters are applied:

- Number of priority and non priority users. Total number of users is 50, and priority user is 30.

- Data size. For priority users bounds for the size randomization selected are 500 and 1500. The upper bound has been selected taking into account a real time application with high traffic demand, video streaming. Assuming a video quality of 300 kbps, and the fact that a 5 ms frame is used; it results into a need of 1500 bits per frame. For the lower bound VoIP requirements (real time application with low traffic demand) is used. VoIP has a data rate of 14.4 kbps and the maximum allowed delay is 30 ms. That means that VoIP data can be packed after 6 frames. This result into a need of 216 bits per burst, but assuming that this value is very low and becomes unoptimal (low usefull data ratio) when adding overhead, 500 bits is selected as the lower bound.
  Non-priority packets would be bigger than the priority ones, see subsection 6.2.2. Therefore the upper bound of priority type packets (1500) is used as the lower bound for non-priority type and an upper bound of 6000 is selected.

- Population size and number of generations. The computational complexity is proportional to the number of generations and population size. The selection of this parameters is a tradeoff between the quality of the results and the complexity. Taking into account what is discussed in a non-selective frame packing problem in OFDMA[26], it has been decided to fix the parameters of simulation to 100 individuals and 1000 generations. By increasing more the complexity, the improvement of the results is not significantly.
- Crossover ratio. The effect of crossover ratio seems to have a not very significantly effect on frame packing, see [26]. A crossover ratio of 0.1 is selected then, because it implies low computational time, as less crossovers will be calculated.
- Target BLER. For priority data target BLER is fixed to 0.1 and for non-priority data to 0.3.
- Replacement. The value fixed for replacement of generations in the steady-state algorithm is 0.5.

- Mean and deviation for the lognormal that models slow fading and path loss is 13 dB.
- Weights of data types in the objective function. $W_p = 0.8$ and $W_{np} = 0.2$.
- Calls and batches. The simulations have been done mainly with 25 calls and 20 batches. This is 500 runs to get a mean value and a confidence margin.

7.1 Genetic operators

In this section various types of mutation operators are compared. Firstly, swap, change, swap & change I and swap & change II are compared. Approaches are done, with the first ones, with the uniform distributed change mutation and then mutation with normal distribution centered in the old position of the packet.

7.1.1 Swap, change and S&C

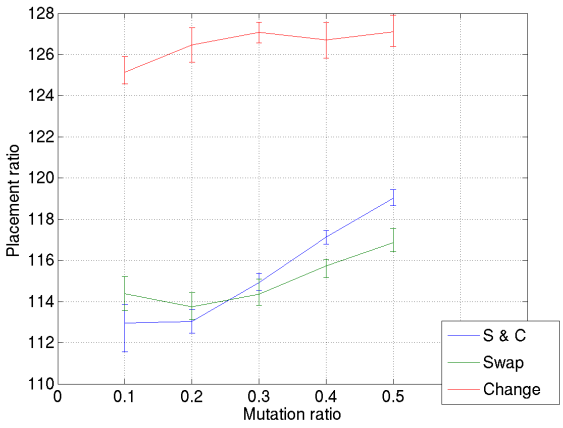

Figure 7.1: Swap, change and swap & change results

In figure 7.1; swap, change and swap & change mutators are compared each other, with mutation rates from 0.1 to 0.5 (it's expected that best results will be achieved with low mutation ratios [26]). It can be seen that best results are achieved with swap & change mutator, with a placement ratio 13 % worst than the maximal placement. Then it's better to swap and change genes at the same time, in order to get better results.
Another important fact of the results is that the change mutation is far away from the swap and change, therefore it's much more important to swap the order of placement than the position where the algorithm starts trying to place the data packet. Another element to be noted is that as mutation increases swap & changes mutation becomes worse than only swap mutator. That's because swap & change applies a higher amount of mutation with the same rate that swap mutation, and as the mutation parameters increase far from its better value, swap & change solutions decrease faster.
As it couldn't be seen in figure 7.1 where were the minimums (best performance) for change and swap and change mutation. In figures 7.2 and 7.3 detail of low mutation ratios are done, respectively. For change mutation it can be observed that minimum is around 0.025 with a placement ratio near 123%, and for the swap & change minimum values is placed from 0.12 to 0.18 mutation rate, being the best value situated in 0.15 with a placement value of 112.4%.
Then, for swap and change mutator the best mutation ratio is placed near the 10% mutation. And from change mutator it can be extracted that change without swapping becomes has to be done in very low rates to get the best results, increasing the probability of changing position of

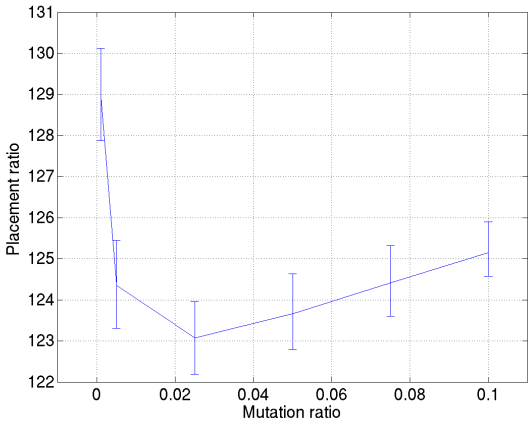

Figure 7.2: Change mutator, detail of low mutation ratios

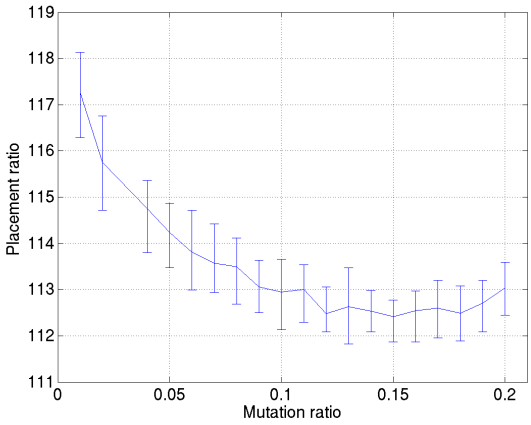

Figure 7.3: Swap & change mutator, detail of low mutation ratios

packet leads to worse results.

7.1.2 S&C II

After the three approaches of mutation, two basic and a combination of both, an other type of combination is tried. With S&C II, swapping and mutating is not done with together, in this case elements can be swapped of changed independently (it's explained in subsection 6.2.7). As can be seen in figures 7.4 and 7.5, results are far away from the first approach to swap and change, and follows the same slope that change mutator did. It has also its best mutator value with a very low ratio with a best placement ratio of 123%. Therefore, the best of the two mutation operators compared in this scenario is swap and change I (doing both actions together, with the same ratio). When change is not done together with swap (either swap is not done or it's done independently) the improvement of the solutions by the genetic algorithm is reduced.

7.1.3 Normal distributed change mutator

Once best combination of mutation operators is found, a variation of the change mutator is evaluated. As is told in subsection 6.2.7, another possibility of facing change was modelled. Instead the randomly distributed change done before, here a normal distribution centered in the

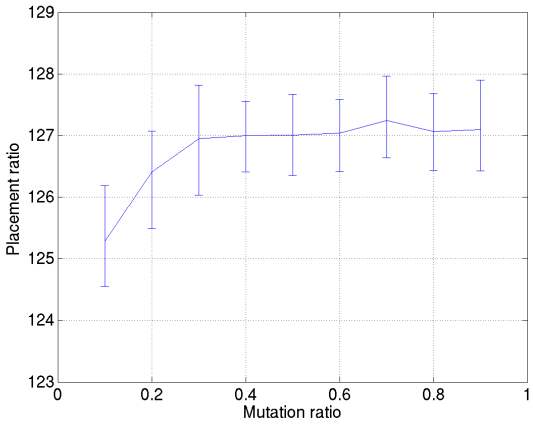

Figure 7.4: S&C II mutator

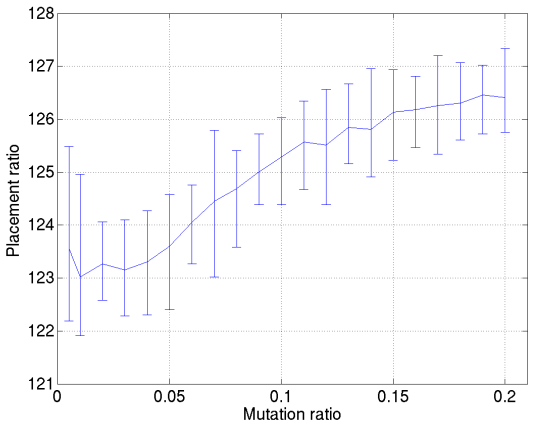

Figure 7.5: S&C II mutator, lower mutation ratios detail

old value is applied. In figure 7.6, various deviation parameters are tried for different mutation ratios, in a S&C approach (swap and change done at the same time). For values of mutation 20 and specially 48, performs in the same way that a uniform distribution; all of the 48 frequency bins are selected with a similar probability. Taking this approach with the lowest mutation ratios evaluated (0.1), it can be observed with this mutation that best results are achieved for deviation=48. In fact, the value is very close to the one obtained by a uniformly distribution. With deviation=1 the value is similar to the (only) swap, mutation as it could be expected (few change mutation is done).
Trying higher mutations leads to worse results when increasing deviation, that's because with high mutation ratios performance decrease and reducing the deviation of the normal deviation is a way to reduce the mutation effect.
It can be concluded that normal distributed change mutator doesn't improve the performance of the genetic algorithm.

7.2 Parameter evaluation

In this section the effect of crossover ratio, population size and number of generations are evaluated.

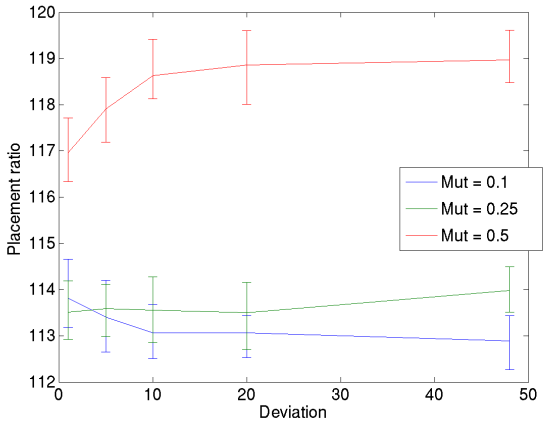

Figure 7.6: Normal distributed mutator with different Deviation values

7.2.1 Crossover parameter effect

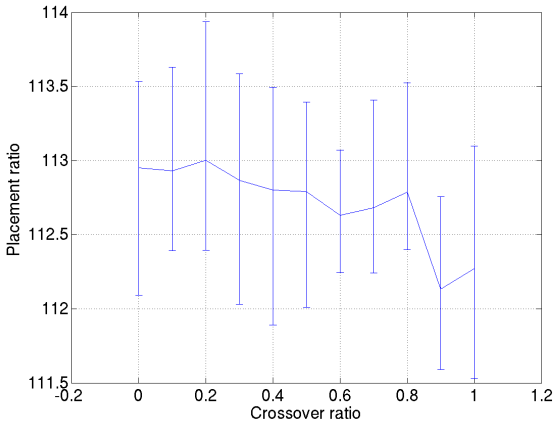

Figure 7.7: Crossover effect

After it has been analyzed the effect of using different mutation operators and which are the parameters to get better results. The effect of crossover ratio is evaluated.
As it can be observed in figure 7.7, the effect of crossover ratio is much lower than the variation on results produced by mutation ratio. The total variation of the results, varying crossover ratio from 0 to 1, is less than 1%. It has to be said that the confidence margin of the results is bigger than the variation, but it can be observed a tendency of the results to improve as more crossovers are produced. It means that new generation created (the part fixed by the steady state algorithm) tends to improve solutions when more crossovers are applied at the cost of increasing the computational time. It has been observed in this thesis that a 7% more of CPU time is needed when crossover ratio is 1 than when no crossover is applied.
It can be concluded that the effect of crossover is very low on the improvement of solutions of the genetic algorithm, and as bigger crossover ratio means more CPU time, the assumption done for all simulations until now of a crossover ratio of 0.1 can is acceptable.

7.2.2 Population size and number of generations

Selection of the population size (P) and number of generations (N_{gen}) in genetic algorithms are a tradeoff between the improvement of the solutions and the computational complexity, as the

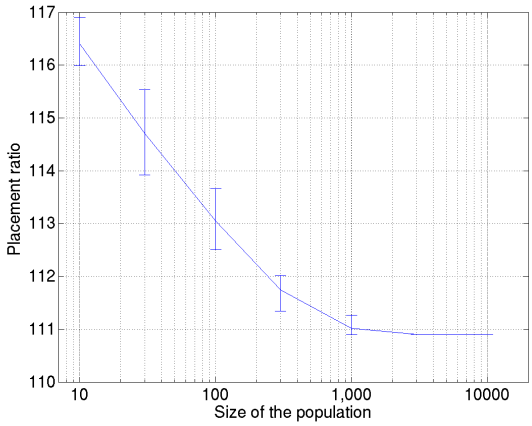

Figure 7.8: Result evolution with number of generations

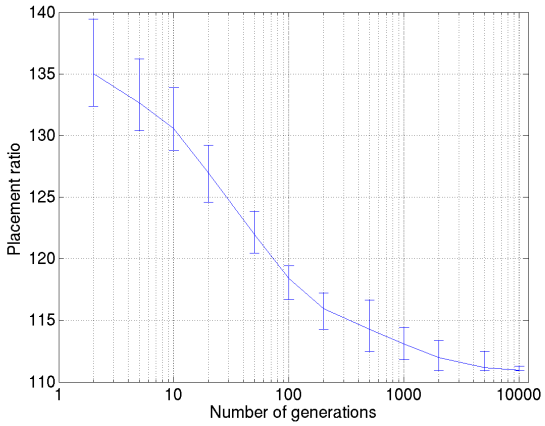

Figure 7.9: Result evolution with population size

complexity is directly proportional to these two parameters.
Figure 7.8 shows the evolution of the results through the size of the population (notice that population is logarithmically scaled) with the number of generations fixed at 1000. It can be seen that solutions improves exponentially until a size of 300 hundred, then it slows down and from 3000 to 10000 there's no more improvement. Also the confidence margin of the results is 0(all batches have the same mean value). That means that a lower bound has been reached and placement algorithm can't go further to 110.9% (10.9% far from the reference value), therefore bigger population sizes doesn't have sense for this scenario.
In this case simulations with a population size of 3000 and 10000 were done with 20 batches 5 and 3 calls respectively, to reduce the total time of execution, this fact can explain that there's no confidence margin for this values, but the fact that there's no evolution from 3000 to 10000 and moreover, that another simulation was done with a population of 3000 and also 3000 generations and the same result was returned, it seems to mean that a lower bound for the placement algorithm for this scenario has been really found.
Taking into account that the improvement of solutions is reduced over a population size of 300, the balanced point between computational complexity and results achieved seems to be under this value. Then the assumption for all the simulations done before of a population size of 100 seems to be correct.
In figure 7.9, the evolution of solutions through the number of generations can be observed, in this case the biggest incremental improve is done from generation 10 to 100, and after that improvement slows down. It can also be observed that lowest bound found in figure 7.8 is also

reached in 2000, 5000 and 10000 generations, but each time with a nearer mean to bound and a smaller margin of confidence.
With the slow down of the solutions improvement from 1000 and ahead, it would mean that when a reduction of the computational complexity would be required, reduction of the number of generations could be a good solution two reduce computational without decreasing much the quality of the results.

7.3 Deterministic crowding

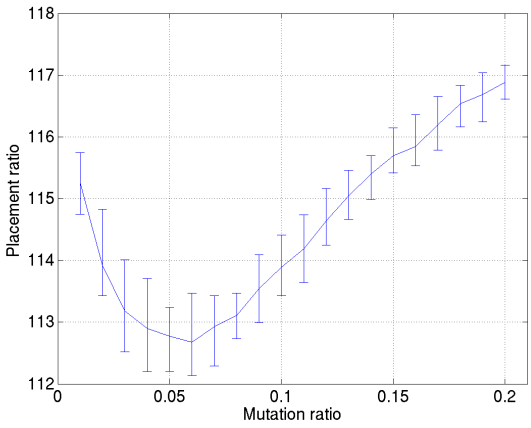

Figure 7.10: Deterministic crowding

As it's told in subsection 4.2.2, deterministic crowding is an evolution strategy that ensures a bigger genetic variety in populations. Therefore, deterministic crowding is evaluated and compared with steady state strategy to notice if there's an improvement.
In figure 7.10 can be observed that the best result achieved is similar than with steady-state strategy, a mean value of 112.7% is achieved with deterministic crowding in $M_r = 0.06$ and with steady state 112.4% was achieved in $M_r = 0.15$. The results are not improved then, but an expectable fact has occurred. The mutation rate for the best position has been reduced, that's because deterministic crowding increases diversity and a high mutation rate also does (in another way), then deterministic crowding (as has a bigger genomic variability) needs less mutation to achieve the required degree of diversity to achieve best results.

7.4 Different scenarios

In this section different scenarios than the one which has been used until now are presented.
Scenario II. Working also with 50 users, the number of priority users is reduced to 10 and the rest of parameters are leaved with the same values.

For the scenario II the M_r where best results are achieved is in the same zone where it was for the scenario I. But, the effect of having more non-priority packets, bigger than the priority ones, is that the placement algorithm loses capacity of placing packets. As the mean size of the packets increase, less packing possibilities exist.
Next, to see how AMC improves SINR in the frequency bins where are placed versus averaging the whole channel, other scenarios are defined.

- Scenario III. 50 users, 45 of them priority packets. The placement results into a mean size

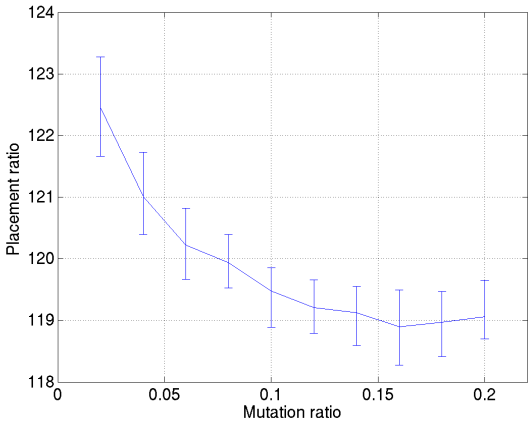

Figure 7.11: Results over mutation for scenario II

of placed packets of 882 bits[1].

- Scenario IV. 10 non-priority users. The placement results into a mean size of 13989 bits[2]
- Scenario V. 10 non-priority users. The placement results into a mean size of 25320 bits[3]

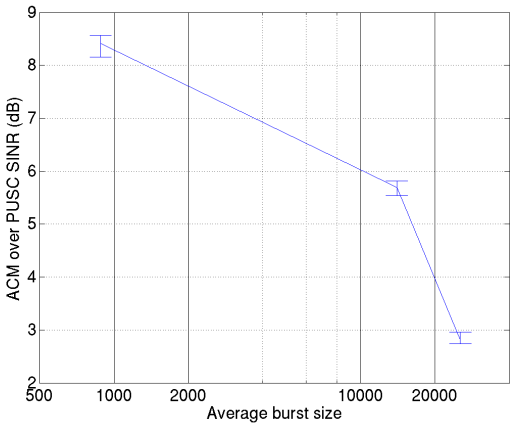

Figure 7.12: SINR over averaging the channel with different mean burst sizes

In figure 7.12 can be observed that maximum values of SINR over averaging the whole channel is for smaller packets. That's because with smaller packets, the scheduler can be more selective, because less bins per packet are used, as the size of packets increase, the scheduler averages a greater number of subchannels. By leading this fact to the maximum (only one packet is placed, using all the subchannels), AMC and FUSC or PUSC subcarrier distribution tends to behave in the same manner.
Concretely; 8.4 dBs of improvement are obtained with scenario III, 5.7 dBs with scenario IV and 2.8 dBs with scenario V.

[1]Bounds for priority: 300 and 1000, non-priority: 1500 and 3000
[2]Bounds are: 10000 and 20000
[3]Bounds are: 20000 and 30000

8 Conclusion and outlook

8.1 Conclusion

As it was presented on chapter 6 a model for the frequency selective scheduler for WiMAX using genetic algorithms was developed and successfully implemented.
Selectiveness leads to packets that are placed without knowing its size in the frequency/time resource a priory. This fact leaded that a concrete a way of coding solutions to genomes were developed; and following to this solution codification an specific placement algorithm and genetic operators were modeled.
The next challenge faced was the implementation. By dividing the execution of the simulation into two phases (startup phase and placement phase), computational complexity is reduced without a reduction on the performance of the algorithm. Moreover, in real time applications, this approach can be implemented as a parallel work. This is, while the FPGA is calculating the packing, it's calculating the sizes for the placement of next packets. Nevertheless, it has to be taken into account, that it would be only feasible in case the environment leads a variation of the channel conditions with less quickness to the computing process of calculating sizes.
Different variations for mutation operator and evolution strategy were modelled and implemented in order to look for a variety of algorithms to face the problem. In chapter 7 this different models are applied. It has to be said that the approaches customized didn't improve in a significant manner the results achieved with the algorithm with the standard GAlib implementations. But, at least it was usefull to know that investigation on trying to do a more locally mutation, when implementing a normal distributed change mutation, or ensuring more genomic diversity, by implementing deterministic crowding, doesn't deserves the biggest efforts.
The effect of genetic operators was also observed. In this way, the crossover doesn't has a significantly effect on the evolve of the genetic algorithm, the results variate few when applying more or less crossover. Also, a significant fact was seen on genetic operators, this is that better performance of the genetic algorithm is achieved when swap and change operators are applied together (depending on the same mutation ratio) and that best results are normally achieved when applying a mutation ratio near 10%.
Parameters of the genetic algorithms were also proved by running genetic algorithms with variation on these parameters. Two of these parameters are size of the population and number of generations. With these two parameters, the tradeoff between computational complexity and quality of the results is faced. For scenario I it was observed that there was a lower bound that when increasing complexity, genetic algorithm seemed not able to improve. Also, when complexity approaches to this value, the incremental improve is significantly reduced. Concretely, it was seen that running the genetic algorithm over 100 generations (with a fix population of 100) the incremental improvement of solutions highly decrease. A similar effect was observed with the size of the population, when increasing the size over 300 the improve of the solutions slowed down.
With the design and implementation done it has been proved that near optimal scheduling can be done with expensive heuristics. With the suitable operators and parameters, a placement only 10.9% far from the reference value was found. This can be used as reference when doing real implementations (cheaper heuristics) of the frequency selective scheduler. Knowing how far can a placement algorithm go without restrictions of complexity can be valuable information. In this way it can analyzed, wether it's usefull to invest resources on improving results or assume that the bound is close enough.

With the same aim of what was exposed last paragraph. A relation of how can AMC improve the SINR of an subcarrier random permutation approach, like FUSC or PUSC, is also presented. This improve, that depends on the mean size of the burst packed in the time/frequency resource, is also a valuable bound, for nearer to real time applications than the one designed and implemented in this thesis, to face the tradeoff between quality of the results and computational complexity.

8.2 Outlook

The model designed was able to face the optimization problem of scheduling with frequency selectiveness in an environment of 1 frame. Further investigation would be interesting applications in a more real case. Doing the simulation for more than one frame leads to be able to manage QoS parameters (delay, jitter, packet dropping probability or bit rate). Simulation of multiple cells would also lead to a more real implementation. By taking into account interference between users of neighbour cells transmitting at the same frequency a further point of view has to be taken to solve the overall problem of trying to find a nearest as possible optimal solutions to all cells. This more realistic approach makes the optimization problem more optimization as more parameters has to be taken into account, because of that the space of solutions increases and then heuristics are even more likely to solve the problem.
Another path to the objective of a real implementation of the scheduler with genetic algorithms would be the use of cheaper heuristics, this means reducing the computational complexity. In the subsection 7.2.2 it was observed that biggest incremental improve was done from 10 to 100, both in size of the population and number of generations. Therefore, it can be interesting to center efforts on working in this zone of computational complexity.
The placement algorithm designed was static over generations. It seems reasonable that a dynamic placement algorithm could face in a better way an optimization problem when using heuristics, as solutions are better over generations, restrictions of the placement algorithm would be progressively relaxed. For example, allowing that packets are placed starting from a subchannel situated in the half of an already started level. It would give, without changing the representation of the solutions, a higher degree of freedom to placement algorithm when the space of solutions have already been improved and this can leads to the encounter solutions that improves when changing the placement algorithm; and that would be not findable with the strict behaviour of the placement algorithm.

A Selective simulation

In this chapter class diagrams of both parts of the program (startup and placement phase) are presented.

A.1 Startup phase

Startup phase consists on two classes and a struct. The class diagram can be seen in figure A.1, most important attributes are presented.

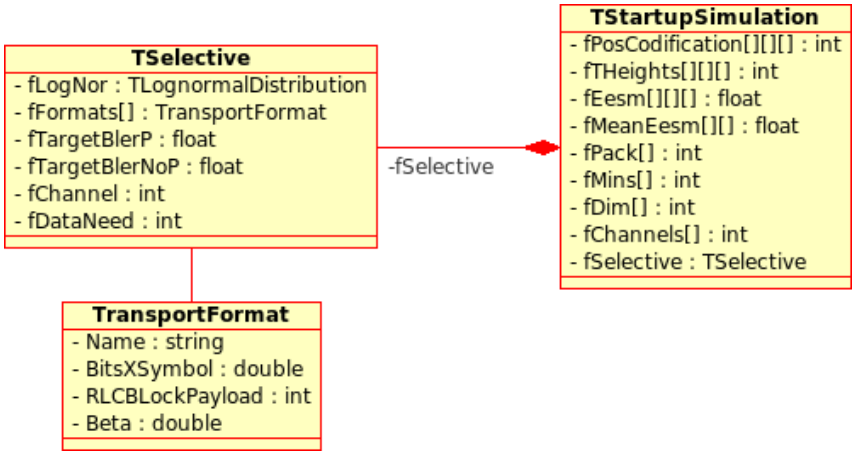

Figure A.1: Class diagram of the startup phase

TStartupSimulation

This class manages the simulation. It asks TSelective to calculate values for all users, subchannels and widths and saves the option that requires less subchannels per user (that are after used to calculate reference values for the results).
It also deals with opening and closing files. It receive the fading sequence calculated in Matlab with the winner model and the BLER tables. Then saves the information calculated (heights, mean SINR over averaging the channel, minimal number of subchannels per user and the positions vector that is used to print placements with the help of fill function of Matlab), because it can be used on the placement phase.

TSelective

TSelective deals with the calculation of the values. Number of FEC blocks necessaries are calculated, EESM methods applied, comparison between burst error rate and target BLER and therefore transport format and height selection.

TransportFormat

Transport format is a struct used to save the values needed from the different transport formats used.

A.2 Placement phase

Placement phase consists on 7 classes, in figure A.2 classes can be consulted, most important attributes are also presented.

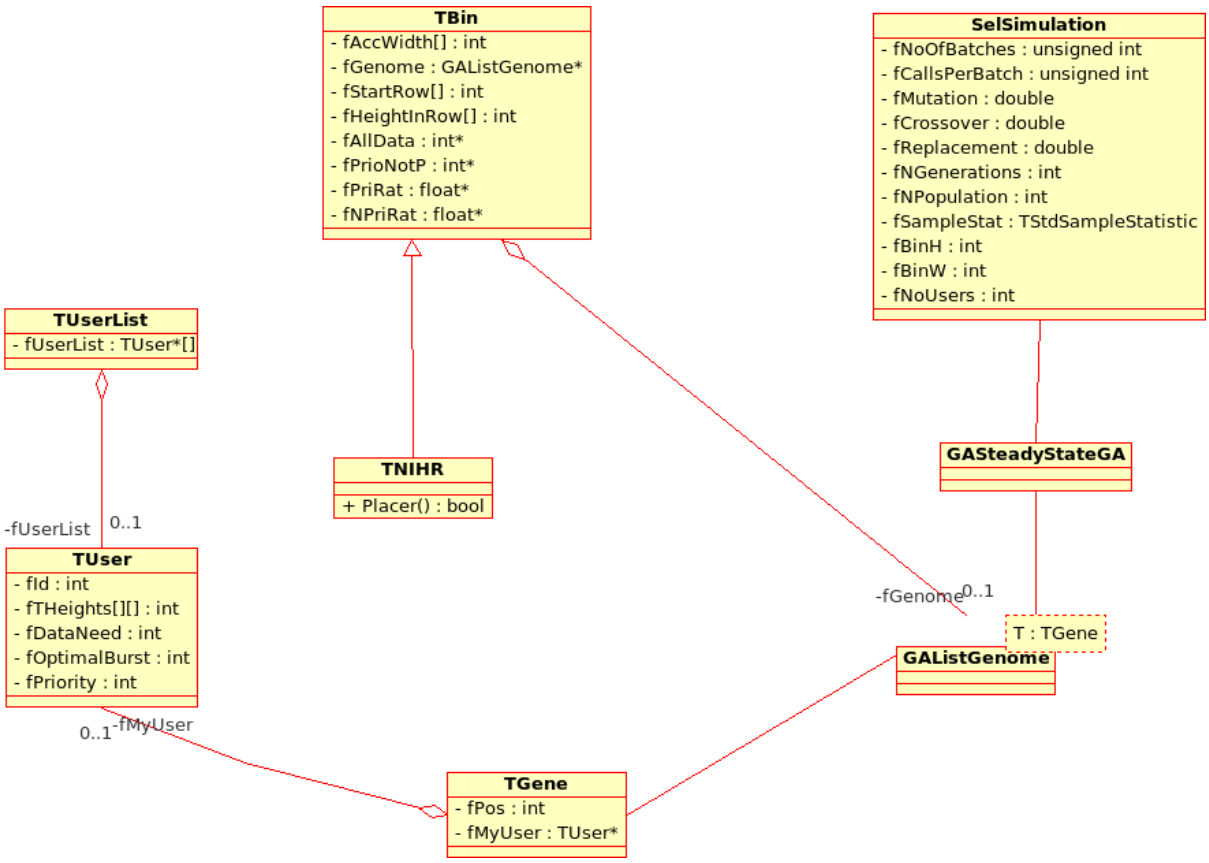

Figure A.2: Class diagram of the placement phase

SelSimulation

Deals with the control of the simulation (Monte Carlo methods), parsing, initialization of classes and variables, management and printing of the results.

GASteadyStateGA

It's a class from the GAlib. Deals with evolution and selection strategy, it has been customized to make the deterministic crowding approach. A genome has to be passed to the constructor of the GASteady State.

GAListGenome

GAListGenome is a genome class from GAlib. The object of the list is a template. This class deals with the initialization of the genome, the objective function and the genetic operators. In this implementation the objective function was done and also mutation operator is implemented to make all the models described in subsection 6.2.7.

TGene

TGene is the template used in GAListGenome class. It has two attributes a pointer to the user which the gene is referred to and the position where the placement algorithm would start to place it.

TUserList

It's an array of pointers to users. Is used in the initialization process to assign users to genes.

TBin

This class deals with the placement algorithm itself, it receives a reference of the genome to manage the genes.. With different arrays controls the state of the subchannels. fAccWidth controls the accumulated width in each of the frequency bins of the common resource, fStartRow saves for each frequency bin which is the first frequency bin of its level, fHeightInRow saves the height of the first element of every level (if there's no packets placed, then it's leaved to 0).

TNIHR

It's the implementation of the the placement algorithm describe NIHR (Not Increasing 1st Height of the Row) for the class TBin. The placer functions deals with placement algorithm implementation described.

B BLER tables

BLER tables that maps SINR with BLER values depending on the transport format extracted from [27] are here presented.

SINR	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
BLER	0.8720	0.629	0.347	0.144	0.0606	0.0363	0.0178	0.0118	0.00838	0.00538	0.00322

Table B.1: BLER table QPSK 1/2

SINR	2.0	2.5	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5	7.0
BLER	0.999	0.988	0.902	0.652	0.333	0.117	0.0337	0.0133	0.0043	0.00129	0.000645

Table B.2: BLER table QPSK 3/4

SINR	BLER
5.0	0.968
5.5	0827
6.0	0.536
6.5	0.258
7.0	0.129
7.5	0.0748
8.0	0.0559
8.5	0.0413
9.0	0.032
9.5	0.0249
10.0	0.0178
10.5	0.00924
11.0	0.00645
11.5	0.0038
12.0	0.00193

Table B.3: BLER table 16QAM 1/2

SINR	BLER
7.0	1
7.5	1
8.0	1
8.5	0.966
9.0	0.941
9.5	0.693
10.0	0.312
10.5	0.09
11.0	0.0228
11.5	0.00881
12.0	0.00365
12.5	0.00279
13.0	0.00129
13.5	0.000215
14.0	0.000215

Table B.4: BLER table 16QAM 3/4

SINR	BLER
10.0	1
10.5	1
11.0	1
11.5	1
12.0	0.998
12.5	0.966
13.0	0.789
13.5	0.425
14.0	0.156
14.5	0.0716
15.0	0.0398
15.5	0.0245
16.0	0.0198
16.5	0.0135
17.0	0.0103
17.5	0.00537
18.0	0.00279

Table B.5: BLER table 64 QAM 2/3

SINR	BLER
12.0	1
12.5	1
13.0	1
13.5	0.999
14.0	0.987
14.5	0.504
15.0	0.186
15.5	0.0542
16.0	0.0542
16.5	0.0269
17.0	0.0191
17.5	0.00989
18.0	0.00430
18.5	0.00172
19.0	0.00172
19.5	0.00107
20.0	0.00107

Table B.6: BLER table 64QAM 3/4

C List of figures

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D References

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F Author's Statement

Hereby I certify that I know and I accept that I have no right to exploit the results of my Master Thesis by any means without the written permission of the Institute of Communication Networks and Computer Engineering (IKR).

Furthermore, I certify that I have realized this work on my own, and that all sources that I have used or consulted are duly noted herein.

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