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Planning Future Cellular Networks: A Generic Framework for Performance Quantification

Ali Imran[1], Elias Yaacoub[1], Zaher Dawy[2], Adnan Abu-Dayya[1]
[1]Qatar Mobility Innovations Center (QMIC), QSTP, Doha, Qatar
[2]American University of Beirut, Department of Electrical and Computer Engineering.
email:{alii, eliasy,adnan}@qmic.com, {zaher.dawy}@aub.edu.lb

***Abstract*—The new pressing expectations from emerging cellular systems such as energy efficiency, heterogeneity of cell sizes and base station types, focus shift to capacity from coverage, and demand for homogeneity of service provided in the coverage area, have increased the need for intelligent and optimal cellular system planning more than ever. While large number of works in literature have focused on various aspects of cell planning for legacy and emerging cellular systems, a common strategy to take into account these new born requirements by formulating them as function of underlying planning parameters, is missing so far, making the research on planning next generation cellular system sporadic. In this paper we address this problem and present a novel framework that can facilitate holistic planning of future cellular system by embodying these requirements through a unified and interrelated set of metrics to reflect the key performance indicators. These metrics can be used to quantify performance of cellular system plan in terms of major deployment parameters of interest. We use an extensive set of numerical results to demonstrate the effectiveness of proposed framework. These results also provide useful insights into the key trade offs involved in planning of emerging cellular networks and thus can facilitate future research in this area.**

***Index Terms*—Holistic Cell planning; Performance Quantification; Capacity; Quality of Service; Energy Efficiency**

I. INTRODUCTION

Despite of being over two decades old [1], Cellular System Planning (CSP) paradigm had continuously required major research effort to cater for the changing requirements and features of each generation of cellular system. For example, goal of CSP in first generation of cellular systems was to merely achieve patchy coverage to serve the elite of society. As the trend moved towards ubiquity of cellular service, fueled by success of GSM concepts, CSP had been researched extensively with the main goal of minimisation of number of Base Stations (BS) while maximising coverage [2].

Introduction of data services seconded by the advent of more data friendly UMTS at the beginning of new millennium, meant CSP concepts have to be revised by shifting the focus from coverage to capacity [3]. While the work on capacity oriented planning solutions for UMTS was yet far from being saturated [4], advent of LTE and LTE-A put forth a whole new set of challenges to the CSP research community. In the wake of rising cost of energy and environmental concerns, energy efficiency is also a newly added constraint to the CSP problem that asks for significantly different if not totally new approach towards CSP [5]. Furthermore, increasing scarcity of spectrum is pushing towards more aggressive frequency reuse recently, leading to intra-cell reuse in the form of widely accepted fractional frequency reuse in emerging cellular systems. All these changes are again asking for revamping and revision of CSP paradigm.

Given CSP problem is NP-Hard, it has been addressed in literature using a number of heuristics such as simulated annealing [6], particle swarm [7], genetic algorithms [8], Taugchi's method [9], ant colony optimisation [10], to obtain near optimal solutions. The basic methodology that is generally followed, involves building a detailed dynamic simulation model that acts as black box to output the Key Performance Indicators (KPIs) as function of planning parameteres of interest. An acceptable solution is then searched by partially exploring the solution space via simulated evaluation of KPIs at parameter combinations selected with help of the aforementioned heuristic. Given the large number of parameters a real cellular system has, and the complexity of the dynamic simulator, generally long time is required for evaluating KPIs through these simulators for given set of parameteres. The large number of planning parameteres also mean the number of potential combinations of parameters are enormous making the solution space virtually unfathomable. Though aforementioned heuristics can help to reduce the search space substantially, still current CSP approach that involves time taking simulation based evaluations is a very time consuming process generally.

Furthermore, each of the prior research works on planning uses different definitions of KPIs while considering different sets of planning parameter. This makes assertion and cross-comparison of quality of solutions produced difficult. Furthermore, the need for KPIs that can incorporate the emerging requirements from cellular systems such as energy efficiency, heterogeneity of cell sizes and base station types, focus shift to capacity from coverage, and demand for homogeneity of service provided in the coverage area, is though well conceived, but is not fully sated yet. The mathematical planning framework we propose in this paper aims to address these challenges.

The contribution of this paper are three fold: First, we develop a Performance Characterisation Framework (PCF) consisting of a set of metrics that can characterise the three Key Performance Indicators (KPIs) of cellular system that ought to be considered in holistic cell planning. PCF can be used to quantify the main performance aspects of a cellular

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deployment plan in terms of major planning parameters such as types of BS, number of sectors per site, azimuth, tilts, heights, frequency reuse, and set of Modulation and Coding Schemes (MCSs) to facilitate holistic planning. The incorporation of MCS ensures that the plan is optimal taking into the standard specific features of the system under consideration. The main advantage of PCF is that KPIs proposed therein, can be evaluated semi-analytically through simple static simulator. Thus use of our PCF can substantially reduce the solution time by avoiding the need for classic dynamic simulators to evaluate classic KPIs such as throughput and rate fairness etc. Second, using PCF we demonstrate how holistic CSP can be addressed through simple manifestation of multiobjective optimization problem. Third, our results and subsequent analysis provide useful insights into the trade offs, various planning layouts for emerging cellular systems have to offer. These insights can lead to simplification of the planning problem in many cases. The rest of the paper is organized as follows: Section II describes background and system model for this work. In Section III we derive PCF. In Section IV we present numerical results and section V concludes this paper.

II. Background and System Model

A. Major Planning Objectives In Emerging Cellular Systems

For emerging and future cellular systems, the planning problem have multiple target objectives like maximization of capacity, coverage, fairness of service in the coverage area, spectral efficiency, throughput, QoS or minimization of cost, energy consumption and outage etc. However all these objectives can be boiled down to three main categories of performance measures:

1) Capacity Oriented Performance Measures: These include cellular capacity, spectral efficiency, throughput, and goodput.
2) QoS Oriented Performance Measures: Rate fairness and outage are well known examples of QoS measures.
3) Cost Oriented Performance Measures: Total cost of ownership of a cellular system over its life has three further major factors:
    a) Capital Cost: cost of hardware, software and deployment labour cost.
    b) Maintenance Cost: Cost of labour required for operation, optimization and maintenance of sites and the switching networks.
    c) Energy Consumption: Energy consumed to keep the cellular system running is increasingly becoming a main factor of operational cost.

For next generation cellular systems, capital cost is being reduced by introduction of low cost BSs (RS, or femto or Pico BSs) [11]. Whereas, the maintenance cost are being cut down by exploiting self organising solutions [12]. Therefore, from planning perspective, minimisation of energy consumption has recently become a major means of cost reduction, particulary due to rising costs of energy and concern for CO2 emissions. Therefore, in this paper we will focus on energy consumption only while dealing with cost related KPI. In the following we present our PCF that can quantify each of the three listed facets of performance of a cellular systems from planning perspective, with more computational efficiency compared to classic metrics for these KPIs.

B. Major Planning Parameters

Cellular system has myriad of planning parameters that jointly determine its performance. These paremeters include BS location, BS type, inter site distance, number of sectors per site, antenna type, antenna gain, antenna height, transmission power, modulation and coding schemes, frequency reuse etc. As explained above, to overcome the size and complexity of the CSP problem, most of the prior research works have mainly relied on some sort of simulation model that acts as black box between the planning parameters and respective KPI values [6]–[10]. Some prior works that do consider an analytical and thus more insightful approach, are confined to considering a single planing parameter at a time only [13], [14], due to the overwhelming complexity of the problem. To overcome this difficulty, in this paper, we propose to exploit a hybrid approach i.e. we consider holistic planning problem using semi analytical approach in which a detailed mathematical system model is first constructed. Building on this model, a PCF for the three main KPIs identified above, is then defined that can be evaluated through simple light weight calculations that can be conducted via a static and thus less time consuming and easily repeatable simulator.

C. A Holistic Planning Problem Formulation

For a concise planning problem formulation, we propose to divide the whole area of interest into set of Q bins. Where q denotes q^{th} bin and $\mathcal{Q}$ denotes set of all bins that constitute the area of interest. Each bin has same size such that $\sum_{i=1}^{Q} q_i = A$, and $\frac{A}{Q} = q, \forall q \in \mathcal{Q}$ where A is the total area. Using the notation defined in Table I, the problem of holistically planning a cellular system while jointly optimising the three objective identified above, can now be formulated as a multi-objective optimisation problem:

$$\max_{\mathcal{Q}_b,\mathcal{S}_b,\mathcal{H}_s,\mathcal{P}_s,\boldsymbol{\phi}^s,\boldsymbol{\theta},\Upsilon_f} f(\Upsilon,\Lambda,\Omega) \tag{1}$$

subject to:

$$B \leqslant B_{max}$$

$$1 \leqslant S_b \leqslant S_{b,max}\ , \quad \forall S_b \in \mathcal{S}_b$$

$$\frac{360}{S_b} i - k_{\phi,max}\delta_\phi \leqslant \phi^s \leqslant \frac{360}{S_b} i + k_{\phi,max}\delta_\phi, \quad i = 1,2,3...S_b$$

$$0 \leqslant \theta^s \leqslant k_{\theta,max}\delta_\theta\ , \quad \forall \theta^s \in \boldsymbol{\theta}$$

$$h_{s,min} \leqslant h_s \leqslant h_{s,max}\ , \quad \forall h_s \in \mathcal{H}_s$$

$$p_{s,min} \leqslant p_s \leqslant p_{s,max}, \quad \forall p_s \in \mathcal{P}_s$$

TABLE I
NOTATION FOR PLANNING PARAMETERS

Symbol	Description
b	b^{th} base station
$\mathcal{B}$	set of all base stations in systems
B	total number of BS i.e. $\lvert\mathcal{B}\rvert = B$
B_{max}	maximum number of BS that can be afforded.
A	Total area of interest
$\mathcal{Q}$	set of Q bins that constitute A
q	q^{th} bin, $\sum_{i=1}^{Q} q_i = A$, & $\frac{A}{Q} = q, \forall q \in \mathcal{Q}$
$\mathcal{Q}_b$	set of bins in which BS are located, $\mathcal{Q}_b \subseteq Q$
$\mathcal{S}$	set of all sectors in the systems
S	total number of sectors in system i.e. $\lvert\mathcal{S}\rvert = S$
s	denotes s^{th} sector
S_b	total number of sectors b^{th} BS has
$\mathcal{S}_b$	$\mathcal{S}_b = \{S_1, S_2, S_3 ... S_B\}$, $S = \lvert\mathcal{S}\rvert = \sum_{b=1}^{B} S_b$
$S_{b,max}$	maximum number of sectors a BS can have
h_s	(antenna) height of s^{th} sector antenna on BS
$\mathcal{H}_s$	set of all sector antenna heights
$h_{s,max}$	maximum allowed h_s
$h_{s,min}$	minimum allowed h_s
δ_{h_b}	step with which h_s can vary
f_s	fractional frequency reuse factors in s^{th} sector
Υ_f	Number of times spectrum is reused within a given area
ϕ^s	azimuth angle of s^{th} sector
$\boldsymbol{\theta}$	set of tilt angles of all sectors
θ^s	tilt angle of s^{th} sector
δ_ϕ, δ_θ	steps sizes for azimuth and tilts change
$k_{\theta,max}$	maximum steps of tilt change
$k_{\phi,max}$	maximum steps of azimuth change
$\mathcal{P}_s$	set of transmission powers of all sectors
p_s	transmission power from s^{th} sector
δ_{p_s}	step with which p_s can vary
$p_{s,max}$	maximum allowed value of p_s
$p_{s,min}$	minimum allowed value of p_s
G_q^s	gain from the s^{th} sector antenna to q^{th} bin.
α	path loss co-efficient
β	pathloss exponent
φ_v	vertical beamwidth of the antenna
φ_h^s	horizontal beamwidth of s^{th} sector antenna
Υ	capacity wise KPI
Λ	service area fairness wise KPI
Ω	Energy consumption wise KPI
$\mathcal{X} \backslash y$	means all elements of $\mathcal{X}$ except y
x_q,y_q,z_q	cartesian coordinates of q^{th} bin

III. DETERMINING QUANTITATIVE MEASURES OF KPIs

The expression in (1) formulates a holistic CSP problem in which optimal location of BS, number sectors per BS, the antenna heights, the transmission powers, the antenna azimuth, the antenna tilts and the frequency reuse has to be optimised to achieve the best possible performance in terms of all three KPIs. The first step to solve the CSP problem in (1) would be to derive quantitative measures for the three KPIs of interest i.e. Υ, Λ and Ω in terms of the planning parameters under consideration. Since these KPIs are admittedly dependent on one common indicator, i.e. SINR distribution in the system, therefore, it is rational to start with derivation of the SINR that can then be used to derive expressions for these KPIs. The SINR perceived in the q^{th} bin from s^{th} sector can be given as:

$$\gamma_q^s = \frac{P_s G_q^s \alpha \left(d_q^s\right)^{-\beta}}{\sigma^2 + \sum_{\forall \acute{s} \in \mathcal{S}} \left(P_{\acute{s}} G_q^{\acute{s}} \alpha \left(d_q^{\acute{s}}\right)^{-\beta} .u\left(\mu, f_{\acute{s}}\right) \right)} s, \acute{s} \in \mathcal{S}, q \in \mathcal{Q} \tag{2}$$

Where $u\left(\zeta, f_s\right)$ is unit function that can be used to model wether or not the q^{th} bin will be receive interference from a particular sector on particular carrier by capturing the impact of both the (fractional) frequency reuse factor and scheduling schemes under consideration. And d_q^s is distance between the s^{th} sector antenna and q^{th} bin given by:

$$d_q^s = \sqrt{\left(x_{q_s} - x_q\right)^2 + \left(y_{q_s} - y_q\right)^2 + \left(h_s - z_q\right)^2} \tag{3}$$

Three dimensional antenna gain can be modelled as proposed in [15] and with simplification introduced in [16] as :

$$G_q^s = 10^{-1.2\left(\lambda_v \left(\frac{\theta_q^s - \theta^s}{\varphi_v}\right)^2 + \lambda_h \left(\frac{\phi_q^s - \phi^s}{\varphi_h^s}\right)^2\right)} \tag{4}$$

where θ_q^s is the vertical angle in degrees from s^{th} sector to q^{th} bin and can be given as $\theta_q^s = \arctan\left(\frac{h_s}{d_q^s}\right)$. The ϕ_q^s is horizontal angle in degrees on s^{th} sector to q^{th} bin with respect to positive x-axis. Subscripts h, a and v denote horizontal, azimuth and vertical respectively. Thus λ_h and λ_v represent weighting factors for the horizontal and vertical beam pattern of the antenna in 3D antenna model [15], respectively. Note that for the practical cellular antennas the relationship between the horizontal beamwidth of sector antenna and the number sectors per site can modeled as $\varphi_h^s = \frac{360}{\mu * \acute{S}_b}$. Where μ is factor representing overlap between the sectors. Thus using (4) in (2) the SINR perceived in q^{th} bin can be determined as in (5). As desired, the SINR derived in (5) is function of the key parameters that are significant in holistic planning. Note that, (5) can be used to calculate SINR anywhere in the area of interest with respect a best serving sector denoted by s, therefore to mark its generality for onward use we have dropped the superscirpt s from the SINR symbol in (5).

A. *Quantifying Υ: Reflecting Capacity Wise Performance from Planning Perspective*

A number of metrics such as throughput, spectral efficiency and area spectral efficiency are used to reflect cellular capacity, with each having its pros and cons. Lets briefly analyse them first. The conventional definition of spectral efficiency is:

$$\text{Spectral Efficiency} = \frac{T}{BW} \left(bps/Hz\right) \tag{6}$$

where T is aggregate throughput in the coverage area and BW is bandwidth of spectrum used. While this metric is widely used to estimate capacity-wise performance of cellular system, it is not a perfectly suitable measure of capacity from planning perspective. The main difficulty with the throughput based capacity evaluation is that a large number of full scale dynamic system level simulations are required to estimate throughput. Also, throughput is strongly dependent on very short term dynamics like fast fading and temporary shadowing. The acute spatio-temporal dynamics of scheduling schemes, that are not part of CSP, also significantly determine the end throughput of the system. Therefore, it may over shadow the effect of planning parameters such as listed above while reflecting the capacity-wise performance of system. A second

$$\gamma_q\left(\mathcal{Q}_b, \mathcal{S}_b, \mathcal{H}_s, \mathcal{P}_s, \boldsymbol{\phi}^s, \boldsymbol{\theta}, \Upsilon_f\right) = \frac{P^s \alpha (d_k^n)^{-\beta} 10^{-1.2\left(\lambda_v\left(\frac{\theta_q^s - \theta^s}{\varphi v}\right)^2 + \lambda_h\left(\frac{\phi_q^s - \phi^s}{\left(\frac{360}{\mu * S_b}\right)}\right)^2\right)}}{\sigma^2 + \sum_{\forall \acute{s} \in \mathcal{S}}\left(P^{\acute{s}} \alpha\left(d_q^{\acute{s}}\right)^{-\beta} 10^{-1.2\left(\lambda_v\left(\frac{\theta_q^{\acute{s}} - \theta^{\acute{s}}}{\varphi v}\right)^2 + \lambda_h\left(\frac{\phi_q^{\acute{s}} - \phi^{\acute{s}}}{\left(\frac{360}{\mu * \acute{S}_b}\right)}\right)^2\right)} .u\left(\zeta, f_b^{\acute{s}}\right)\right)} \quad (5)$$

option for measuring capacity-wise performance is conventional area spectral efficiency. However for evaluating this metric too throughput calculation is prerequisite rendering it unsuitable as well.

Our basic aim here is to quantify the long term performance of cellular system by incorporating its dependencies on planning parameter listed above rather than short term dynamics of cellular eco-system. Therefore conventional throughput based metrics are not exact match to our purpose mainly because of their dependency on short term dynamics as well as their complexity of evaluation. Rather a metric to reflect the capacity oriented performance of cellular system that can be evaluated without resorting to complex dynamic simulators is required.

To this end, here we present a metric namely *Effective Spectral Efficiency* (ESE) to quantify Υ. This metric has semantics similar to the area spectral efficiency but it does not require throughput estimation for its calculation, rather it can be determined through simple semi analytical approach with help of static less time consuming simulator. A key advantage of ESE is that it can also serve as the basis for calculation other two KPIs i.e.Λ and Ω, to nail down the coupling between these contradicting planning objectives. Below we explain calculation of ESE.

Since the sub carrier bandwidth in emerging cellular system (e.g. LTE) is fixed so the throughput on single sub-carrier in a given BS-user link and hence the total throughput of the system depends on Modulation and Coding Efficiency (MCE) on each link. The MCE in turn depends on SINR available on that link. Thus, with total bandwidth fixed, the actual long term average spectral efficiency of a BS-user link depends on the SINR's geographical distribution in the coverage area that in turn depends mainly on planning parameters as given by (5). Therefore, the long term average SINR available at point n is mainly dependent on the location of n. Thus, the SINR at point n can be abstracted as function of its distance d_n^s and angle ϕ_n^s from the BS and in cylindrical coordinate system, can be simply written as:

$$\gamma_n = f\left(\phi_n^s, d_n^s\right) \quad (7)$$

This SINR then can be mapped to MCE using theoretical Shannon bound or using practical SINR thresholds of the MCSs used in the cellular standard under consideration. Now the average modulation and coding efficiency theoratically achievable in a cell can be given as:

$$M\bar{C}E_{cell} = \frac{1}{A_{cell}} \int_\phi \int_d \log_2\left(1 + \gamma_n(\phi_n^s, d_n^s)\right) d\Delta\phi\Delta d \quad (8)$$

Where A_{cell} is the total coverage area of cell. In order to evaluate the system wide theoretical area spectral efficiency in more practical manner, let's consider $\mathcal{N} = \{1, 2, 3...N\}$ is set of all points in the coverage area. Then (8) extended for whole coverage area can be written as:

$$M\bar{C}E_{area} = \frac{1}{|\mathcal{N}|} \sum_{n=1}^{N} \log_2\left(1 + \gamma_n\right) \quad (9)$$

In order to have an actual area measure $N \longrightarrow \infty$. For ease of evaluation we invoke our bin-grid concept introduced above i.e. area is divided into finite set of Q virtual bins of equal size, so small that within each bin the long term average SINR can be assumed to be constant. Now (9) can be written as:

$$M\bar{C}E_{area} = \frac{1}{Q} \sum_{q=1}^{Q} \log_2\left(1 + \gamma_q\right) \quad (10)$$

Let $\mathcal{L} = \{0, 1, 2, 3, ...L\}$ is set of modulation and coding schemes available to be used in the given standard (e.g. in LTE) and MCE_l denotes the respective modulation and efficiency of l^{th} scheme. Where $l = 0$ means modulation and coding scheme with zero spectral efficiency i.e. no link representing outage and L is modulation and coding scheme with highest spectral efficiency. Now the average spectral efficiency achievable in the coverage for given cellular system plan can be obtained as:

$$\Upsilon_{MCE_e} = \sum_{l=0}^{L}\left(MCE_l \times \frac{Q_l}{Q}\right) \quad (11)$$

where Υ_{MCE_e} is expected spectral efficiency. Q_l is the number of bins in coverage area in which γ_q meets the threshold required to use l^{th} modulation and coding scheme.

A key advantage of quantifying spatial spectral efficiency in this manner is that it has the potential to reflect geographical areas of high importance with weighting factors to pronounce their importance and reflect them in the ESE measure proportionally. This provides freedom to tailor the optimisation objective to the operator's policy. For setting different coverage priorities for different regions, Q in (11) that represents number of bins, can be replaced with sum of weights associated with each bin. i.e.

$$\Upsilon_{MCE_w} = \sum_{l=0}^{L}\left(MCE_l \times \frac{\sum_{l=\acute{l}} w_{q_{\acute{l}}}}{\sum_{q=1}^{Q} w_q}\right) \quad (12)$$

Where Υ_{MCE_w} denotes weighted MCE, w_q denotes weight assigned to the q^{th} bin in proportion to its relative importance in the area of interest. Thus these weights can be used to model QoS requirements of different demographic groups or differentiate areas with different user densities. $w_{q_{\acute{l}}}$ denotes weight of q^{th} bin using $\acute{l}^{th}$ modulation and and coding scheme, where $\acute{l} \in \mathcal{L}$. If not enough data is available to the planner so that precise weight to individual bins can be assigned and operator in general wants to make sure the plan is such that spatially fair data rates are available throughout the coverage area, then instead of using arithmetic mean in (11), harmonic mean can be used. Unlike the arithmetic mean, the harmonic mean will aggravate the impact of bins with low MCE and will damp down the impact of bins having very large MCE on the overall spectral efficiency of system. In this case:

$$\Upsilon_{MCE_h} = \frac{Q}{\sum_{q=1}^{Q}\left(\frac{1}{MCE_q}\right)} \tag{13}$$

where Υ_{MCE_h} denotes harmonic mean spectral efficiency in the area of interest and MCE_q denotes the MCE achievable in q^{th} bin based on the SINR γ_q perceived in that bin which can be determined by (5).

We can now define a suitable capacity wise KPI to be used in the planning framework. It can be defined as:

$$\Upsilon = \Upsilon_{MCE} \times \Upsilon_f \tag{14}$$

Υ_{MCE} reflects average BS-user link spectral efficiency achievable with a particular cellular plan/design. Υ_{MCE} can be modeled using (11), (12) or (13) depending on the planing objectives and service priorities of operator. Υ_f denotes the spectral efficiency achieved through spectrum reuse. For numerical results, we use Υ_f essentially as 'number of times spectrum is reused within a site'. Thus, the Υ represents the effective spectral efficiency while directly reflecting the effect of key planning factors. The main advantage of this metric is its ease of calculation as evaluation of throughput through dynamic simulation is not required. Rather only the SINR geographical distribution for given set of planning paratmeters need to be known, that can be obtained by numerically evaluating (5).

B. Quantifying Λ: Reflecting QoS Wise Performance from Planning Perspective

For a measure of fairness appropriate to be used in CSP problem as an optimisation objective, we have to significantly depart from the conventional notion of fairness that is considered when designing very short time scale adaptive mechanisms e.g scheduling or power allocation. While planning a cellular system, all such short term dynamics can be neglected as they are averaged out. From planning perspective by fairness we mean the homogeneity of the level of service that can be provided in the coverage area. More precisely it is fairness in space rather than fairness in time. We build on above derivations and define a metric for the Service Area Fairness (SAF) in terms of the BS-user link MCE . SAF also can be evaluated by the SINR in (5) and can be given as:

$$\Lambda = 1/\sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\left(MCE_q - \sum_{l=0}^{L}\left(MCE_l \times \frac{Q_l}{Q}\right)\right)^2} \tag{15}$$

The advantage of this metric of fairness is that it exclusively captures geographical variation of the BS-user link spectral efficiency and hence achievable data rates in area of coverage which is key factor to be considered in CSP. Furthermore, SAF is also capable to implicitly counter measures the dilemma of cell-center and cell-edge rate differences. This is because, having spatial connotation instead of temporal, SAF gives the cell edge users judiciously higher importance because as area is square function of radius, thus more area lies farther from the cell center. In case of uniform user distribution this means more users will lie farther from the cell center and thus should have naturally larger influence in determining SAF.

C. Quantifying Ω: Reflecting Energy Consumption Wise Performance from Planning Perspective

Energy consumption in cellular system has many complicated and interrelated factors. Considering the scope of this paper, we focus on three selected planning parameters that affect the energy consumption i.e. base station types, transmission powers and number of sectors per site, that make energy consumption in various cellular system plans different from each other. To this end we model power consumption on a site while incorporating both fixed, as well as, variable power consumption per site that in turn depend on the type of base stations. Fixed power consumption is the power that is consumed in keeping the circuitry of BS sectors alive no matter if there is traffic or not, until all sectors on that base station are completely switched off. Variable power consumption is power required for transmission on air interface and varies with the traffic load. Thus, total power consumption in a site consisting of a generic BS can be written as:

$$\Omega = \sum_{s=1}^{S}\left\{P_f^s + P_v^s\left(G\left(\Gamma^s, D^s\right), P_t^s, \omega^s\ \right)\right\} \tag{16}$$

where subscripts f, v and t denote fixed, variable, and transmission powers respectively. For sake of simplicity we do not consider any stray losses e.g. feeder loss, connectors loss as they are negligible for the purpose of this analysis. Variable power consumption further depends on the transmission power P_t , traffic loading factor ω and antenna gain G. Antenna gain is further a function of efficiency of antenna Γ, and directivity D that can be approximated as: $D = \frac{4\pi}{\varphi_h \varphi_v}$. In commercial cellular systems the typical vertical beam width of antenna is around $\pi/18 \approx 10^o$ and horizontal beam width depends on the number of sectors per site e.g. for three sectors and six sectors, beamwidths of around 70^o and 35^o are usually used respectively. Using the previously defined inter-sector overlap factor μ we can write horizontal beamwidth as a function of S as $\varphi_h = \mu\pi/S$. Then directivity can be written as: $D \cong \frac{72S}{\mu\pi}$

The P_t required to achieve a desired Effective Isotropic Radiated Power ($EIRP_d$) with an omnidirectional antenna can be given as: $P_t = \frac{EIRP_d}{\Gamma \times D}$.

Therefore, for given coverage level, if more more sectors per site are used, less transmission power would be required due to high directivity and hence higher gains of the antennas. Thus the variable circuit power per sector for desired $EIRP_d$ can be written in dB as:

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$$P_v^s = 10\log_{10} P_t^s - 10\log_{10}\left(\frac{4\Gamma^s S}{\mu\varphi_v^s}\right) + 10\log_{10}\omega^s \quad (17)$$

Putting (17) to in (16) and

$$\Omega = \sum_{s=1}^{S}\left\{P_f^s + \mu\left(\frac{\omega^s\varphi_v^s P_d^s}{4\Gamma^s S}\right)\right\} \quad (18)$$

Equation (18) provides a metric to quantify the power consumption of cellular system plan as a function of number of sectors per site, transmission powers, traffic load and sector over lap (i.e. antenna beamwidths). The split between the fixed power consumption and transmission power can be used to model various BS types as well.

IV. Numerical Results

In this section we demonstrate the usefulness of our proposed PCF for holistic planning with help of selected numerical results. Given the limited space, impact of only a few planning parameters on the KPIs derived is investigated while others are kept fixed at values listed in Table II. Figure 1 plots values of KPIs Λ, Υ_{MCE} and Υ_f as function of two major important planning parameters i.e. 'number of sectors per site' S and the 'number of times spectrum is reused per site' i.e Υ_f. Thus, for example the notation 'S=6,Υ_f=2' that denotes plan number 11, means there are six sectors per site and spectrum is used two times within a site. i.e. the spectrum is divided in three equal parts, each part is allocated two three adjacent sectors and the pattern is repeated for other three sectors on the site such that sectors using the same spectrum are apposite to each other. Trade off among the average link spectral efficiency Υ_{MCE}, spectrum reuse efficiency Υ_f and the spatial fairness Λ can be clearly observed in Figure 1. For example, plan no. 9 (S=6,Υ_f=6) offers the maximum service area fairness and highest spectrum reuse efficiency but the average BS-user link spectral efficiency achievable with this plan is the worst among all the twelve plans evaluated. On the other hand, plan no. 12 (S=6,Υ_f=1) offers maximum average BS-user link spectral efficiency but with lowest service area fairness and spectrum reuse efficiency. Whereas, plan no. 10 (S=6,Υ_f=3) does not maximise performance in any of the three aspects but rather offers medium level performance in all the three KPIs. The detailed analysis of these tradeoffs is beyond the scope of this paper and will be covered in future work. Here, the key observation to be made is that no single plan is optimal in terms of all the three performance metrics plotted. Therefore, the PCF's capability to precisely quantify this tradeoff with computation efficiency can actually help to design a cell plan that is optimal to simulatnesouly meet the multiple planning objectives closely. Although, S and Υ_f are only two of the many key planning parameters that have to be optimised; the key advantage of proposed analytical framework is that it enables readily available insights into the impact of individual parameters on three major aspects of cellular system performance. These insights can be then exploited to define better problem structure and possibly reduce the solution search space significantly. Such application of the proposed framework is explained through result in Figure 2. Figure 2 plots mean SINR from (5) as function of a planning parameter, antenna tilt, that plays an important role in determining the performance of cellular system and is often planned empirically or heuristically. With our framework the three KPIs of interest can be easily determined as function of SINR that is further determinable as function of planning parameters including tilt through (5). This result illustrates how our framework can be used to analyse the impact of tilt on different aspects of cellular system and thus the optimal tilt angle can be quickly determined by exploiting (5) and the PCF that builds on it. The knowledge of the optimal tilt value for typical range of other key planning parameters can lead to significant reduction in the size of planning problem by presetting the tilts in the optimal range, during the heuristic based searches for holistic planning solutions.

Figure 3 and 4 plot Ω i.e. the derived metric for power consumption, as function of sector beamwidth and expected traffic load factor, for 3 and 6 sector per site respectively. It can be observed that power consumption is more heavily dependent on the number of sectors per site, while sector beam width, generally overlooked in literature also has significant impact on the total power consumption. On the other hand, contrary to the importance given while investigating energy efficient planning schemes, load factor can be observed to play a small role in total power consumption (as variable power consumption is generally very small compared to the fixed power consumption in BS).

TABLE II
Modelling Parameters

Parameters	Values
System topology	19 sites (1-6 sector/site)
BS Transmission Power	39 dBm
BS Inter site distance	1200 meters
BS height	32 meters
User antenna	0 dB (Omini directional)
BS antenna vertical beamwidth, B_v	10^0
BS antenna vertical Gain Weight , λ_v	0.5
BS antenna vertical Gain Weight , λ_h	0.5
BS antenna maximum gain, G_{max}	18 dB
BS antenna maximum attenuation, A_{max}	20 dB
Frequency	2 GHz
Pathloss model	Cost Hata
Shadowing STD	8 dB

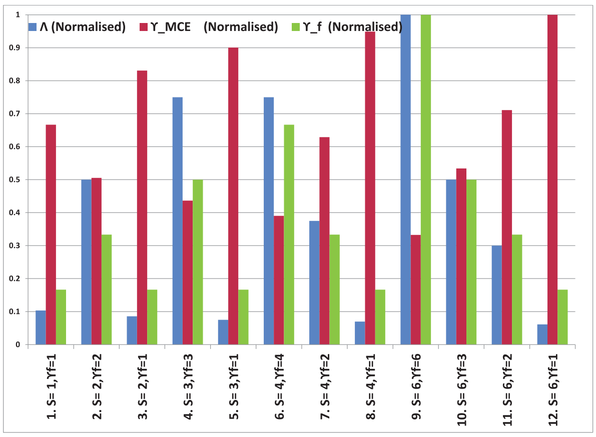

Fig. 1. Quantification of the impact of number of sectors and frequency reuse on performance of a cellular system plan using proposed PCF framework. For comparison on same scale, each metric is normalised by its maximum value.

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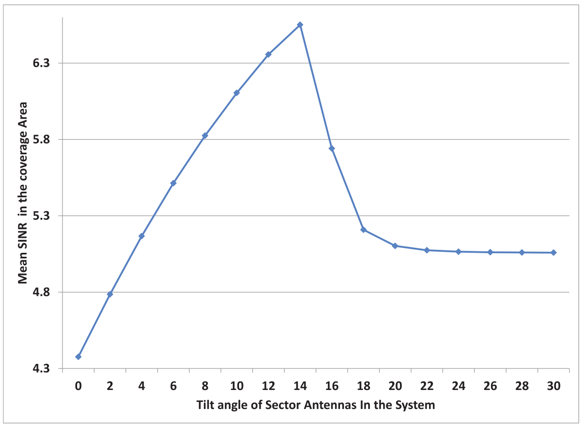

Fig. 2. Average SINR as function of tilt angle, obtainable using(5).A cell plan with three sectors per site and full frequency reuse is used.

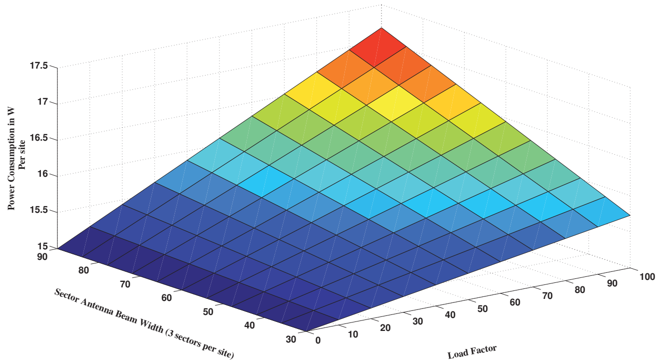

Fig. 3. Power Consumption vs Sector Beam width and Load Factor for S=3.

V. Conclusions

In this paper we present an analytical framework to quantify three major key performance indicators that are used in cellular system planning i.e. capacity, service area fairness and energy efficiency, as functions of a detailed set of planning parameters. The proposed metrics can be quickly evaluated semi-analytically and thus can facilitate the solution of multi-objective holistic planning problem that otherwise is tackled heuristically, using black box type complex dynamic simulation models providing little insights into system behavior. The insights given by proposed framework can help to identify the the critical planning parameter that can play more important role than others to address new requirements from future cellular networks. An added advantage of proposed framework is that it can not only be used to reduce the solution space thereby making the heuristic solution searching approaches more efficient, it can also be exploited to assert the quality of solution produced in many cases. The analysis of the impact of other key parameters on the KPIs and the detailed demonstrations of the possible use cases of the proposed framework will be the focus of our future work.

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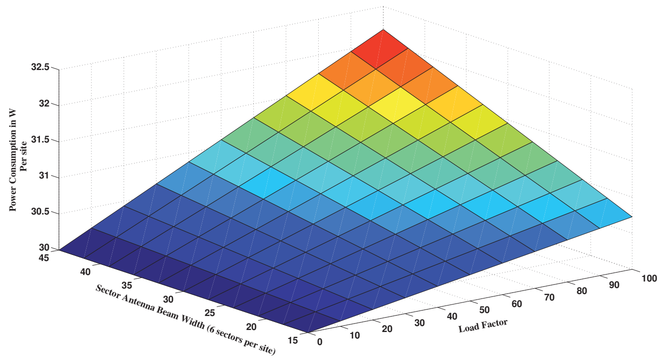

Fig. 4. Power Consumption vs Sector Beam width and Load Factor for S=6.

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