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Game Theoretic Framework for Future Generation Networks Modelling and Optimization

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Abstract

A new cost efficient automated planning and optimization method is proposed for OFDMA future generation cellular networks targeting throughput maximization. The mathematical formulation is a non-linear multi-objective optimization problem subject to minimum interference, cost and similar resource constraints at each cell within a defined heterogeneous traffic environment. The fundamental objective is to maximize the individual cell throughput without deteriorating it over other cells, which results in a throughput equilibrium maximization over multiple cells. This implicitly implies traffic and co-channel interference congestion avoidance across the network whilst maintaining both cost efficiency and quality of service (QoS) policies. Optimal solution existence is subject to the network size, traffic and computational complexity constraints which converges to a throughput equilibrium or alternatively to the well known Nash Equilibrium (NE).

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I. Introduction

Wireless network design involves modelling numerous factors that define the performance of the network. It is therefore necessary to comprehend and assess the impact of each parameter on the network performance in order to determine the most precise optimization model that guarantees maximum network efficiency. However, the complexity of the model grows rapidly with the network size and the traffic complexity. As a consequence, a minor adjustment of a single parameter may cause a significant impact on the entire network performance.

Future generation wireless networks (FGWNs) offer users heterogeneous traffic which demands different levels of data rate, quality of service (QoS) and bandwidth. This diversity in traffic demands implies high complexity management to maintain network cost efficiency.[1] In order to provide an economical solution that balances network cost and efficiency, network designers have to develop new deployment methods that can balance QoS and network cost whilst counting a list of constraints and influential factors that govern the network performance.

As a solution to this challenge, orthogonal frequency-division multiple access (OFDMA) is adopted in FGWNs as a promising candidate not only due to its high immunity against multipath but also because it enables simultaneous multi-user transmission along with exploiting both multi-user and multi-path diversities [1]. As a result of power and bandwidth constraints, capacity at BS is bounded by the available resources and the channel coefficients between a BS and the surrounding traffic density distribution. The most dominant factors governing the channel coefficients are the propagation loss and the interference between the co-channels assigned to the cells/sectors across the network. Additionally, traffic distribution and density shape the probability density function of the channel coefficients between a BS and the surrounding traffic. Hence, optimizing BSs number and distribution results in optimizing the network parameters and maximizing capacity whilst maintaining both QoS and network cost.

Traditional and advanced planning methods treat these conditions either separately or insufficiently, which often leads to inaccurate network design. Therefore, all the aforementioned factors must be treated simultaneously to achieve maximum network performance. To handle resource efficiency, interference and traffic congestion, a unique solution must unify and satisfy all the aforementioned objectives, which if

[1]Cost efficiency is indicated by the number of base stations (BSs); a smaller number outcomes a more cost efficient network.

it is achieved over one objective, it implicitly achieves the others. Maximum throughput equilibrium is the only solution that can unify all targeted objectives and it can be achieved by loading all cells with a similar amount of traffic, minimizing the interference symmetrically[2] and distributing resources optimally.

Automated network design has been evolving over the last decade, e.g. in third generation (3G) network designs [2]-[4]. The significance of combining power control and BS placement simultaneously emerged as a promising approach to satisfy both traffic demands and power constraints via mixed integer programming (MIP). In [3], equal cell loading was considered as the fundamental objective, whilst a parallel meta-heuristic was proposed in [4] to meet the coverage and QoS service constraints.

In [5]-[8], similar methods were applied for indoor network planning over homogeneous traffic environments based on IEEE 802.11. In [6], a hybrid heuristic Pareto approach was proposed, while in [7] the problem was solved by a pure heuristic approach under varying interference assumptions and a Pareto based automated approach was proposed in [8].

On the other hand, for outdoor scenarios such as IEEE802.16e, [9] modelled the planning problem as a multi-objective optimization to address both BS placement and resource allocation problems simultaneously. The positioning decision is made based on the efficiency of the uplink and downlink capacity over a given set of cell site candidates, nominated by a similar criterion as in [2] and other MIP methods. Besides, an extensive study for the MIP-based solutions was carried out in [11], where the authors concluded that the quality of MIP-solutions may not be great, nevertheless, they should still be considered particularly since the solution complexity is considerably low compared to traditional exhaustive approaches, e.g. in [10] maximal location coverage was targeted by greedy-heuristic programming combining facility location and resource allocation for CDMA based networks.

As the aforementioned research on automated network design adopted CDMA, it is vital to develop new methods for FGWNs based on OFDMA. In particular, this paper exploits the findings of the aforementioned research, [4]-[11]-[18], into a new integrated planning model for OFDMA-based systems. Since solution quality is not guaranteed by MIP approaches, we propose a new game theoretic model, which is convex in nature, to converge to Nash equilibrium. The proposed approach breaks the NP-hard problem into multi-

[2]Interference reciprocity among all sectors is necessary to maintain throughput equilibrium in the network as in some cases a sector could be highly congested consuming all the available power and bandwidth. Existence of such scenarios generate constantly high interference to lower loaded sectors and consequently deteriorate their resource efficiency.

convex problem, [12], [13], controlled by a decentralized heuristic to exploit the encountered iterations during the optimization process to approach optimal positions for the BSs. The heuristic algorithm is necessary to handle the solution conditions of each individual convex problem to minimize the amount of signal propagation and steer iteratively towards throughput equilibrium.

In contrast to [9] in which resources are predefined[3] prior to network deployment, here a hybrid[4] resource allocation is adopted jointly with fair traffic clustering to avoid inappropriate resource consumption.

Simulation results, in Section VI-A, provide an optimal solution for a homogeneous Normal traffic distribution. As the service outage probability remains unconstrained, Dynamic Multi-objective Steering towards Nash Equilibrium (DMSNE) iterates to converge to optimality. For a worst case scenario where a uniform random distribution of a heterogeneous traffic is considered, results suggest that our proposal avoids significant sacrifice in the optimality, which makes it close-optimal whilst solution uniqueness may not exist in NP-hard problems [14].

II. System Model

In this section, we describe the nature of the problem, target, objectives, environmental conditions, traffic characteristics and resource constraints along with problem formulation.

A. Target and Objectives

The target of this paper is to construct an optimal network design framework either to meet a certain outage probability (OP) target or to converge to an optimal solution in case if the outage probability is unconstrained.

A solution is considered optimal if an OP target is achieved by the minimum number of BSs' in which each operates to its maximum throughput level as well as each has the minimal interference impact on other BSs. The distributed pattern of throughput maximization results in a non-fragile or with no-regret system as the throughput gain is not dominated by specific cells over others. This solution is considered cost-efficient since it avoids deploying low-loaded BSs. This is carried out by optimizing BSs' locations simultaneously to balance the amount of interference, signal propagation and traffic assignment among

[3]Bandwidth is divided into a set of fixed packet length.

[4]Packet length and power allocation are both dynamically optimized.

BSs. Implicitly, the boundary of the individual cell's maximum capacity is conditioned or limited by the performance bound of the other surrounding cells/BSs, e.g. the avoidance of both excessive interference and unfair traffic assignment allows a collaborative approach among cells to converge to a throughput equilibrium.

However, Equilibrium conditions are hard to exist in realistic scenarios, therefore our proposal attempts to converge to the nearest equilibrium solution.

Common inaccurate planning methodologies start with assigning BSs or building the network at and from the centre of the traffic population. The consequences of such solutions are highly co-channel interference (CCI) congested around the network centre caused by direction of transmissions from outer interfering cells. In contrast, cells around traffic boundaries are highly congested with traffic as they experience less CCI and therefore they stretch towards the centre of the traffic. This increases the amount of signal propagation loss, results in unbalanced cell throughput and inefficient resource utilisation.

Recent advanced planning methods based MIP approaches set a determined set of cite candidates to search for a solution. This indeed simplifies the planning problem and reduces its complexity. However, optimal equilibriums most probably do not exist in the predetermined cite-domain.

B. Problem Notations and Descriptions

In this section we parametrize the planning scenario to enable a mathematical formulation for the problem. We proceed with a traffic distribution over bounded by a continuous domain of $\mathbf{x}$ and $\mathbf{y}$ dimensions, denoted by $\mathbb{C}^{u\times v}$. In order to examine DMSNE's robustness under extreme conditions, the nature of the distribution is uniform random with heterogeneous traffic which consists of K active users requesting different types of services. Services are classified as time delay sensitive (TDS) and time delay insensitive (TDI), and for these services, users can request any in the network. Each type of service requires a different set of conditions to be successfully delivered within the transmission period. A user k requesting a TDS service requires a specific data rate ($\mathcal{R}_k$) within a limited period of time and a guaranteed level of QoS (ϵ_k[5]) while TDI services are not restricted to a fixed bit rate, but a minimum allocation unit (ρ_k) and require a lower level of QoS. Traffic QoS policies are considered to be one of

[5]Bit error rate is the QoS indicator for a specific service

the fundamental objectives that DMSNE has to achieve and are mathematically formulated as:

$$\mathcal{R}_k = \sum_{n=1}^{N} \omega_{k,n} C_{k,n},\ \forall k \in \ \{1, 2, \ldots, K\},$$

$$\sum_{n=1}^{N} \omega_{k,n} = \rho_k, \qquad \forall k \in \ \{1, 2, \ldots, K\},$$

index N refers to the total bandwidth segmented into subcarriers in which each subcarrier has a bandwidth of Δf and is addressed by an integer assignment variable $\omega_n \in [0, 1], \forall n$. While $C_{k,n}$ is the capacity of subcarrier n assigned to user k, i.e. $\omega_{k,n} = 1$, and is calculated by Shannon formula:

$$C_{k,n} = \Delta f \log_2 (1 + p_{k,n} \gamma_{k,n}),$$

where $p_{k,n} \in [0, P^T], \forall n$ is the allocated power at $\omega_{k,n}$ and $\gamma_{k,n}$ is the channel coefficient between the transmitter and user k experienced by subcarrier n.

Under these conditions, it required to minimize the outage probability of service coverage to meet a certain target (ε) by positioning a minimum number of BSs ($\mathcal{Q}$) which is the fundamental objective of this research.

C. Problem Formulation

As the traffic grows in space, a single cell is no longer sufficient for ε and hence the scenario is transformed from a single cell to a multi-cellular network of $\mathcal{Q}$ BSs. A BS has a z coordinate within the traffic area dimensions, i.e. $\{z : (x, y) \longrightarrow \mathbb{C}^{u \times v}\}$. Number of sectors at each BS is I, e.g. $\mathtt{BS}_q$ at z_q has I sectors, with a sector's maximum transmit power $P_{q,i}$ where $\mathcal{P} = \{P \in \mathbb{R}_+^{iq}, \sum_{q=1}^{\mathcal{Q}} \sum_{i=1}^{I} P_{q,i} \leq \mathcal{Q} \times I \times P_{q,i}\}$. Every user is served by a unique sector and denoted by k_i, while the remaining network sectors interfere with user k_i by an amount of power $\sum_{j \neq i}^{i \times \mathcal{Q}} P_{q,j}$ over similar shared bandwidth.

As a consequence of bandwidth constraint, it is then reused at each BS. Thus, BW is spread over N_T orthogonal subcarriers which consist of N data, N_P pilot and N_G guard subcarriers. In this approach, the subcarrier bandwidth, Δf, is considered to be smaller than the coherence channel bandwidth which results in inter-carrier interference (ICI) cancellation. Furthermore, subcarriers are assumed to be narrow enough to experience flat fading. Therefore, data loss over deep faded subcarriers will not affect data recovery over other subcarriers. The total number of subcarriers N are partitioned equally by I and each partition (set of subcarriers N_{sec}) is allocated to a sector within the cell. However, CCI occurs among the reused frequency bandwidths across the network and is considered to be the major limiting factor in OFDMA cellular networks. The exact amount of interference at user k, served by sector i and allocated a packet length of Ω_{k_i} is:

$$I_{k_i} = \sum_{n=1}^{\Omega_{k_i}} \sum_{j \neq i}^{i \times \mathcal{Q}} \sum_{n'=1}^{N} p_{n' \circledast n} d_{j,k_i} G(\phi_{j,k_i}) \mid H_{n' \circledast n} \mid^2, \tag{1}$$

where the operator $\circledast$ is the power cross correlation between the allocated reused-subcarrier $n' \in \{1, 2, \ldots, N\}$ with the adjacent sector's allocated-subcarriers ($n \in \{1, 2, \ldots, \Omega_{k_i}\}$) to the user of interest k_i to obtain the interferer subcarrier as well as the interferes channel coefficients H. Index j refers to the interferer sector where $J = (I \times Q) - 1$. Path loss (PL) and the antenna gain between the interferer sector j and user k_i are denoted by d_{j,k_i} and $G(\phi_{j,k_i})$, respectively.

Further traffic expansion implies further BW reuse over the additional assigned BSs, and as a consequence, the performance of the individual cells is severely degraded due to the increase in collisions between the reused frequency bands (BW) in the adjacent BSs. Therefore, cells will experience different amount of CCI, which reflects throughput gaps across all cells. Some cells achieve higher throughput than others as they stretch their resources widely, taking an advantage over other CCI-highly congested cells allowing them to exploit a higher diversity gain. As a result, cells' performance are categorized by over-loaded and inefficient cells. To avoid this dilemma, dynamic throughput penalty factor (Φ_q) are applied at over-loaded cells via a multi-localization method to achieve a distance balance between each user, serving sector and the adjacent interfering sectors, which implicitly yields the optimal solution and convergence to a throughput equilibrium. To this end, the network design problem tends to be a Game-theoretic problem of a multi-objective optimization nature, where each BS in the network performs equally to other neighbouring cells while achieving maximum cell capacity and traffic-interference congestion avoidance. Therefore, the automated planning problem is formulated as a non-linear multi-objective optimization problem as follows:[6]

$$\min_{\mathcal{Q} \in \mathbb{Z}_+} \max_{f \forall q \in \mathcal{Q}} \mathcal{F} = \sum_{q=1}^{\mathcal{Q}} \left[\left(f_q \left(\mathbf{p}, \mathbf{w}, \mathbf{z} \right) - \chi_q \Phi_q \right] \right., \tag{2}$$

subject to:

$$\chi_q \in \{0, 1\}, \qquad \forall q \in \{1, 2, \ldots, \mathcal{Q}\}, \tag{3a}$$

[6]Table I summarizes the dominant parameters of the problem formulation

$$\Phi_q \in [0, f_q], \qquad \forall q \in \{1, 2, \ldots, \mathcal{Q}\}, \tag{3b}$$

$$\mathbf{p} = \left\{ p \in \mathbb{R}_{+}^{ikn} : \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{n=1}^{N} p_{k_i,n} \leq P_q^T \right\}, \ \forall i \in I \times \mathcal{Q}, \tag{3c}$$

$$\mathbf{w} = \left\{ \omega \in \mathbb{Z}_{+}^{ikn} : \sum_{k \in \Psi_q} \omega_{k_i,n} \leq 1 \right\}, \ \forall i \in I \times \mathcal{Q}, \tag{3d}$$

$$\mathcal{R}_{k_i} = \sum_{n=1}^{N} \omega_{k_i,n} C_{k_i,n}, \ \forall k \in \ \{1, 2, \ldots, K\}, \tag{3e}$$

$$\sum_{n=1}^{N} \omega_{k_i,n} = \rho_{k_i}, \qquad \forall k \in \ \{1, 2, \ldots, K\}, \tag{3f}$$

$$\mathbf{z} = \big\{ \, (\mathbf{x}, \mathbf{y}) \in \mathbb{C} : x_l \leq \mathbf{x} \leq x_u, y_l \leq \mathbf{y} \leq y_u \big\}, \tag{3g}$$

$$\min I_k \left(\mathbf{z} \right), \qquad \forall k \in \ \{1, 2, \ldots, K\}, \tag{3h}$$

$$\min \parallel z_q - z_{k_i} \parallel, \qquad \forall k \in \ \{1, 2, \ldots, K\}, \tag{3i}$$

where $\mathcal{F}$ is the vector of the network cells' throughput $\left\{ \mathcal{F} : (\mathcal{P}, \mathcal{W}, \mathbf{z}) \longrightarrow \mathbb{R}_{+}^{\mathcal{Q}} \right\}$, with $\mathcal{W}$ representing a multi-dimensional matrix which defines subcarrier assignments at each sector associated with the cell index. Individual cell throughput is given by f_q, which is the sum of the individual users' throughputs in cell q. The integer variable $\chi \in \{0, 1\}$ represents a penalty decision factor and its value along with the penalty factor Φ_q will be discussed in Section IV. In the above formulation, constraints (3c) and (3d) represent the total power constraint (sector/cell) and the subcarrier binary sharing factor $\omega_{k_i,n}$ for subcarrier n for the q^{th} cell, respectively. Constraint (3e) defines the QoS demands in terms of data rate for TDS on user k_i, while constraint (3f) defines the maximum allocation allowance ρ_{k_i} for TDI users. As for $C_{k_i,n}$, it represents the delivered data rate over a single subcarrier and given by:

$$C_{k_i,n} = \Delta f \log_2 \left[1 + p_{k_i,n} \gamma_{k_i,n}(\mathbf{z}) \right]. \tag{4}$$

Hence, $f_q = \sum_{i,k,n} \omega_{k_i,n} C_{k_i,n}$. Traffic geometries are given by (3g) and each BS's location (z_q) should be within the traffic boundaries while $(u, \ v)$ are the matrix dimension of $\mathbf{z}$. Constraint (3h) refers to the CCI effects at each user in the network, while (3i) represents the Euclidean distance between $\texttt{BS}_q$ and user k_i, which is subject to minimization in order to reduce the propagation loss on the transmitted signals between $\texttt{BS}_q$ and k_i. γ is the effective channel coefficient which is position-dependent and it is given by:

$$\gamma_{k_i,n}^{(\mathbf{z})} = \frac{\mid H_{k_i,n} \mid^2 d_{i,k_i} \ G(\phi_{i,k_i})}{\Gamma_{k_i} \left[N_o + \sum_{j \neq i}^{J} \sum_{n'=1}^{N} p_{n' \circledast n} d_{j,k_i} G(\phi_{j,k_i}) \mid H_{n' \circledast n} \mid^2 \right]} \tag{5}$$

and the channel frequency response matrix for the K users is given by $\mathbf{H} \in \mathbb{C}^{K \times N_T}$. d_{i,k_i} is the PL between sector i of cell q and user k, following SUI model [15] according to

$$PL_{i,k_i} = 20 \log_{10} \left(\frac{4\pi D_o}{\lambda_o} \right) + 10\alpha \log_{10} \left(\frac{\parallel z_q - z_{k_i} \parallel}{D_o} \right), \tag{6}$$

where D_o is the reference distance, α is the propagation factor, $\parallel z_q - z_{k_i} \parallel$ is the Euclidean distance between user k_i and the serving sector i, and λ_o is the wavelength. Γ is the gap value which determines the required QoS in terms of bit error rate (ϵ, BER) for each service/user.

$$\Gamma_{k_i}(\epsilon_{k_i}, m) = \frac{-\ln 5\epsilon_{k_i}}{1.5}(2^m - 1), \tag{7}$$

with ϵ_{k_i} denoting the service BER target for user k_i, and m the modulation index. $G(\phi_{i,k_i})$ is antenna gain of user k_i with sector i modelled as in [16] by the following formula:

$$G(\phi_{i,k_i}) = G_{max} - \min \left\{ 20 - \left(\frac{\phi^o - \phi_{k_i}}{\theta_{3dB}} \right)^2 \right\}, \tag{8}$$

where G_{max} is the maximum achievable antenna gain at the sector boresight (ϕ^o) and θ_{3dB} is the half power beamwidth. Finally, thermal noise is denoted by N_o.

III. Problem Decomposition

The network planning formulated in (2) is a decision problem, which involves mixed integer non-linear programming. Therefore, problem (2) is NP-hard [2]. Exhibiting non-deterministic polynomial time complexity and being also boundary value problem (BVP) by the traffic dimension constraint ($\mathbf{z}$), analytical and exact solutions for the problem may not be possible. Therefore, the problem $\{\mathcal{F} : (\mathcal{P}, \mathcal{W}, \mathbf{z}) \longrightarrow \mathbb{R}_+^{\mathcal{Q}}\}$ is decomposed according to the Additive Schwarz method into sub-problems to reduce the solution complexity [17]. In order to achieve this, the problem is decomposed into two problems; 1) Facility Location: $\left\{\mathcal{G} : (\hat{\mathbf{z}}) \longrightarrow \mathbb{R}_+^{kq}\right\}$ and 2) Resource Allocation: $\{\mathcal{C} : (\mathbf{p}, \omega) \longrightarrow \mathbb{R}_+\}$ [10]. The former optimization problem is constrained by the traffic dimensions, where $\hat{\mathbf{z}}$ represents the set of site candidates which are obtained by Metaheuristic, while the latter is modelled as a mixed integer non-linear problem (MINLP), constrained by power, bandwidth and service requirements [18]. Both problems are then solved and composed sequentially as follows:

$$\mathcal{G} \circ \mathcal{C}_{\mathcal{T}} = \hat{\mathcal{F}} \left(\mathcal{C}_{\mathcal{T}}, \mathcal{G}^{-1} \left(\mathbb{R}_+^{kq} \right) \right), \tag{9}$$

where $\mathcal{C}_{\mathcal{T}}$ is the obtained cell throughput over the set $\hat{\mathbf{z}}$,

$$\hat{\mathbf{z}} = \mathcal{G}^{-1} \left(\mathbb{R}_+^{kq} \right) = \left\{ \hat{\mathbf{z}} \in \mathbb{C}^{kq} : \mathcal{G} \left(\hat{\mathbf{z}} \right) \in \mathbb{R}_+^{kq} \right\}, \tag{10}$$

and to obtain the desired solution we apply the following:

$$\mathcal{F} = \arg \max_{1 \le k \le K} \left\{ \hat{\mathcal{F}} \right\}, \qquad \forall q \in \{1, 2, \ldots, \mathcal{Q}\}. \tag{11}$$

Hence, the final set positions are obtained by $\mathbf{z} = \hat{\mathbf{z}}\left(\mathcal{F}\right)$. The adopted decomposition implies no optimality sacrifice since the mutual effects between the sub-problems are fully considered.

A. Facility Location

In the facility location problem, $C_{k_i,n}$ is maximized by considering the maximization of $\gamma_{k_i,n}$, which is carried out by minimizing the Euclidean propagation distance of each subcarrier n between $\mathtt{BS}_q$ and assigned user k_i. Implicitly, severity of multipath fading is significantly reduced. We therefore eliminate the multipath effect and try to minimize the effect of the propagation loss as well as minimizing CCI amount at each user. At this stage, both $p_{k_i,n}$ and $\omega_{k_i,n}$ are constants or uniformly distributed and will be optimized in the resource allocation problem. The facility location problem is then formulated as:

$$\max_{\gamma_{k_i,n} \in \mathbb{R}_+} \mathcal{G}\left(\mathbf{z}\right) = \sum_{q=1}^{Q} \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{n=1}^{N} C_{k_i,n}, \tag{12}$$

subject to:

$$\mathbf{z} = \left\{ (\mathbf{x}, \mathbf{y}) \in \mathbb{C} : x_l \le \mathbf{x} \le x_u, y_l \le \mathbf{y} \le y_u \right\}, \tag{13a}$$

$$\min I_{k_i}\left(\mathbf{z}\right), \qquad \forall k \in \{1, 2, \ldots, K\}, \tag{13b}$$

$$\min \parallel z_q - z_{k_i} \parallel, \qquad \forall k \in \{1, 2, \ldots, K\}. \tag{13c}$$

1) Metaheuristic Based Greedy Approach: The facility location problem is another multi-objective problem, since it handles the positioning process for a $\mathcal{Q}$ number of BSs in the network. Pareto is a well-known method for tackling such problems, however it has a drawback which limits the achievements of this method. The randomized version may require a long time to obtain the Pareto optimal and, therefore, we propose a hybrid method which consists of speeded-Pareto and Metaheuristic to overcome this drawback. The former approaches a suboptimal solution rapidly by avoiding solution candidates repetition, while the latter efficiently steers the outcomes of Pareto towards a better sub-optimal solution. Metaheuristic can be summarized by deriving the steepest descent direction of the objective function (f) as follows:

$$\hat{\mathbf{z}} = \begin{cases} x_q^+|_{1 \le k \le K} = x_q^o \pm \eta_t \frac{\nabla \mathcal{G}_x}{\|\nabla \mathcal{G}_x + \nabla \mathcal{G}_y\|}, & \forall q \in \{1, 2, \ldots, \mathcal{Q}\}, \\ y_q^+|_{1 \le k \le K} = y_q^o \pm \eta_t \frac{\nabla \mathcal{G}_y}{\|\nabla \mathcal{G}_x + \nabla \mathcal{G}_y\|}, & \forall q \in \{1, 2, \ldots, \mathcal{Q}\}, \end{cases} \tag{14}$$

where η_t is the step size. By using (14), constraints (3g $\equiv$ 13a $\&$ 3i $\equiv$ 13c) are satisfied. That is, if there are no users, then there is no direction of maximization, while in case of highly dense area, the normalized gradient vector $\left(\frac{\nabla\mathcal{G}}{\|\nabla\mathcal{G}_x+\nabla\mathcal{G}_y\|}\right)$ directs the BS towards the traffic peak. x_q^o and y_q^o are the initial coordinates for $\texttt{BS}_q$. Finally, $\nabla\mathcal{G}_x$ and $\nabla\mathcal{G}_y$ are the gradients of f with respect to x and y dimensions respectively.

B. Traffic Fair Allocation and Clustering

Traffic growth across the network under resource constraints results in the outage probability exceeding the limit, ε. Therefore, a network upgrade is required to accommodate the additional traffic under similar QoS policies and resource constraints. This upgrade is carried out by planning an additional BS. To avoid the new cell being inefficient, the traffic shared among all BSs need to be clustered and assigned to achieve equal cell loading.

A balanced throughput over all cells is achieved when the traffic is clustered according to a criterion that prevents a BS from assigning resources to a user that would otherwise have a better channel coefficient (γ) with a different BS. This guarantees higher resource efficiency for each BS by avoiding inappropriate allocation which mostly suffers significant amount of CCI. We therefore formulate the clustering problem according to the following criterion:

$$\Psi_q = \arg\max_{1\leq i\leq(Q\times I)}\left(\gamma_{k_i}^q\right), \qquad \forall k\in\ \{1,2,\ldots,K\}, \tag{15}$$

where $\{\Psi_q \subseteq K\}$ represents the set of users assigned to cell q.

The traffic in this paper is a snapshot of the worst case scenario of the expected or observed traffic within a specific period of time.

C. Resource Allocation

In the preceding sections, $C_{k_i,n}$ has been maximized by optimizing the channel coefficient under uniform resource allocation. Further improvement indeed requires an efficient power/bandwidth allocation to maintain the optimality of the planning. The objective function f is modified to concave as in [20] and the resource allocation problem is formulated as in [18]. It should be noted that $s_{k_i,n}$ is equivalent to $p_{k_i,n}\omega_{k_i,n}$, and the MINLP resource allocation for a set of positions $(\hat{\mathbf{z}})$ is formulated as follows:

$$\begin{aligned} &\max && (\mathcal{G}\circ\mathcal{C}_{\mathcal{T}})_{k,q} = \sum_{i,\forall k\in\Psi_q,n}\omega_{k_i,n}C_{k_i,n}\left(\frac{s_{k_i,n}}{\omega_{k_i,n}},\gamma_{k_i,n}^{(\mathbf{z}')}\right), \\ &s_{k_i,n}\in[0,\infty) && \\ &\omega_{k_i,n}\in\{0,1\} && \end{aligned} \tag{16}$$

subject to:

$$\left\{\mathbf{p} \in \mathbb{R}_{+}^{ikn} : \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N} p_{k_i,n} \leq P_q^T\right\}, \tag{17a}$$

$$\left\{\mathbf{w} \in \mathbb{Z}_{+}^{ikn} : \sum_{k=1}^{K} \omega_{k_i,n} \leq 1\right\}, \tag{17b}$$

$$\mathcal{R}_{k_i} = \sum_{n=1}^{N} \omega_{k_i,n} C_{k_i,n}, \qquad \forall k \in \Psi_q, \tag{17c}$$

$$\sum_{n=1}^{N} \omega_{k_i,n} = \rho_{k_i}, \qquad \forall\ k\ \in\ \Psi_q. \tag{17d}$$

The problem is relaxed as $\omega_{k_i,n} \in \{0,1\}$, which implies that each subcarrier can only be occupied by one user. If subcarrier n is allocated to user k_i, then $\omega_{k_i,n}$ =1 or otherwise 0. This condition is necessary to hold, since the theoretical optimal solution allows more than one user to share one subcarrier. This approach cannot be implemented in realistic scenarios as it breaks the orthogonality between the subcarriers, hence an additional induced intra-interference occurs following such allocation scheme. Additionally, it changes the resource allocation into a combinatorial problem which increases the complexity of the optimization process. Different resource allocation formulations can be found in [21], where each formulation exhibits different priority objectives which in turn, changes the final planning solution to satisfy the objectives of each formulation.

1) Subcarrier and Power Allocation: In the previous section, the resource allocation problem was modelled to concave and, hence, the MINLP problem was solvable in the convex optimization framework by taking the Lagrangian $\mathcal{L}$ [21]-[18], namely

$$\begin{aligned}\mathcal{L}(\Omega,\mu,\beta,\varphi) = \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N} \omega_{k_i,n}\log_2\left(1+\frac{s_{k_i,n}\gamma_{k_i,n}}{\omega_{k_i,n}}\right) - \sum_{i=1}^{I}\Omega_i\left(\sum_{k=1}^{K}\sum_{n=1}^{N} s_{k_i,n} - P_q^T\right) - \sum_{i=1}^{I}\sum_{n=1}^{N}\mu_n\left(\sum_{k=1}^{K}\omega_{k_i,n} - 1\right) \\ - \sum_{i=1}^{I}\sum_{k=1}^{K}\beta_{k_i}\left[\sum_{n=1}^{N}\omega_{k_i,n}\log_2\left(1+\frac{s_{k_i,n}\gamma_{k_i,n}}{\omega_{k_i,n}}\right)\right] - \sum_{i=1}^{I}\sum_{k=1}^{K}\varphi_{k_i}\left(\sum_{n=1}^{N}\omega_{k_i,n} - \rho_{k_i}\right).\end{aligned} \tag{18}$$

In order to guarantee the optimality of the resource allocation, the duality gap between the Lagrangian and the objective function should be vanished and therefore the optimal solution is obtained when the following condition is true $(\mathcal{L} - (\mathcal{G} \circ \mathcal{C}_{\mathcal{T}})_{k,q} = 0)$. Optimum power and subcarrier allocations are obtained by taking the partial derivative for $\mathcal{L}$ with respect to $s_{k_i,n}$ and $\omega_{k_i,n}$, respectively. We then rearrange the outcomes to derive optimum power allocation for a single subcarrier as well as optimum subcarrier allocation. The latter should satisfy the Karush Kuhn Tucker (KKT) conditions for this problem, which are summarized as follows [19]: 1) Feasibility of both the constraints and the Lagrangian multipliers. 2) The gradient of the Lagrangian with respect to $s_{k_i,n}$ and $\omega_{k_i,n}$ become zero. 3) Optimized parameters should be within the feasible domain whilst all objectives are satisfied. By setting $\frac{\partial \mathcal{L}}{\partial s_{k_i,n}} = 0$, optimum power allocation for single subcarrier is obtained as follows:

$$s_{k_i,n}\left(\lambda_i, \beta_{k_i}\right) = \omega_{k_i,n}\left[\lambda_i\left(1-\beta_{k_i}\right) - \frac{1}{\gamma_{k_i,n}}\right]. \tag{19}$$

By setting $\frac{\partial \mathcal{L}}{\partial \omega_{k_i,n}} = 0$ and substituting (19), we obtain μ_n:

$$\mu_n\left(\lambda_i, \beta_{k_i}, \varphi_{k_i}\right) = \left(1-\beta_{k_i}\right)\left\{\log_2\left[\lambda_i\left(1-\beta_{k_i}\right)\gamma_{k_i,n}\right] - \left[\frac{1}{\ln 2} - \frac{1}{\lambda_i \gamma_{k_i,n} \ln 2 (1-\beta_{k_i})}\right]\right\} - \varphi_{k_i}, \tag{20}$$

where $0 \leqslant \beta_{k_i} \leqslant 1, \mu_n \geqslant 0$ and $\varphi_{k_i} \geqslant 0$ are the Lagrangian multipliers and λ_i is referred to as the $water\ level$ in units of W/bps. Subcarrier assignment is carried out according to the following condition:

$$k_i' = \arg\max_{\forall k \in \Psi_q} \mu_n\left(\lambda_i, \beta_{k_i}, \varphi_{k_i}, \gamma_{k_i,n}\right), \ \forall i \in \ \{1, 2, \ldots, \mathcal{Q} \times I\}, \tag{21}$$

$\omega_{k_i',n} = 1$ means that subcarrier n is allocated to user k_i' and this is followed by the power allocation. Finally, constraint (2a) consists of an inequality in its formulation which is $s_{k_i',n} > 0$ and, thus, solution feasibility depends on the satisfaction of this inequality. Therefore the following condition must be met:

$$\gamma_{k_i,n} > \frac{1}{\lambda_i}\left(1-\beta_{k_i}\right). \tag{22}$$

This condition represents the resource allocation threshold channel domain in which power allocation should be restricted only for subcarriers experiencing channel coefficient greater than the ratio $\frac{1}{\lambda_i}\left(1-\beta_{k_i}\right)$ [19]. We have assumed that the whole bandwidth exists in one sub-band which contains N data subcarriers. In case of considering B sub-bands, where each sub-band contains $N_b = \frac{N}{B}$ data subcarriers, then user's k bandwidth and sub-band sharing factors $\left(\varrho_{k_i}, \varrho_{k_i,b}\right)$ become:

$$\varrho_{k_i,b} = \frac{\sum_{n=1}^{N_b} \omega_{k_i,n}}{N_b}, \qquad \forall b \in \{B\}, \forall k \in \{K\}, \tag{23}$$

where $\sum_{k=1}^{K} \varrho_{k_i,b} \leq 1, \ \forall \ b \ \in \{B\}$, and hence, $\varrho_{k_i,b}$ is continuous in $[0,1]$. For the total bandwidth sharing:

$$\varrho_{k_i} = \frac{1}{N}\sum_{b=1}^{B}\left(\sum_{n=1}^{N_b} \omega_{k_i,n}\right), \tag{24}$$

where $\sum_{k=1}^{K} \varrho_{k_i} \leq 1$, and hence, ϱ_{k_i} is again continuous in $[0,1]$. We have only relaxed the subcarrier sharing factor $(\omega_{k_i,n} \in \{0,1\})$ as subcarrier is the minimum allocation unit and thus sharing a single subcarrier by more than one user is not allowed due orthogonality-loss. As such, the derived solution is referred to as the practical optimal solution. In the optimal theoretical solution, where subcarrier sharing is allowed, a non-relaxed model is adopted and turns the problem into a combinatorial optimization problem. The following formulated criterion allows multi-users to fairly share a single subcarrier:

$$\omega_{k_i,n} = \frac{\mu_{n,k_i} \mid_{\gamma_{k_i,n} > \frac{1}{\lambda_i}(1-\beta_{k_i})}}{\sum_{k=1}^{K} \mu_{n,k_i} \mid_{\gamma_{k_i,n} > \frac{1}{\lambda_i}(1-\beta_{k_i})}}, \forall n \in \{1, 2, \ldots, N_1, \ldots, N_b, \ldots, N\}. \quad (25)$$

Subcarrier assignment is no longer restricted to the user who only maximizes μ_n as in (21), but this sharing is conditioned by $\gamma_{k_i,n} > \frac{1}{\lambda_i}(1 - \beta_{k_i})$ in order to guarantee solution feasibility in constraint (2a). The domain for $\omega_{k_i,n}$ becomes then continuous in $[0, 1]$. In this context, intra interference occurs over each shared subcarrier and is calculated at a given cell by:

$$I_{k_i,n}^{int} = \sum_{k' \neq k}^{\Psi} \omega_{k',n} p_{k',n} G(\phi_{i,k'_i}) \mid H_{k',n} \mid^2 . \quad (26)$$

In conclusion, optimal theoretical allocation breaks system orthogonality, which results in users extra collisions over same shared-subcarriers inside each sector and across the whole network.

2) Dual-Variable Calculations: Simultaneous computations of λ_i and β_{k_i} are not possible. Therefore, to avoide inaccurate initializations and speed up the convergence of each allocation process, an approximate expression for λ_i is obtained after deriving the optimum power allocation $s_{k_i,n}$ and subcarrier assignment $\omega_{k_i,n}$. Hence, we first derive an approximate solution for λ_i and, subsequently, obtain an exact solution for β_{k_i} to meet each service requirement. We proceed by substituting (19) into (2a) to obtain λ_i as shown below:

$$\sum_{k=1}^{\Psi_q} \sum_{n=1}^{N} s_{k_i,n} = P_{q,i}, \qquad \forall i \in I, \forall q \in \mathcal{Q}, \quad (27)$$

$$\lambda_i = \frac{P_{q,i} + \frac{1}{\sum_{k=1}^{\Psi_q} \sum_{n=1}^{N} \gamma_{k_i,n}}}{\sum_{k=1}^{\Psi_q} (1 - \beta_{k_i}) \sum_{n=1}^{N} \omega_{k_i,n}}. \quad (28)$$

Once λ_i is approximated, the BS starts allocating power and subcarriers according to the allocation method requirements until the target bit rate of user k_i is either achieved exactly or exceeds the threshold. We can then adjust last-subcarrier power allocation by β_{k_i} to achieve exact QoS:

$$\Delta \mathcal{R}'_{k_i} = \Delta f \log_2 \left[1 + \frac{s_{k_i,n} \gamma_{k_i,n}}{\omega_{k_i,n}} \right] = \mathcal{R}_{k_i} - \sum_{n' \in N}^{n' + \Omega_{k_i} - 1} \Delta f \omega_{k_i,n} \log_2 \left(1 + \frac{s_{k_i,n} \mid_{\beta_{k_i}=0} \ \gamma_{k_i,n}}{\omega_{k_i,n}} \right), \quad (29)$$

where $\Delta \mathcal{R}'_{m,k_i}$ is the exact required bit rate over the last subcarrier for user k_i. By substituting $s_{k_i,n}$ in (29) and manipulating, we obtain the optimum value for β_{k_i}:

$$\beta_{k_i} = 1 - \frac{1}{\lambda_i \gamma_{k_i,n}} 2^{\frac{[\mathcal{R}_{k_i} - \sum_{n' \in N}^{n' + \Omega_{k_i} - 1} \Delta f \omega_{k_i,n} \log_2 (1 + \frac{s_{k_i,n} \mid_{\beta_{k_i}=0} \gamma_{k_i,n}}{\omega_{k_i,n}})]}{\Delta f}}. \quad (30)$$

In the case of fixed resource allocation, the penalty factor φ_{k_i} is required to be adjusted so that the condition $\sum_{n=1}^{N} \omega_{k_i,n} = \rho_{k_i}$ is fulfilled. The value of φ_{k_i} is initialized to zero; subsequently, an incremental update is necessary to approach the desired allocation [23]. In order to reduce complexity, μ_n in (20) can be simply set to zero. The obtained value for φ_{k_i} works as the optimal value.

IV. Dynamic Multi-objective Steering towards Nash Equilibrium

Since (2) is a multi-objective problem, then a parallel optimization method is necessary to obtain the maximum equilibrium throughput so as to avoid traffic congestion across the network. Once we obtain the initial positions $\mathbf{z}_o$, either by random initialization or by early Pareto solution, (14) is applied followed by (15) and (16). Since throughput achievement is position dependent, then the mathematical relation between the position of the optimized cell and its throughput can be derived as:

$$z_q = f^{-1}\left(\arg\max_{1\leq k\leq K}\{\mathcal{G}\circ\mathcal{C}_{\mathcal{T}}\}_{q,k}\right), \quad \forall q\in\{1,2,\ldots,\mathcal{Q}\}, \tag{31}$$

considering that continuous throughput maximization of a cell will deteriorate the others. For instance, in a 2-cell scenario, maximizing throughput of cell A continuously in an independent knowledge of cell B results in continuous minimization of cell B throughput. Hence, a control method is required to maintain a balance and achieve an optimized throughput equilibrium.

In [24], a hybrid Pareto-Heuristic technique was adopted to derive an initial non-dominated solution by Pareto and maximize all cells together despite the existence of throughput gaps. Therefore, final solution of such hybrid approach tends to be highly sensitive and dependent on the NE quality derived by Pareto, which demands high computations to obtain a well balanced NE. In contrast with [24], DMSNE detects and implies throughput maximization only over the worst cell performance, while it penalizes the other greedy cells with a dynamic penalty factors in order to maintain throughput balance over all cells. This allows to displace cells from traffic peaks/troughs towards average traffic regions, hence achieving fairness in network traffic allocation. As a result, the cell associated with the minimum throughput will be always maximized while the others will be continuously minimized to a certain threshold. An integer variable $\chi\in\{0,1\}$ representing a penalty decision factor is given on the basis of the following criterion:

$$\chi_q = \begin{cases} 1, \text{if } \ f_q > \min\{\mathcal{F}\}, \\ 0, \text{if } \ f_q = \min\{\mathcal{F}\}. \end{cases} \tag{32}$$

Once a greedy cell is determined, χ_q is set to 1, ($\chi_q = 1$), to identify that $\texttt{BS}_q$ must be penalized by:

$$\Phi_q\left(\mathbf{z}|\psi_q\right) = \arg\min_{1\leq k\leq K}\left\{f_{q,k} - \min\left\{\mathcal{F}\right\}\right\}, \tag{33}$$

where Φ_q is the displacement penalty factor and its feasible domain is given by $\Phi_q \geq 0$. CCI minimization is guaranteed by maximizing the Euclidean distance between the co-channels in the contiguous sectors which is given by:

$$\psi_q = \max \left\| z_q - z\Big(\min \{\mathcal{F}\} \Big) \right\|. \tag{34}$$

BSs are enabled to reposition and to reorganize themselves by considering the set of equations (31)-(34), hence the solution iterates continuously to maximize NE. For further illustration on DMSNE, given Fig. 1 summarizes the way it operates.

V. Outage Probability

In addition to the previous objectives, namely, throughput equilibrium (NE) maximization, traffic congestion avoidance, CCI and network cost minimization, the outage probability is an extra objective that can also be handled in the optimization process since throughput maximization can be considered as an indicator for outage probability minimization. Outage probability can be formulated as a service probability maximization subject to a certain outage target. Service probability (Θ) can be calculated as:

$$\Theta = \frac{1}{K}\left[\sum_{q,i,k} \Pr\left(\sum_{n=1}^{N} C_{k_i,n} = \mathcal{R}_{k_i} \right) + \sum_{q,i,k} \Pr\left(\sum_{n=1}^{N} \omega_{k_i,n} = \rho_{k_i} \right) \right]. \tag{35}$$

Hence, the outage probability problem is formulated as follows:

$$\max \Theta, \tag{36}$$

subject to:

$$(1 - \Theta) \leq \varepsilon, \tag{37a}$$

$$\max f_q = \sum_{i=1}^{I} \sum_{k \in \Psi_q} \sum_{n=1}^{N} \omega_{k_i,n} C_{k_i,n}, \qquad \forall q \in \{1, 2, \ldots, \mathcal{Q}\}, \tag{37b}$$

where ε is the outage probability target.

VI. Numerical Results and Discussions

The proposed DMSNE method is applied to meet an outage probability less than or equal to $\varepsilon = 30\ \%$. Two types of services are randomly distributed for K users over a terrain dimension of $\| x_u - x_l \| \times \| y_u - y_l \|\ m^2$. All other simulation parameters are listed in Table I. The fundamental objectives are; throughput equilibrium maximization across the network (i.e. no traffic congestions), outage probability satisfaction $(\varepsilon \geq 1 - \Theta)$ and minimization of the network cost ($\min \mathcal{Q}$). The formulation in (36) is very likely to cause unbalanced trade-off between service probability (Θ) and throughput equilibrium ($\mathcal{F}$) due to low data rate users (TDI). In other words, serving TDI users maximizes (36), however (2) is not satisfied as TDS users request guaranteed high data rate. Therefore, to balance this trade-off, resource allocation dominates and prioritizes TDS over TDI services as these services demand higher data rate and are considered to be more profitable for the service provider.

The interfering power for packet/user $P'_k = \sum_{n' \in N}^{n'+\Omega_{k_i}-1} \sum_{n=1}^{N} p_{n' \circledast n}, \ \Omega_{k_i} \subseteq N$ is assumed to be unity (30 dBm) as $\mathbb{E}\{P'_k\} < 1$ for a cell loading higher than 50 users where this finding is obtained on the simulation layer.

In order to simplify equation (28), approximations and assumptions can be made to accelerate the convergence. The denominator is bounded between:

$$0 \leq \sum_{k=1}^{\Psi_q} (1 - \beta_{k_i}) \sum_{n=1}^{N} \omega_{k_i,n} \leq N_{sec},$$

where N_{sec} is achieved using the full consumed sector bandwidth. The right side of the numerator in (28) is:

$$\frac{1}{\left(\sum_{k=1}^{\Psi_q} \sum_{n=1}^{N} \gamma_{k_i,n} \right) >> 1} << 1.$$

After these considerations, the water level can be approximated as $\lambda_i \gtrapprox \frac{P_i}{N_{sec}}$. For further details on resource allocation algorithms please refer to [18]-[21].

A. Optimality Test

In order to justify the solution quality, we consider symmetrical homogeneous traffic with Gaussian distribution. All users are requesting similar service associated with data rate of 150 kbps and BER of 10^{-5}. According to the k-means clustering method, the BS position should be in the mean of the clustered distribution which represents the traffic peak.

In high density distributions, clustering complexity is quasi-linear with the number of users, K, the Euclidean distance, d, and the number of clusters, s. Hence, complexity can be exactly calculated by $\mathcal{O}\left(K^{sd+1} \ \log K\right)$. To avoid this, we generate one cluster and then replicate it to have one exact symmetrical traffic distribution. Thus, k-means clustering can be applied directly to obtain the BSs' positions.

In order to examine the performance of the DMSNE, BSs' positions in this scenario should be located in the mean of each cluster or around its vicinity, i.e. $z_q = \mathbb{E}\{\Psi_q\} \forall q \in \mathcal{Q}$. Therefore, formulating the problems in (11), (14) and (15), and solving them simultaneously should exhibit optimal throughput equilibrium.

Performance obtained based on both positioning approaches is demonstrated in Fig. 4, where $\texttt{BS}_1$ and $\texttt{BS}_2$ are positioned by DMSNE which were both initialized in at the positions 1.2204e^{+003} and -2.0196e^{+001} respectively, while in Fig. 3 both are localized according to k-means clustering. It can be noted in Fig. 4.a that DMSNE achieves *optimal NE* and the throughput gaps are negligible between iteration 50 and 100 until it converges to less than 0.7 Mbps. When considering only k-means, throughput gap is more than 2.6 Mbps, which consequently reflects on increasing the probability of service outage and of traffic congestion (see Fig. 4.b). Conventional network planning methods based on manual or limited search, e.g. k-means clustering and MIP, have inadequate accuracy in determining the network design. This is due to the fact that cells being sectorized, the CCI is not symmetrical or reciprocal, which degrades the network efficiency in terms of cost, resource efficiency and QoS. For instance, sector 2 (180^o) of $\texttt{BS}_1$ in Fig. 3 lies in the exact transmission direction of sector 2 in $\texttt{BS}_2$, which severely reduces the performance of sector 2 in $\texttt{BS}_1$. While this is not the case in Fig. 2 where the affected sectors (1 and 3) in $\texttt{BS}_2$ have shifted interferes-sectors, thus resulting in a better performance. If both cells have omni BSs, then CCI becomes symmetrical and k-means returns with a more balanced NE.

In contrast with k-means, DMSNE yields optimal NE and proves its capacity to achieve optimality.

B. Influence of Extra CCI on the Network Cost and Performance

A more challenging scenario of heterogeneous traffic with an area of $3000\ m \times 3000\ m$ is considered, where $K = 900$ users are distributed in a random-uniform pattern over the area. Each user requests a certain type of service, and the service requirements are summarized in Table I.

A non-dominated solution (NE) is obtained from Pareto front. The computational complexity of Pareto front is high and grows rapidly with the size and density of the traffic. It is common that Pareto generates solution candidates randomly for a certain number of iterations and then Pareto front is constructed from the non-dominated solution [22]. Pareto optimal is then obtained from Pareto front using the derived algorithm in [22]. In order to exactly calculate the computational search complexity which Pareto exhibits for a given traffic map, the possible solution combinations (BSs' positions) are given by $\binom{\mathcal{A}+\mathcal{Q}-1}{\mathcal{Q}} = \frac{\mathcal{A}^{\overline{\mathcal{Q}}}}{\mathcal{Q}!}$, where $\mathcal{A}$ is the traffic dimensions in meter square (m^2).

Fig. 5 illustrates that a network of 3 BSs is sufficient to meet QoS and outage probability targets. The initial non-dominated solution obtained by Pareto is shown in Fig. 5-a). Significant throughput gaps are observed between cell 3 and the others and as a result DMSNE penalizes the greedy cell which is $\mathtt{BS}_3$ in this scenario while it maximizes the others ($\mathtt{BS}_1$, $\mathtt{BS}_2$) to minimize throughput gaps, see Fig. 5-b). As a consequence, this yields a service probability gain (Θ) by DMSNE over Pareto up to 9 units as in Fig. 5-c).

We surround a traffic environment with 8 BSs in order to examine DMSNE performance under high CCI conditions. In this scenario, DMSNE is initialized by an early Pareto solution as Pareto optimal exhibits high computational complexity implied of $\frac{(9\times10^6)^{\overline{4}}}{4!}$. We therefore consider 500 iterations, where 100 solution candidates are generated for each iteration. As this process progress further, Pareto efficiency becomes less observable. Therefore, DMSNE, which is faster and more accurate in narrowing solutions feasibility domain.

In Fig. 6 Pareto early-solution is represented by iteration one with considerable throughput gaps particularly a 5 Mbps between $\mathtt{BS}_3$ and $\mathtt{BS}_4$. However, initializing DMSNE by an early Pareto solution can significantly reduce overall complexity. As a result, each BS is displaced according to the penalty factor in (33) to maximize NE until the solution starts to converge after 40 iterations. In terms of outage probability, Fig. 6 c) shows a significant improvement in service probability after only few iterations to converge to the solution around the outage probability threshold after 32 iterations. Due to space limitations, the final visual network plan is not included in this paper.

To this end, involving the extra CCI sources, 8 BSs, has a cost of assigning an extra $\mathtt{BS}$ to meet the OP target.

In the proposed integrated approach, CCI management is minimized twice, first during the facility location problem, where propagation distances between users, serving sectors and the interferers are balanced. Second, it is performed during the resource allocation, i.e., for subcarriers which experience high CCI, the decision variable in (20) will be penalized and as a result these subcarriers will not be allocated unless the sector is over loaded. Finally, failure to achieve either balanced CCI or balanced traffic distribution breaks NE.

VII. Conclusion

In this paper, the problem of network planning for FGWNs OFDMA systems has been tackled as a multi-objective optimization problem subject to several constraints and limitation factors, e.g., lack of resources, propagation loss, non-uniform antenna pattern, CCI, heterogeneous traffic, network cost, high data rate demands and different levels of QoS, to emulate more realistic scenarios. Since the planning problem is NP-hard and is also a boundary value problem (BVP), the proposed method decomposed the problem according to Additive Schwarz method into two fundamental sub-problems, facility location and resource allocation, while traffic allocation is performed as a mid-layer problem. The solution of the multi-objective problem was steered by DMSNE to locate the minimum number of BSs in positions that achieve maximum throughput equilibrium, which implicitly avoids both traffic and CCI congestion whilst achieving the target outage probability. The proposed integrated method has utilized various optimization techniques, e.g. convex optimization, parallel heuristic, Pareto and mix integer programming, to deliver the best QoS under minimum resource consumptions. Applications of DMSNE are for both complete and partial network deployments as illustrated in Section VI. It can optimize an upgrade in a network as well as optimizing a complete deployment. Complexity can be adjusted by the following, maximise the heuristic step size, subgroup DMSNE in which the size of a each is inversely proportional to the frequency as the long reach effect of interference at high frequencies becomes insignificant, prior clustering which impacts load-balancing in cells/sectors and finally sub-optimal/predefined resource allocation.

References

[1] IEEE802.16-2004, IEEE Standard for Local and Metropolitan Area Networks Part 16: Air Interface for Fixed Broadband Wireless Access Systems,www.ieee.org.

[2] E. Amaldi, A. Capone, and F. Malucelli,“Planning UMTS base station location: Optimization models with power control and algorithms,” *IEEE Trans. Wireless Commun.,* Vol.2, no 5, September 2003.

[3] G. Hampel, K. L. Clarkson, J. D. Hobby and P. A. Polakos,“The Tradeoff Between Coverage and Capacity in Dynamic Optimization of 3G Cellular Networks ,”IEEE 2003.

[4] T. G. Crainic; B. D. Chiara; M. Nonato; L. Tarricone,“Tackling Electrosmob in Completely Configured 3G Networks by Parallel Cooperative Meta-Heuristics,”*IEEE J. on Wireless Communications*, vol. 13, no. 6,pp 34-41, 2006.

[5] A. Eisenblatter, H. Geerdes ,“Integrated Access Point Placement and Channel Assignment for Wireless LANs in an Indoor Office Enviromen”, IEEE 2007.

[6] K. Jaffres-Runser, J.M. Gorce and S. Ubeda,“ Multiobjective QoS-oriented planning for indoor wireless LANs,”In *Proc. IEEE VTC*, 2006.

[7] J.-L. Lu, K. Jaffres-Runser, J.-M. Gorce and F. Valois, “Indoor wLAN Planning with a QoS constraint based on a Markovian Performance Evaluation Model,” In *Proc. IEEE WiMob*, 2006.

[8] O. M. Lopez, I. A. Gonzhlez,“Automatic Planning Optimal Quality-Cost Wireless Networks, The Indoor Pareto Oriented ABSPAD Approach,” In *IEEE PIMRC*, 2004.

[9] F. Gordejuela-Sanchez, A. Juttner, and J. Zhang “A Multiobjective Optimization Framework for IEEE802.16e Network Design and Performance Analysis,”*IEEE J. on Selected Area in Commun.*, vol. 27, no. 2, February 2009.

[10] K. Tutschku,“Demand-based Radio Network Planning of Cellular Mobile Communication Systems,” In *Proc. IEEE. INFCOM.*, 1998.

[11] A. Eisenblatter, A.G.F. Geerdes,“Solution-Oriented Modelling and Mathematical Optimization,” *IEEE J. on Wireless Communications*, vol. 13, no. 6,pp 8-14, 2006.

[12] K. Yang and X. Wang,“Cross-Layer Network Planning for Multi-Radio Multi-Channel Cognitive Wireless Networks,”*IEEE Trans. on Commun.*, vol. 56, no. 10,pp 1705-1714, 2008.

[13] Y. Wu, P.A. Chou, Q. Zhang, K. Jain, W. Zhu, and S.Y. Kung,“Network Planning in Wireless Ad Hoc Networks:A Cross-Layer Approach,”*IEEE J. on Selected Areas Commun.*, vol. 23, no. 1,pp 136-150, 2005.

[14] G. Scutari, D. Palomar, F. Facchinei and J.S. Pang,“Convex Optimization, Game Theory, and Variational Inequality Theory,”*IEEE J. on Signal Processing Magazine,* vol.27, no.3, pp 35-49, 2010.

[15] V.S. Abhayawardhana, I.J. Wassell, D. Crosby, M.P. Sellars, and M.G.Brown, “Comparison of empirical propagation path loss models for fixed wireless access systems,” in *Proc, IEEE Vehicular Technology Conference (VTC’05)*, vol. 1,pp.73-77, Stockholm, Sweden, May-June 2005.

[16] F. Gunnarsson, M. N. Johansson, A. Furuskar, M. Lundevall, A. Simonsson, C. Tidestav and M. Blomgren,“Downtilted base station antennas a simulation model proposal and impact on HSPA and LTE performance,” Ericsson Research, 2008.

[17] B. Smith, P. Bjostard and W. Gropp,“Domain Decomposition, Parallel Multilevel Methods for Elliptic Partial Differential Equations,” Cambridge University Press 1996.

[18] A.F. Al Rawi, B.S. Sharif and C.C. Tsimenidis,“Fair Scheduling and Hybrid Resource Allocation in OFDMA Cellular System,”in *Proc. IEEE PIMRC*, Sep. 2010.

[19] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge University Press, 2004.

[20] C.Y. Wong, R.S. Cheng, K.B. Letaief and R.D. Murch, “Multiuser OFDM with adaptive subcarrier, bit and power allocation,” *IEEE J.Select. Areas Commun.*, vol. 17, no. 10, pp. 1747-1758, Oct. 1999.

[21] A.F. Al Rawi, B.S. Sharif and C.C. Tsimenidis,“User Priority Aware Scheduling and Dynamic Resource Allocation in OFDMA,” *IET J. on Commun.*. Aug. 2010

[22] E. K. P. Chong and S. H. Zak, “*An Introduction to Optimization*,”. Wiley-Interscience Series in Discrete Mathematics and Optimization, third edition, 2008.

[23] E.S. Lo, P.W.C. Chan, V.K.N. Lau, R.S. Cheng, K.B. Letaief, R.D. Murch, and W.H. Mow, “Adaptive Resource Allocation and Capacity Comparison of Downlink Multiuser MIMO-MC-CDMA and MIMO-OFDMA”, *IEEE Trans. Wireless Commun*., vol 6, no. 3, pp. 1083-1093, Mar. 2007.

[24] A.F. Al Rawi, B.S. Sharif and C.C. Tsimenidis “Pareto-Metaheuristic Multi-Objective Network Optimization for OFDMA-based Systems,” in *Proc, IEEE WiMob*, Niagara Falls,Ontario, Canada, Oct 2010.

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TABLE I: Problem Formulation and Simulation Parameters

Notation	Description	Parameter	Value
$\mathcal{F}$	network throughput over $\mathcal{Q}$ BSs	Bandwidth	10 MHz
f_q	cell q throughput	Total transmit power/sector	43 dBm
p	subcarrier-user power allocation	Reuse factor	1.3.3
ω	subcarrier-user allocation factor	Sector boresight	60°, 180°, 300°
$\mathcal{R}$	time-delay required data rate	Transmitter antenna	3 sectored 15 dBi
ρ	time-delay insensitive maximum allocation unit	Receiver antenna	Omni 10 dBi
Ψ	clustered traffic assigned to a specific cell	Data, Pilot, Guard subcarriers	768, 224, 32
χ	cell penalty decision factor	PL exponent, Thermal noise	-4, -140 dBm
Γ, ϵ	gap value and bit error rate	$\mathcal{R}_{TDS}$, ρ_{TDI}	{150, 128, 64 Kbps}, {1}
Θ, ε	service coverage and outage probability[7]	BER_{TDS}, BER_{TDI}	10^{-5}, 10^{-3}

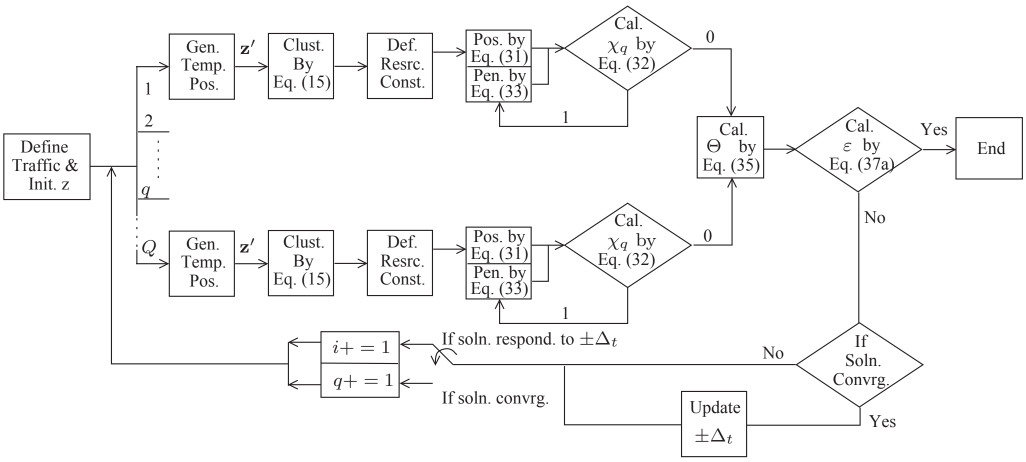

Fig. 1: DMSNE outline.

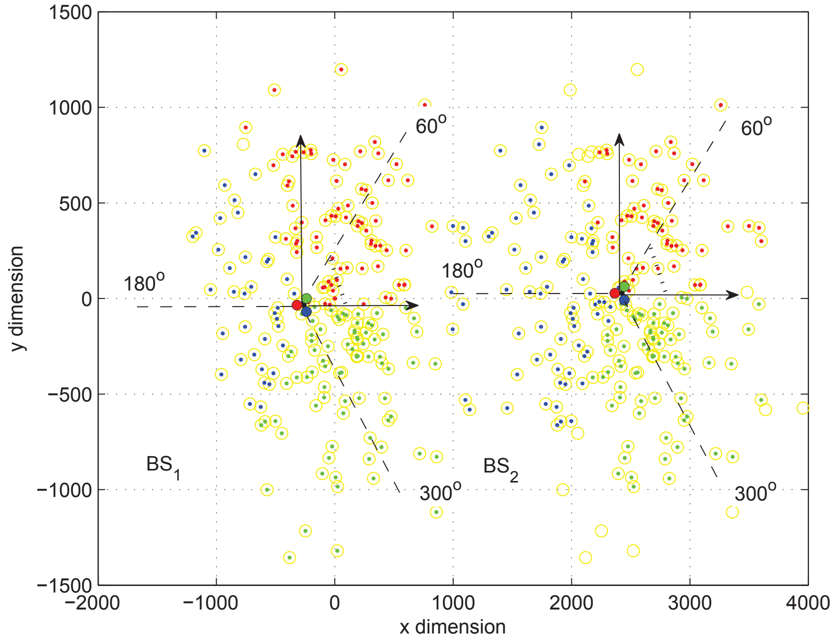

Fig. 2: BSs' positions by DMSNE in a Gaussian traffic distribution.

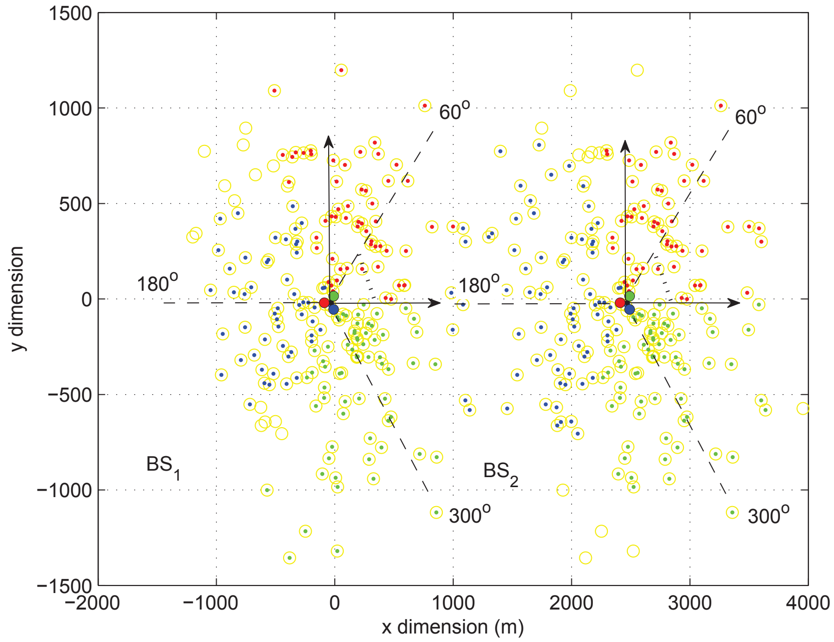

Fig. 3: BSs' positions by k-means clustering in a Gaussian traffic distribution.

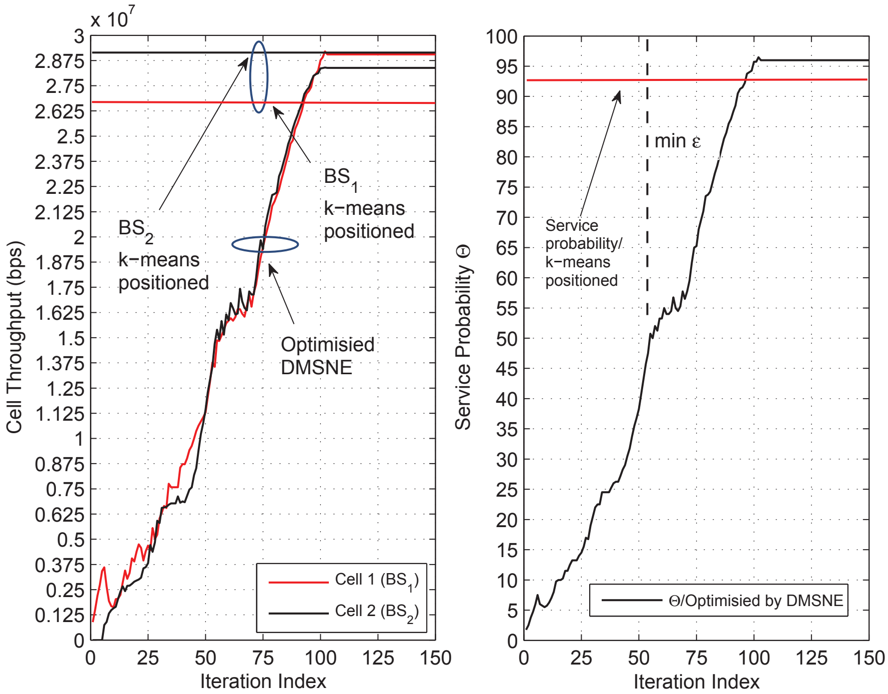

Fig. 4: Cell throughput/Service probability vs. iteration number.

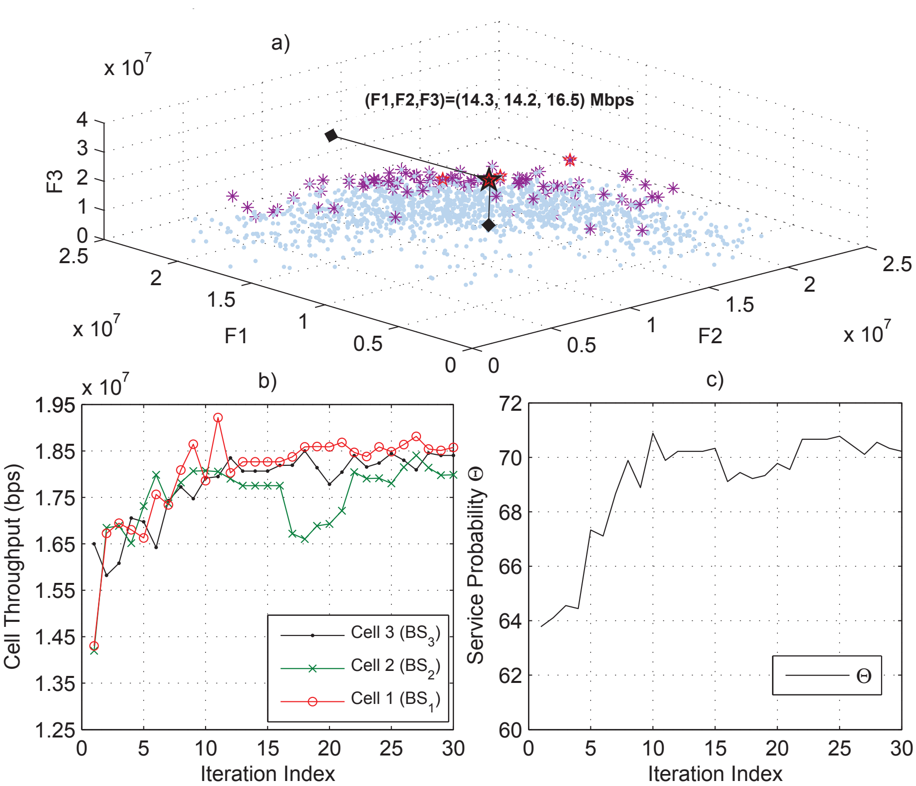

Fig. 5: a)Throughput by Pareto, b) and c) Throughput/Θ gain by DMSNE.

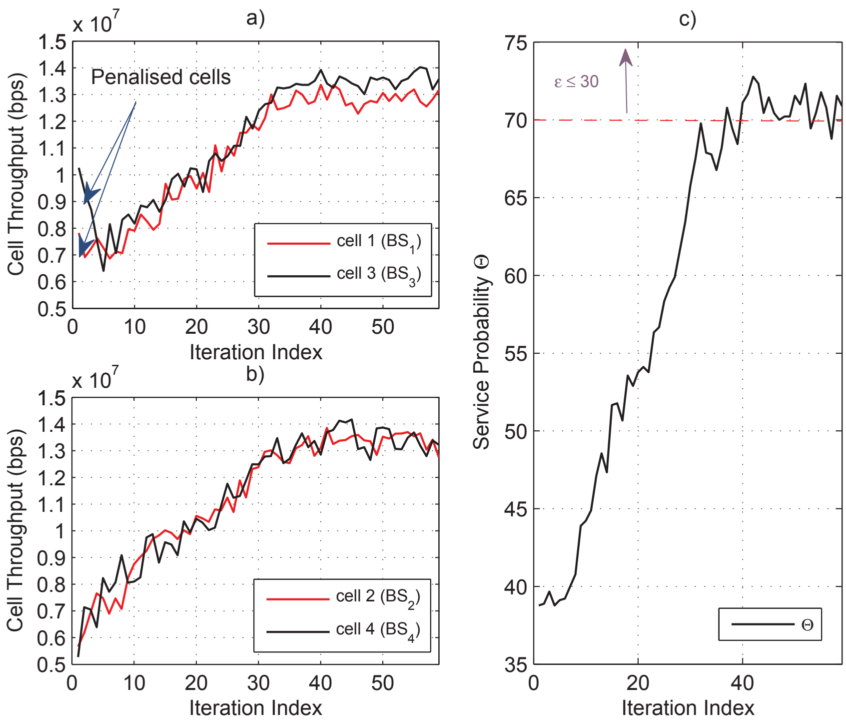

Fig. 6: Throughput/Service probability improvement by DMSNE.