Optimisation Methods for Dynamic Frequency Planning in OFDMA Networks

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***Abstract*—To overcome interference, OFDMA networks support different but fixed frequency reuse schemes and sub-channel allocation techniques. However, these fixed schemes and techniques are not the most suitable solutions in mobile scenarios, where the behaviour of the channel and the users are continuously changing during the day-time. This paper presents a new approach to the frequency assignment problem adapted to OFDMA networks, called Dynamic Frequency Planning, which in turn may decrease the interference and increase the capacity of the network by around 20%. DFP operates in a regular basis, adapting the network configuration to the time-dependent channel conditions and user requirements. On the other hand, DFP uses novel algorithms to estimate the inputs of the frequency assignment problem and tailored versions of meta-heuristic such as Simulated Annealing and Tabu Search, or Greedy Algorithms to solve it. Further discussion about the trade off between the quality of the solution and computing time when using meta-heuristic or greedy algorithm is provided. This paper also indicates, when running DFP, how to check the improvements in the network performance. Experimental evaluations carried out using system level simulations show the boost in the capacity when using DFP.**

I. INTRODUCTION

In the recent past, technologies such as *GSM (Global System for Mobile Communication)*, *DCS (Digital Cellular System)* and *GPRS (General Packet Radio Service)* were used to satisfy the user requirements, which were principally based on voice and small bit rate packet services.

Nowadays, technologies such as *WCDMA (Wide-band Code Division Multiple Access)* and HSPA *(*High-Speed Packet Access) are used to fulfill the user desires. These networks are based on packets circuits, being able to provide new services such as *VoIP (Voice over IP)* and *WB (Web-Browsing)* with a certain quality of service and throughput.

In the near future, however, the demands of the users will grow up and new services will be needed, requiring higher levels of quality of service and throughput.

To satisfy these requirements, the manufacturers, operators and research community are working in the standardization and development of new networks such as *WiMAX (Wireless Interoperability for Microwave Access)* [1] and *LTE (Long Term Evolution)* [2], which are considered one of the most suitable technologies for future deployments of cellular networks due to its capability of supporting quality of service and high data rates.

Both WiMAX and LTE are based on an *OFDMA (Orthogonal Frequency Division Multiple Access)* physical layer [3] [4], which supports several key features necessary for delivering broadband services at low and high speeds, for example, scalable channel bandwidths, high spectral efficiency, simple implementation and interference tolerance due to sub-carrier orthogonality in both *DL (DownLink)* and UL *(UpLink)*.

In OFDMA, different users are allocated to different subsets of sub-carriers called sub-channels, facilitating the possibility of multi-user or frequency diversity to significantly improve the system capacity.

On the other hand, WiMAX or LTE networks will not be able to operate efficiently without the help of advanced network planning and optimisation tools, which include functions such as automatic coverage planning or capacity improvement by frequency planning, common/joint radio resource management with other technologies, etc. Such optimisation tools may enhance network performance by more than 20% [5] .

Interference avoidance is always desirable when performing network planning and optimization, since the interference damages the signal quality of both DL and UL transmissions, reducing the capacity of the network.

In WiMAX or LTE networks, intra-cell interference may be neglected due to the features of OFDMA (sub-carrier orthogonality). Therefore, operators must cope with inter-cell interference in order to enhance the network performance.

To overcome inter-cell interference, OFDMA networks are flexible in terms of radio resource management techniques, supporting different frequency reuse schemes and sub-channel allocation techniques, which in turn may decrease the inter-cell interference and increase the network capacity [6]. However, these fixed schemes and techniques are not the most suitable solution in mobile scenarios, where the behaviour of the channel and the users are continuously changing [7].

This paper provides to the network operators a new approach to the frequency assignment problem adapted to OFDMA networks, called *DFP (Dynamic Frequency Planning)*, which can decrease the interference and increase the capacity of the network significantly by dynamically adapting the radio frequency parameters to the environment. This paper also indicates, when running DFP, how to check the improvements in the network performance.

On one hand, DFP operates on a regular basis, tailoring the network configuration to the time-dependent environment and user requirements. On the other hand, DFP uses novel algorithms to estimate the constraints of the frequency assignment problem and adapted versions of meta-heuristic such as *SA (Simulated Annealing)* and *TS (Tabu Search)*, or Greedy Algorithms to solve it. Further discussion about the trade off between accuracy and computing time when using meta-heuristic or greedy algorithm is provided.

Experimental evaluations carried out on system level simulations, using *EMI (Experimental WiMAX simulator)* [8] show the boost in the capacity when using DFP.

OFDMA DFP problem is interdisciplinary as it involves communications and operations research subproblems.

This paper is organized as follows. Section II introduces the DFP approach, indicating how the inputs are calculated and how the problem is formulated. Section III summarizes the optimization algorithms used to solve the DFP: meta-heuristics and greedy algorithms. Section IV indicates how to check the improvements of the network when using DFP. Section V presents several experimental evaluations and the derived results about the optimization process and also about the network performance. Finally, some conclusions are drawn in Section VI.

II. DYNAMIC FREQUENCY PLANNING

The *RFP (Radio Frequency Planning)* is one of the key techniques used in multi-carrier wireless communication networks such as GSM *(Global System for Mobile communications)* or DCS *(Digital Cellular System)* to minimize inter-cell interference [9].

The aim of the RFP is to allocate a certain subset of frequencies to each sector of the network while minimizing the global inter-cell interference of the system. The challenge comes from the fact that the solution must satisfy different constraints. For example, in contemporary networks a high degree of frequency reuse is imposed, due to the limited number of available frequencies [10]. On the other hand, there are different frequency interference constraints which determine that the frequencies assigned to some sectors must satisfy different restrictions. Finally, equipment constraints should also be taken into account.

Since OFDMA is a multi-carrier technology where the available bandwidth is broken down into sub-carriers, frequency reuse schemes and radio frequency planning can be used to mitigate inter-cell interference.

In WiMAX and LTE , the available subcarriers may be divided into several groups of subcarriers called sub-channels, since the OFDMA PHY layer allows sub-channelization in both the DL and the UL. Therefore, different subchannels may be allocated to different users as a multiple-access mechanism.

When using *TDD (Time Division Duplex)* and OFDMA, the frequency and time domain are divided into sub-channels and symbols, respectively, as can be seen in Figure 1. The sub-channels and symbols form the minimum frequency and time resource-unit allocated by the base station, respectively. The number of available sub-channels and symbols in the TDD/OFDMA frame depends on the network configuration and they could vary to support different traffic profiles. The sub-channels may be built by using pseudo-randomly distributed or contiguous sub-carriers among the channel [6]. Sub-channels using distributed sub-carriers benefits from frequency diversity (suitable for mobile traffic), while sub-channels using contiguous sub-carriers benefits from multi-user diversity (suitable for static and nomadic traffic).

As a result, the slot is the minimum frequency-time resource that can be allocated by the base station. The slot is composed of one sub-channel and one, two or three OFDM symbols, which depends on the network configuration. The bandwidth allocation depends on demand, channels conditions and QoS requirements.

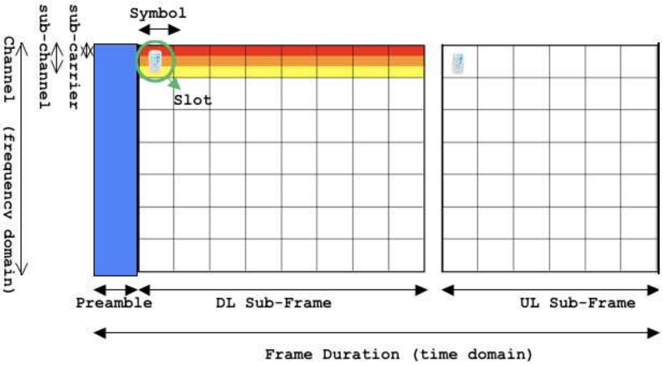

Fig. 1. OFDMA Frame.

DFP is a new approach to the frequency assignment problem tailored to OFDMA networks. DFP operates on a regular basis to cope with the changing behaviour of the traffic throughout the day. It can run from few times a day to on a second by second basis depending on the needs of the operator. The second option is challenging in terms of computing time and network optimisation. However, it can be done due to the speed of the algorithms used to determine the inputs and the techniques used to solve the optimisation problem.

DFP will lead to remarkable improvements in the network performance, breaking with the concept of the classical RFPs used in GSM and DCS networks, which are usually operated on a week per week basis. In OFDMA, different to GSM or DCS, *TRX (Transceivers)* do not exist, and the information is modulated and demodulated by using *IFFT* and *FFT (Inverse/Fast Fourier Transform)*, respectively. It permits the radio resource management engine to rapidly select which frequencies are allow to send information. Therefore, different aspects need to be considered when applying RFP theory to OFDMA technologies.

In the rest of the paper, only downlink is considered. The reason behind this is that the primary use of WiMAX or LTE is for data services, which are asymmetrical, i.e., more demands on the downlink than uplink.

A. DFP Inputs

Let us model an OFDMA network as a set of N sectors $\{S_1, S_2, ..., S_N\}$, where each sector S_i requires a certain number of sub-channels D_i.

The DFP problem consists of assigning a certain number of sub-channels D_i to each sector S_i, while minimizing the global system interference, taking into account interference restrictions between sectors. Since the number of required sub-channels is typically bigger than that is available, sub-channel reuse is needed. The sub-channel reuse leads to frequency interference.

Frequency interference occurs when two different signal overlap in the frequency domain. It happens when two different signals are using the same or different but insufficiently separated frequencies within the same space area. They are called co-channel and adjacent-channel interference, respectively. When both transmissions are carried by the same sector, the interference is called intra-cell interference, while when the transmissions are carried by different sectors, the interference is called inter-cell interference. Since adjacent-channel and intra-cell interference can be neglected due to the features of OFDMA (sub-carrier orthogonality), inter-cell interference is the source of interference that must be avoided. Inter-cell interference can be accurately represented by a *Restriction Matrix* W of size $N \times N$.

Therefore, the first key step is to estimate the number of sub-channels required D_i to satisfy the users bandwidth demand per sector. Then, the second key step is to characterize the inter-cell interference $w[i, j]$ between the sectors of the network. The algorithms used for both capacity and interference estimation are depicted in detail in the next subsections. Moreover, the constraints introduced by the nature of OFDMA must also be taken into account. For example, different sub-channels of the same sector cannot use the same frequency because it is not physically possible.

Once all the inputs are obtained, optimisation algorithms will be used to assign the available frequencies to the required sub-channels.

Capacity Estimation

In this process, the optimal number of required sub-channels D_i per sector S_i, which is function of the traffic and changes during the daytime, is approximated.

First, the set of users $UE_i \in \{1, 2, ..., M_i\}$ in sector S_i, which are able to decode the preamble, is estimated.

Afterward, the number of requested slots RS_m for each user m of sector S_i is calculated, dividing the requested capacity RC_m from the user in $kbps$ by the supported average symbol efficiency SE from the slot in $kbps$:

$$RS_m = RC_m / SE \tag{1}$$

Note that the average symbol efficiency SE depends on the average modulation and coding selected by the users within the sector. SE can be obtained from previous frames or it can be derived from the following formula taking into account network statistics:

$$SE = SaSc \cdot RAB_{eff} / T_{frame} \tag{2}$$

where $SaSc$ is the number of sub-carrier per sub-channel, RAB_{eff} is the average radio access bearer efficiency in bits per sub-carrier (modulation and coding), and T_{frame} is the frame duration.

Finally, the requested sub-channels D_i for each sector S_i is calculated, dividing the aggregated number of requested slots RS_m for each user m of each sector S_i by the number of symbols per sub-channel $SySc$:

$$D_i = \frac{1}{SySc} \sum_{m=1}^{M_i} RS_m \tag{3}$$

The higher the accuracy of the capacity estimation is, the better the performance of the RFP will be.

The number of sub-channels needed for each sector is presented in form of a *Demand Vector*, which is used by the optimization algorithms together with other information to calculate the global interference of the system.

Interference Estimation

This process approximates the inter-cell interference between sectors of the network in terms of percentage of time. This can be implemented by taking into account either measurement data or accurate path loss simulations, as follows.

It is considered that two sectors, S_i (server) and S_j (neighbour), interfere with each other (*interference event*$_{ij}$) every time the power level of the carrier signal (coming from S_i to a served user) is smaller than the power level of a neighbouring interfering signal (coming from S_j to the user) plus a threshold (Figure 2).

The reader may think that the comparison carrier signal to sum of all the interferers should be more appropriated. However, due to the target here is to characterized the sector to sector interference and given that one slot can be used by one user at a time, the ratio signal to interferer is more appropriate.

The threshold is considered as a protection margin against interference and it is set by the operator, depending on planning targets. The bigger the protection margin is, the bigger the number of estimated interference events will be.

The percentage of time of interference between both sectors S_i and S_j is calculated as the ratio between the total number of interference events and measurement reports. Note that this ratio does not accurately quantify the real interference between sectors, but accurately characterizes it.

This information, the total number of interference events and measurement reports can be obtained from real measurement data or accurate path loss simulations.

Since measurement data is accurate but dominated by calls and the position of the users, we prefer to use both real measurement data and accurate path loss simulations.

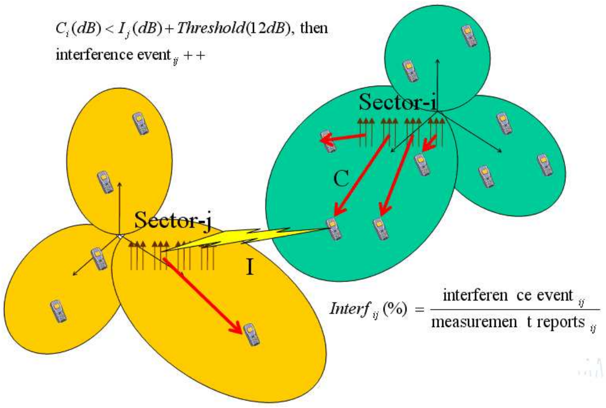

Fig. 2. Interference Estimation.

Why measurement data is dominated by the calls? Consider an scenario of a large shopping centre and a small office building, the average measures will be dominated by the users in the shopping centre, being unfair the situation and the resulting planning for the users in the office building nearby, if only measurement data is taking into account.

Monte Carlo simulations and propagation models are used as follows to reduce the correlation between the results and the position of the users First, using different independent and random distribution of the user within the planning area by means of different snapshots. Afterwards, calculating the strength of the carrier and interfering signals by means of accurate path loss estimation and finally, counting the number of interference events and measurement reports by means of fast simulations.

The higher the accuracy of the interference estimation is, the better the performance of the radio frequency planning will be.

The calculated sector to sector coupling or interference is given in form of a restriction matrix W of size $N \times N$. The Restriction Matrix is used by the optimization algorithms jointly with other information to calculate the global interference of the system.

The idea of the restriction matrix described here is similar to the coupling matrix presented in [11], In this research the coupling matrix is used for UMTS network planning and optimisation. Although, the idea is similar the way that both matrices is calculated is different, since they represent the interference of different kind of networks, WCDMA and OFDMA.

Finally, note that DFP does not to be perform in a frame by frame basis, it can be run on per second, per minute or per hour basis. Then, fast fading is irrelevant in the calculations and it can be neglected for simplicity, since the average performance of the network is taken into account .

Example Case on Inputs Calculation

An example of how the demand vector and restriction matrix look like is given Table I. In the following, the scenario and the values used to obtain both inputs are presented.

The scenario is given in Figure 3, where the density of the traffic maps are $40\, users/km^2$ in the surroundings and $80\, users/km^2$ in the hot spot, while the requested capacity of each user is $12.2\, kbps$ (VoIP).

On the other hand, the number of sub-channels and symbols of the TDD/OFDMA frame for all the sectors of the scenario are 16 and 19, respectively, while the average symbol efficiency and frame duration are $19.9\, kbps$ and $5\, ms$, respectively.

Finally, the interference margin used is 12dB.

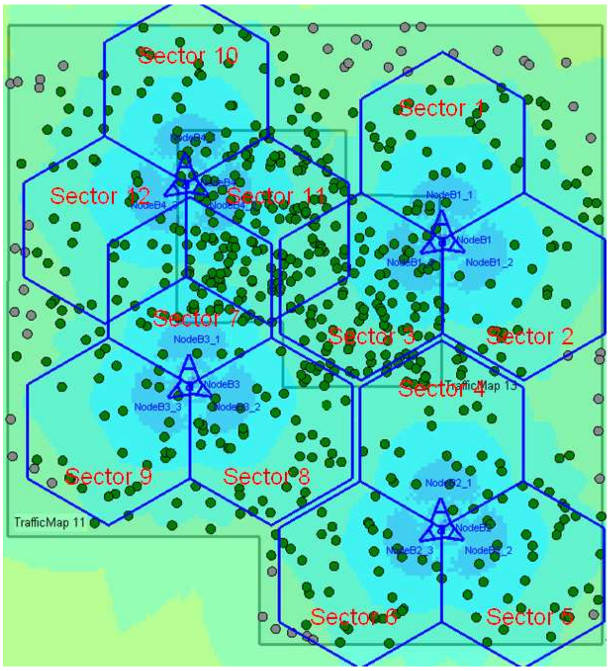

Fig. 3. Example Scenario.

TABLE I
DEMAND VECTOR AND RESTRICTION MATRIX

Sector	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	D_i
1	0	38.2	41.1	0	0	0	2.9	0	0	11.7	26.4	0	4
2	30.4	0	47.8	34.7	4.3	0	0	0	0	0	0	0	3
3	23.2	45.3	0	24.4	0	3.4	31.3	37.2	0	4.6	45.3	0	8
4	0	39.2	46.4	0	28.5	25	0	32.1	0	0	0	0	4
5	0	0	0	52.9	0	29.4	0	0	0	0	0	0	4
6	0	0	0	39.2	42.8	0	0	21.4	10.7	0	0	0	4
7	0	0	23.4	4.2	0	0	0	44.6	23.40	0	76.5	65.9	6
8	2.1	8.6	36.9	56.5	0	43.4	39.13	0	34.7	0	23.9	2.1	6
9	0	0	0	0	0	0	39.2	42.8	0	0	3.57	3.14	4
10	20	0	12.5	0	0	0	17.1	0	0	0	45	22.5	5
11	30.6	0	45.5	0	0	0	50.49	19.8	0	37.6	0	29.7	8
12	0	0	0	0	0	0	65.2	0	4.3	39.1	30.4	0	3

Note that the demand vector coherently characterizes the traffic sectors. For example, sectors S_3 S_{11} situated in the hot spots require more sub-channels than all the rest.

When reading the Restriction Matrix, the coupling between sectors can be derived. For example, if S_1 S_2 would use the same sub-channel, there would be an interference event in the

38.2% of the transmissions, while, if S_1 S_3 would use the same sub-channel, there would be an interference event in the 41.1% of the transmissions. Then, if we would have to decide between allocate the same sub-channel to the pair S_1 S_2 or S_1 S_3, we would choose the first option.

Moreover, the restriction matrix coherently characterizes the interference relationship between sectors, for example, the restriction is null when sectors are far away form each other such as the pair $S_5 S_{10}$. On the other hand, the restriction between adjacent sector grows when more user are situated in the cell edge such as $S_7 S_{11}$ and $S_7 S_{12}$.

B. Optimization in DFP

Given a network defined by N sectors $\{S_1, S_2, ..., S_N\}$ with D_i required sub-channels, K available sub-channels $\{1, 2, ..., K\}$, and the restriction matrix W, the optimisation problem can be defined as a Mixed Integer Program as follows:

$$min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} \frac{w_{i,j}}{D_i \cdot D_j} \cdot y_{i,j,k} \tag{4}$$

subject to:

$$\sum_{k=1}^{K} x_{i,k} = D_i \qquad \forall i, k \tag{5}$$

$$x_{i,k} + x_{j,k} - 1 \leq y_{i,j,k} \qquad \forall i, j, k \tag{6}$$

$$y_{i,j,k} \geq 0 \qquad \forall i, j, k \tag{7}$$

$$x_{i,k} \in \{0, 1\} \qquad \forall i, k, \tag{8}$$

where $x_{i,k}$ is a binary variable that indicates whether sector S_i uses sub-channel k or not. Constraint (5) imposes that sector S_i must use D_i sub-channels. Inequality (6) and (7) together force that in an optimal solution, $y_{i,j,k} = 1$ if and only if both sectors S_i and S_j use sub-channel k, and $y_{i,j,k} = 0$ otherwise. Finally, the cost function is the sum of the interference between all pair of sectors S_i, S_j taking into account all the frequencies k. Since the capacity of the sectors is not considered when the restriction matrix W is built, the interference restrictions $w_{i,j}$ must be divided by the number of used sub-channels D_i, D_i for both sectors S_i, S_j. The bigger the number of sub-channels per sector, the smaller the chance of interference. In this way, the percentage of time in which both sectors S_i and S_j are transmitting at the same time with the same sub-channel k is estimated.

Unfortunately, the formulation (4)–(8) is too complex to be solved directly by using an *ILP (Integer Linear Programming)* solver, therefore one must apply some kind of heuristic approach.

III. SOLVING DFP BY USING DIFFERENT OPTIMIZATION ALGORITHMS

This section briefly presents two meta-heuristics and various greedy algorithms to solve the DFP problem. Detailed information about their behaviour and tuning will be given in the next section.

Note that meta-heuristics will find higher quality solutions than greedy algorithms at the expense of running time. However the faster the optimization method is, the more responsive the system can be to the traffic changes. Therefore when using DFP in an on-line scenario, it may worth using faster algorithm even if they may produce slightly worse solutions.

A. Computing the solution by using Meta-Heuristic

Meta-heuristic algorithms are general optimization frameworks used to find good solutions in reasonable time to intractable optimisation problems. These methods are based on a search within the solution space. Though, they do not guarantee the optimality of the solution, they often performs very well in practice. Next section shortly sketch the main features of the meta-heuristic used in this work: Simulated Annealing and Tabu Search.

In our case, a solution s is a frequency assignment fulfilling all the constraints. On the other hand, two solutions s and $s' \in S$ are neighbors if only if they differ at the value of only one sub-channel of one sector. The neighborhood of the solution s is composed of all neighbor solutions or a set of them. The cost function $f(s)$ of a solution $s \in S$ corresponds to the global system interference of such solution. Note that for an interference free assignment s, $f(s) = 0$.

Simulated Annealing

SA [12] is a meta-heuristic algorithm, based on a random search within the solution space.

When applying SA to a minimisation problem, we move from the current solution s to a random neighbour s' based on a probabilistic process. The probabilistic process is defined by an acceptance probability function $P(f(s), f(s'), T)$ depending on the value of $f(s)$ $f(s')$ and on a factor T called temperature .

The essential properties of a good acceptance probability function are the followings: First, it must be one when $f(s) > f(s')$, meaning that the system must move to a neighbor state when it is better than the current solution. Second, it may be higher than zero when $f(s) < f(s')$, meaning that the system may move to a neighbor state even when it is worse than the current solution. But the higher increment in the cost the lower the possibility of the acceptation. This feature prevents the search from becoming stuck in local minima.

The temperature is a global parameter that decreases with the time in an exponential fashion dictated by the so called *annealing factor*. The initial temperature and the annealing factor are set by the user. The smaller the temperature, the more likely the algorithm will reject worsening neighbours. The slower the annealing factor, the better solution we may expect.

In this way, the system is expected to wander initially around a broad region of the search space containing good solutions, then drift toward better and better solutions and finally move downhill similarly to the steepest descent heuristic.

A general SA algorithm that can be directly used to solve the DFP problem is given below.

```
begin
    $s = s0; fs = f(s)$ // Random solution
    $bs = s; fbs = fs$ // Best solution
    $t = 0$ // Initialise temperature and iterations
    $k = 0$
        while $k < kmax$ do
            $k = k + 1$ // Increase iterations
            $sn = neighbour(s)$ // Select a neighbour
            $fn = f(sn)$ // Compute its cost function
            if $fn < fbs$ then // Is this a new best so far?
                $sb = sn; fbs = fbn$ // Yes, save it
                $continue$ // Go for another iteration
            if $P(fs, fn, t)$ then // Should we move to it?
                $sb = sn; fbs = fbn$ // Yes, move to it
        end
        $t* = annealing\_factor$ // Update Temperature
end
```

Tabu Search

TS [13] is a meta-heuristic algorithm, based on a so called *clever search* within the solution space.

When applying TS for a minimisation problem, first the neighbourhood of the current solution need to be identified. If the problem is small all the neighbours can be considered within the neighbourhood. If the problem is large the neighbourhood can be limited to a certain value, decreasing the quality of the search but improving the running time. In our case, the size of the neighbourhood is limited to a certain value and the neighbours are randomly selected. Afterwards, we move from the current solution s to the best neighbour s'. The best neighbour is the one which achieves the best cost function within the neighbourhood. Therefore, when looking for the best neighbour, all the neighbours in the neighbourhood needs to be checked. Note that the best neighbour does not need to improve the cost function. The system may move from a current state to a neighbor state even when worsening the cost function to avoid getting stuck in local minima.

TS introduces the concept of tabu list [10] to avoid the problem of possible cycling or infinite loop. In its simplest form, a tabu list forbids solutions that have certain attributes or solutions that have been visited in the recent past.

```
begin
    $s = s0; fs = f(s)$ // Random solution
    $bs = s; fbs = fs$ // Best solution
    $tl = 0; k = 0$ // Initialise tabu list and iterations
        while $k < kmax$ do
            $k = k + 1$ // Increase iterations
            $n = 0$ // Initialise checked neighbours
            while $n < nmax$ do
                $n = n + 1$ // Increase checked neighbours
                $sn = neighbour(s)$ // Select a neighbour
                $fn = f(sn)$ // Compute its cost function
                if $fn < fbs$ then // Is this a new best so far?
                    $sb = sn; fbs = fbn$ // Yes, save it
                    $continue$ // Go for another iteration
                $check\_tabu\_list(sn))$ // Check if the movement is tabu
                if $ok$ then
                    $N.push\_back(sn)$ //Ok, possible movement
            end
        end
        $[sbn, fbn] = best\_neighbourh(N)$ //Select best neighbour
        $s = sbn; fs = fbn$ // Move to best neighbour
        $update\_tl(s)$ // Update Tabu List
end
```

A general TS algorithm that can be directly used to solve the DFP problem is given here.

B. Computing the solution by using Greedy Algorithms

To obtain good approximate solutions within a reduced amount of computing time, we have devised greedy and reverse greedy procedures that construct a solution. They run incomparably faster than meta-heuristics, which it is a desirable feature for on-line solution.

Here, we presented the main features of the seven greedy algorithms used in this research work.

Selected Insertion SI

In this greedy algorithm , the sectors which have the larger coupling or restricction $w_{i,j}$ are identified in the restriction matrix. Afterwards, both sector are given frequencies which minimize the global system interference. During the assignment of the frequencies the constraints are always taken into account. Once both sectors have been served, a new pair of sectors is identified and new frequencies are allocated to them. This process finish when all sectors meet their requirements.

Insertion Algorithms

The following algorithms maintains a list of assigned frequencies to each node. This assignment consists of at most as many frequencies as it is required. We start with empty assignments. At each iteration, we first compute the *the best* frequency f_i to be added to sector S_i, i.e. the frequency which increases the cost function the least. Then we choose a sector S_i according to the rules RI, $MinI$ or $MaxI$ (see below) and add f_i to its list.

Random Insertion (RI): By using this algorithm, simply a random sector is selected at each iteration.

Minimum Insertion (MinI): Here the sector increasing the cost function *the least* is selected.

Maximum Insertion (MaxI): In contrast to $MinI$, here the sector increasing the cost function *the most* is selected.

Removal Algorithms

The following set of algorithms similar to the previous one, but here we store at least as many frequencies as it is required. We start with full assignments. At each iteration, we first compute the *the best* frequency f_i to be removed from sector S_i, i.e. the frequency which decreases the cost function the most. Then we choose a sector S_i according to the rules RI, $MinI$ or $MaxI$ (see below) and remove f_i from its list.

Random Removal (RR): By using this algorithm, simply a random sector is selected at each iteration.

Maximum Removal (MaxR): Here the sector decreasing the cost function *the most* is selected.

Minimum Removal (MinR): In contrast to $MinI$, here the sector decreasing the cost function *the least* is selected.

Note that the point of view of the assignment is changed from RI, $MinI$ and $MaxI$ to RR, $MaxR$ and $MinR$. In the first cases the assignment is started from the scratch, where no frequencies have been assigned to any sector, however, in the second cases, we assume that all sectors are using all frequencies, and then we remove frequencies from all the sectors till all the sectors fulfill their capacity needs.

Intuitively, we can say that $MinI$ tries to delay the difficulties by choosing a sector to which it is cheap to assign a new frequency, while the algorithms $MaxI$ tries to face the difficulties by choosing a sector to which it is costly to assign one. The conceptual difference between $MaxR$ and $MinR$ is similar.

IV. KEY PERFORMANCE INDICATORS

In this section, we will briefly overview, how the improvements of the system should be check when running DFP in a network.

Firstly, *DT (Drive Test)* measurements in dedicated mode can be performed to check the signal quality over the planned area. Afterwards, such DT must be compared to previous DTs performed over the same area, day and time. The percentage of good quality samples is a good *KPI (Key Performance Indicator)* in this case.

Secondly, network statistics such as handovers and intra-cell handovers can be applied to estimate the behavior of the frequency planning. The number of intra-cell handovers is reduced when the interference of the cell is reduced.

Also, measurement reports can be employed since the number of interference reports should be decrease when the interference of the planned area decreases. Tools such as BA-List Recording are suitable for this task.

Finally, commercial tools or system level simulations such as Forsk Atoll [14] or EMI [8] can be used to check the goodness of the frequency plan. These tools are able to provide interference predictions based on fragments frequency assignment.

V. RESULTS

This section presents an experimental evaluation of the proposed solutions to the DFP problem. First, we evaluate the meta-heuristics. Afterwards, we compare the meta-heuristics to the greedy algorithms. Finally, by comparing the solutions by using system level simulations, we quantify the real improvement in the network performance. This simulation has been carried out using CWIND's static system level simulator EMI [8].

A. Optimisation Results, SA versus TS

To compare SA and TS, the parameters of both algorithms were tuned in order to achieve the best performance in $4\, second$. After tuning SA, the initial temperature and annealing factor were set to 1000 and 0.9999763, respectively. Whereas, after tuning TS, the neighbourhood and tabu list sizes both were set to 25.

The performance of tuned SA and TS in terms of interference versus time is depicted in Figure 4. In both cases, the optimisation process lasted about $4\, s$.

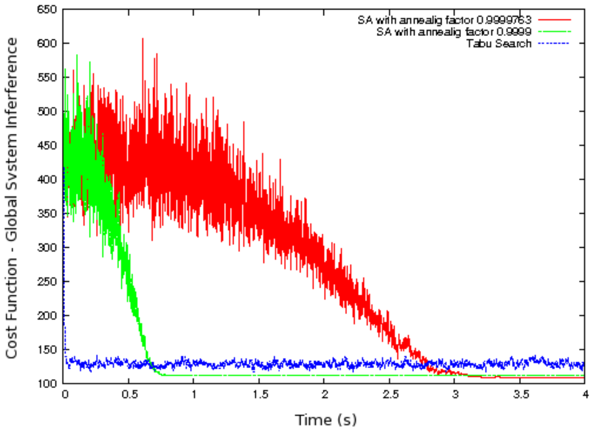

Fig. 4. SA versus TS.

Note that the running time of a single iteration for both algorithms is different. In SA only one neighbour within the neighbourhood needs to be identified and checked per iteration. Whereas, in TS, all neighbours or a subset of them need to be processed.

A second curve about SA is provided for comparison with an initial temperature and annealing factor of 1000 and 0.99995, respectively.

When analysing SA, it can be seen from Figure 4 that during the first iterations when the temperature of the system is high, the algorithm searches across a wide broad region of the search space accepting solutions that may decrease or increase the cost function. Afterward, as the number of iterations increases and the temperature decreases, the probability of accepting solutions that may increase the cost function is getting smaller and smaller and the search space narrower and narrower. Finally, at the end of the execution, only improving neighbours are accepted and the graph moves downhill similarly to a local search. The process finishes when the stop condition is reached, in this case is the available time, 4s.

On the other hand, when analyzing TS, after the first random solution is taken, the algorithm performs a local search minimizing rapidly the cost function. Afterwards, in each iteration, the algorithm performs clever movements always towards the best neighbour of the current neighbourhood, which can or cannot improve the cost function. The tabu list is taken into account when selecting a new neighbour to avoid infinite loops or getting stuck in local minima. The process finishes when the stop condition is reached, in this case is the available time.

It can be also seen from Figure 4 that when the annealing factor decreases, the search obtains a worse optimization result but converges quicker. Therefore, when using SA, a fine tune of the parameters is needed, given the trade off between accuracy and computing time.

Because of the quality of the results of both algorithms is similar and due to the fact that the performance of SA highly depends on the parameter tune process, one may prefer using TS in practice for solving the DFP problem.

B. Optimisation Results, SA and TS versus Greedy Algorithms

In the following, a comparison between the performances of meta-heuristics and the proposed greedy algorithm is given.

Three different scenarios were used to check the quality of the solution and the running time of SA, TS, RI, $MinI$, $MaxI$, RR, $MaxR$, $MinR$ and SI.

The first scenario has 18 sectors and three traffic patterns: one for the surroundings and two hot spots. Three variants of this scenario have been studied. The density of users in the traffic pattern changes for each variant. The density of the hot spots are 40, 60 and 80 $users/km^2$, while the density of the surroundings is 20, 30 and 40 $users/km^2$. The number of available sub-channels is 8.

The second scenario has 36 sectors and two traffic patterns: one for the surroundings and one hot spot. The same variants than in the case before have been studied. In this case the number of available sub-channels was set to 8.

Finally, the third scenario has 33 sectors and the same two traffic patterns and variants as before. In this case the number of available sub-channels was set to 16.

All the parameters used in the calculation of the demand vector and the restriction matrix are given in Table II.

TABLE II
SIMULATION PARAMETERS

Parameter	**Value**	**Parameter**	**Value**
Sites	Variable	CPE Ant. Gain	$0\,dBi$
Sector/site	3	CPE Ant. Pattern	Omni
Carrier Frequency	$3.5\,GHz$	CPE Ant. Height	$1.5\,m$
Channel Bandwidth	$10\,MHz$	CPE Noise Figure	$5\,dB$
DL:UL Ratio	1:1	CPE Cable Loss	$0\,dB$
Permutation Scheme	AMC	Min Service TP	$12.2\,kbps$
Frame Duration	$5\,ms$	Max Service TP	$42.2\,kbps$
Sub-channels	16	Average Symbol Eff.	$19.9\,kbps$
DL symbols	19	σ(Shadow Fading)	$8\,dB$
BS TX Power	$43\,dBm$	Intra BS correlation	0.7
BS Ant. Gain	$18\,dBi$	Inter BS correlation	0.5
BS Ant. Beam Width	120	Path Loss Model	Hata231
BS Ant. Height	$30\,m$	Traffic Map Density	Variable
BS Ant. Tilt	3	Hot spot Density	Variable
BS Noise Figure	$4\,dB$	Admission	BP[1]
BS Cable Loss	$3\,dB$	Resource Allocation	CA[2]
CPE Tx Power	$23\,dBm$	Snapshots	20

[1]Best Path loss, [2]Contiguous Allocation

On the other hand, the optimization results determined by the cost function are presented in Table III.

First of all, note that the *random* case represents the average value of 100 random frequency assignment solutions. It is given for further comparisons.

It can be stated that the performance of SA and TS are similar, but SA performs a bit better in most of the cases.

Note that a major improvement is achieved when using optimization compared to the random case. The cost function representing the global system interference decreases by around 70%.

TABLE III
OPTIMIZATION RESULTS

Scenario	1^{st}			2^{nd}			3^{rd}		
$users/km^2$	**20/40**	**30/60**	**40/80**	**20/40**	**30/60**	**40/80**	**20/40**	**30/60**	**40/80**
random	397.6	374.3	353.6	1086.2	941.6	991.2	435.1	435.1	444.0
SA	56.2	**180.7**	**222.3**	**151.7**	**292.2**	**500.4**	**1.0**	**52.5**	**108.1**
TS	**55.2**	181.8	224.3	182.4	317.3	516.8	**1.0**	53.3	115.7
SI	79.5	197.7	246.2	283.4	**331.9**	**547.3**	40.9	111.5	137.5
RI	86.1	192.1	236.9	274.3	377.8	569.7	33.2	88.4	134.1
MinI	98.8	**188.4**	230.2	**222.9**	392.9	587.9	27.6	84.5	137.7
MaxI	**60.8**	199.1	249.1	231.7	343.5	579.9	**25.8**	**79.2**	151.2
RR	116.5	203.7	243.7	346.9	439.2	599.8	71.0	97.9	174.4
MaxR	80.0	215.9	**230.1**	337.1	365.1	570.4	121.2	274.6	224.4
MinR	113.4	224.4	247.3	2928.4	395.8	571.4	4192.0	105.4	**127.6**
Best MH	55.2	180.7	222.3	151.7	292.2	500.4	1.0	52.5	108.1
Improv(%)	**86.1**	**51.7**	**93.7**	**86.0**	**69.0**	**49.5**	**99.8**	**87.9**	**75.7**
Best GA	60.8	188.4	230.1	222.9	331.9	547.3	25.8	79.2	127.6
Improv(%)	**84.7**	**49.7**	**34.9**	**79.5**	**64.8**	**44.8**	**94.1**	**81.8**	**71.3**
GAvsBest(%)	**-1.4**	**-2.0**	**-2.2**	**-6.6**	**-4.2**	**-4.7**	**-5.7**	**-6.3**	**-4.4**

Comparing the performance of the greedy algorithms to each other, there is no absolute winner amongst them, although $MaxI$, $MinI$ and SI have been demonstrated to perform better than the others. On the other hand, they run very fast, thus one can afford to execute all of them and select the best.

Contrary to intuition, the attitude of facing the problem, finding first the frequency which increases *the least* the cost function for all the sector and updating later the sector which increases *the most* the cost function, which seems no a good idea a priori, provide the best solution in most of the cases.

Finally and most importantly, it can be seen that the solution provided by the greedy algorithms is not far from the one given by the meta-heuristics. In our experimental study, the greedy algorithms provide at most 6.6% worse results than the meta-heuristics.

C. Simulation Results

Here, the improvement in the network capacity when using DFP is presented.

The scenario used for the experimental evaluation is a non-uniform deployed OFDMA network formed by 11 3-sector sites, having a total of 33 sectors. Two traffic patterns can be distinguished: one common area with a density of 40 $users/km^2$ and one hot spot with a density of 80 $users/km^2$. These values follow the recommendation of Forsk Atoll [14] for urban and dense urban areas. The number of available sub-channels is 16. The environment and parameters of the system level simulation are shown in Figure 5 and Table II.

The *KPIs (Key Performance Indicators)* used to analyze the behaviour of the network is the network capacity in terms of users and throughputs.

If there is no frequency planning method in use, the base stations allocate the resources to the users independently from each other and also without any knowledge about the choices of other sector. Thus, this process can be considered random from our point of view. The resources are allocated from

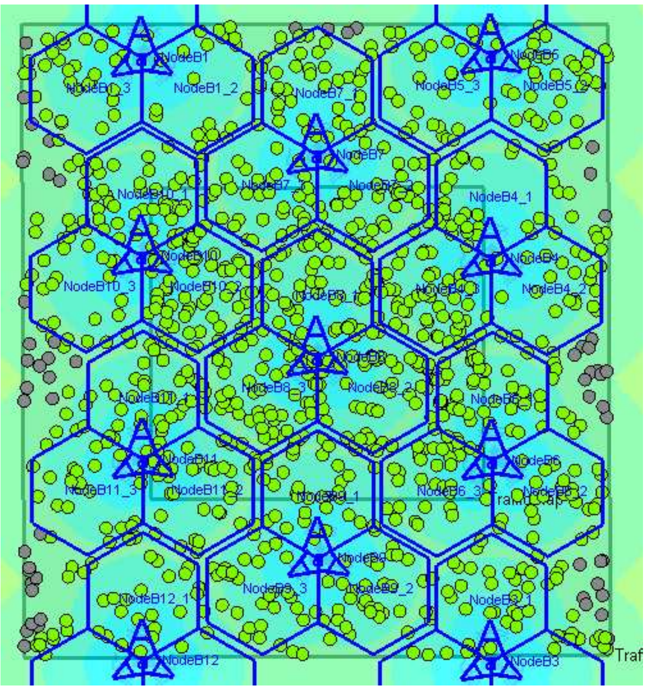

Fig. 5. Simulation Scenario and Traffic Map.

the whole frame domain, no frequency planning is taken into account. The set of sub-channels allocated must be contiguous in the frequency and time domain [8]. On the other hand, in the simulation with frequency planning the resources are allocated from the set of sub-channels estimated by the plan.

Note that the user states shown in Figure 6 and Figure 7 are two: *TX success* and *Blocked*. TX success means that the user has been admitted by the network and it is receiving data, while Blocked means that the user has been rejected by the network because of interference issues. On the other hand, the users that cannot access the network because other reasons, such as the lack of power to access the minimum radio access bearer or lack of resources to achieve the minimum throughput are not shown in the figure, and they, for the sake of simplicity, will not be taken into account in this analysis.

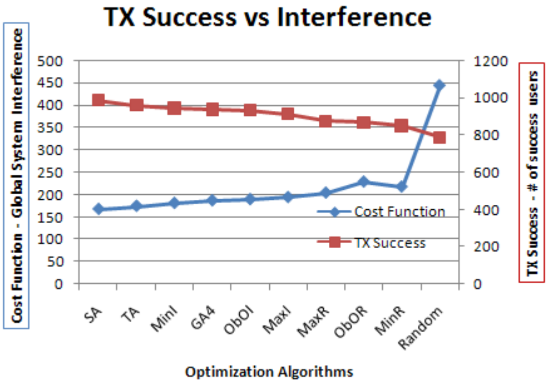

Fig. 6. TX Success versus Interference.

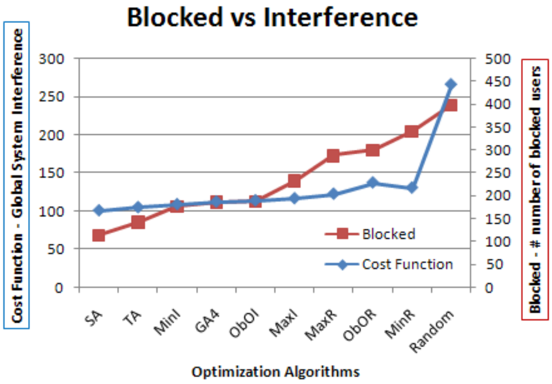

Fig. 7. Blocked versus Interference.

It can be seen from both pictures that when the global system interference decrease by using optimasation, the number of success user increase and the number of blocked users decreased. In the simulation without DFP - i.e. random case, the number of successful users is 74.02 %. On the other hand, the number of blocked users because of interference is 22.42 %. However, in the simulation with DFP found by SA or MinI (best meta-heuristic and best greedy algorithm in this case), the number of successful users is 92.57 % and 88.74 %, respectively. On the other hand, the number of blocked users because of interference is 6.47 % and 9.94 %, respectively. This shows that DFP improves notably the performance of the network in terms of number of users by around 20 %.

Taking a look at the throughput graph, Figure8, it can be checked that the capacity of the network in terms of throughput also increases by around 20 % when using DFP, following the same fashion as the capacity in terms of number of users.

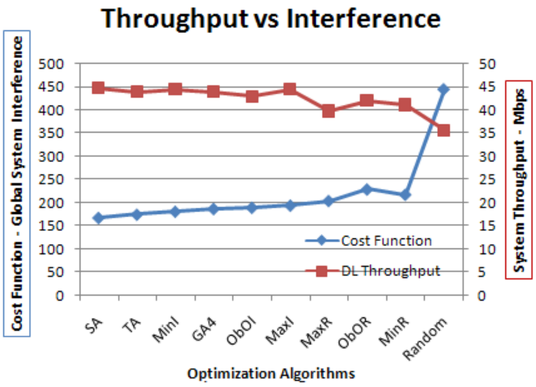

Fig. 8. Throughput versus Interference.

Finally, note that the performance of the network is better when using SA than TS. It is logical, since the global system interference achieved by the TS plan is better. It is another example of how the performance increases when the interference decreases.

VI. CONCLUSION

This paper had presented a new approach to the frequency assignment problem for OFDMA networks. On one hand, DFP had proposed a novel model for capacity and inter-cell interference estimation. On the other hand, tailored SA, TS and greedy algorithms had been used to solve this optimisation problem.

The accuracy and efficiency of the restriction matrix had been proved. By using this concept, the use of time consuming system level simulation could be avoid when performing network planning and optimisation, The restriction matrix could be calculated in much shorter time than the mentioned system level simulation, increasing the number of iteration that optimisation algorithm such TS and SA can perform, when looking for a good solution.

Greedy algorithms had been demonstrated to be very useful for solving the DFP problem, since they run so fast that we could even execute all of them on a frame by frame basis, while having a solution with a quality similar (by around 6 % worse) to the mentioned meta-heuristic.

This paper had also indicated to the RF engineers how to implements the DFP approach and how to check the improvements in their networks. DFP significantly reduces the global inter-cell interference (by around 70 % in the given scenario) of the system and notably improves the capacity in terms of number of users and throughput (by around 20 %) of the network.

DFP also presents new challenges for future research. The ideas presented here depend on a centralized network architecture, where a centralized entity should collect the data, generate the plan and distribute the information. However, a distributed architecture where each sector is able to select its own sub-channels will be more suitable. We are researching fast algorithms that can be used for on-line and truly dynamic frequency allocation for OFDMA networks.

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