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Exploiting heterogeneity for cost efficient 5G base station deployment using meta-heuristics

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Abstract: A key concern in the design of 5G is the radio access network, which is expected to be significantly denser and more advanced, with considerably higher infrastructure and power consumption cost than that of conventional mobile network standards. Novel algorithms/approaches for optimal planning of the radio access network are required for tackling the additional complexity of the problem of cost-efficient radio access planning in 5G, which cannot be properly handled by conventional approaches. This study proposes a novel optimisation framework for the cost-efficient deployment and configuration of 5G base stations. The main idea of the proposed optimisation framework is to exploit heterogeneity in three key 5G technologies, heterogeneous base station architecture, cell range extension and multiple-input–multiple-output spatial multiplexing, by jointly optimising their configurations during network design. In addition, the proposed optimisation framework includes generic steps for applying meta-heuristic algorithms to the problem, which are necessary to overcome the problem's complexity, especially for large problem instances. The authors' results show that their novel optimisation framework improves the cost efficiency of the network planning both in terms of power and infrastructural cost to operators.

Nomenclature

CRE	cell range extension
MIMO	multiple-input–multiple-output
CAPEX	infrastructural cost
l	set of existing macro base stations/sites with no MIMO
M	set of candidate sites for macro base station deployment
S	set of candidate sites for small cell deployment
N	set of base station *models*
v_i	site acquisition cost of site i, $i \in M \cup S$
$i_{x,y,z}$	3D Coordinates of site $i, i \in M \cup S \cup l$
b_i	Backhaul cost of site $i, i \in M \cup S$
$e_{(i,n,o)}$	RF equipment cost of BS *model n* with MIMO antenna *configuration o* installed in site i
P	set of transmission power levels of base stations
O	set of antenna *configurations*
D	set of deployed base stations
A^d	number of transmit RF chains of base station d
∂	MIMO efficiency
SINR^u	signal to interference and noise of UE u
$\omega^{\max}$, BW	maximum achievable spectral efficiency, available bandwidth
Cov	service area coverage percentage threshold

1 Introduction

A key concern in the design of 5G for mobile network operators is the radio access network, which is expected to be significantly denser and more advanced, with considerably higher infrastructure and power consumption cost than that of conventional mobile network standards [1, 2]. This increased complexity motivates the development of novel approaches for optimising the 5G radio access network, which will account for most of the system infrastructural and power consumption costs [3–7]. This paper proposes and studies a novel 5G radio access network deployment optimisation framework, where the main idea is to *jointly* optimise three key 5G technologies, heterogeneous base station (BS) architecture, cell range extension (CRE), and multiple-input–multiple-output (MIMO) spatial multiplexing, during network design to minimise the 5G radio access system cost of ownership.

2 Background

The general objective is to optimise the radio access network topology/structure to achieve certain quality of service (QoS) targets while minimising system cost. To achieve this objective, many system models and optimisation problems have been proposed over the last two decades engineered towards different cellular system standards [8–10]. The most representative works aim to exploit advanced system architectures such as small cell BSs (heterogeneous network) and consider novel objectives. The authors in [11] considered the problem of site selection for 5G BS equipment that abides by downlink electromagnetic field limits. However, their work does not include a mathematical BS planning model or algorithm. The authors in [12] proposed an optimisation for a two-tier cellular network containing BSs with fibre backhaul and BSs with wireless backhaul. Although a metaheuristic approach is proposed, their work only considered the problem of BS site selection but not site configuration, which is not sufficient for 5G networks. In [13], the authors proposed approximation algorithms to select a subset of candidate sites to deploy macro or small cells to minimise the total cost of ownership of the cellular system while satisfying coverage and capacity constraints. However, their work simplifies the 5G network planning task. For example, their work assumes that the BS transmit power is always fixed and that the type of BS to install in each candidate site is known. Furthermore, their work does not consider the optimisation of key 5G technologies like CRE and MIMO. The authors in [14–16] formulated the same problem as in [13] as a multi-objective problem and tackled it using different metaheuristic algorithms. The main criticism of these works is the simplicity of the network planning problem model assumed which is inadequate for the proper planning of a 5G network. Furthermore, 5G networks will leverage multiple key technologies like MIMO and CRE which is not considered in these works. Hence, these works take a one-dimensional approach focusing on optimising a single technology. Our work uniquely builds on these works by jointly optimising both the BSs structure and MIMO transmission *configuration*.

More specifically, we make the following contributions:

i. A novel 5G radio access network planning optimisation problem framework is proposed that aims to *jointly* optimise three key 5G technologies, heterogeneous BS architecture, CRE and MIMO spatial multiplexing. Since different configurations of these technologies will have different system capacity and cost implications, the idea is to *jointly* optimise the technologies during network design. This is in contrast to the existing literature that focuses on optimising only one technology.
ii. To solve the proposed 5G optimisation problem, we show the application of meta-heuristic algorithms by proposing a generic solution representation to the problem and a fitness function. This allows **any** meta-heuristic algorithm to be applied and studied. Meta-heuristics algorithms are important to tackle the complexity of the proposed optimisation problem which resembles the facility location problem and has been proven to be NP-hard [17]. Meta-heuristic algorithms are also important to tackle the large search space of the problem, especially as the number of candidate sites and BS configurations increases. This makes meta-heuristic algorithms a suitable candidate for practical application to the problem of 5G BS deployment over exact methods. Additionally, meta-heuristic algorithms are important for optimising towards multiple 5G objectives, simultaneously.
iii. Finally, using the proposed 5G optimisation problem framework, we investigate the impact of the different MIMO configurations using a capacity biased power efficiency metric. Results indicate that MIMO sizably increases the throughput capacity of a heterogeneous cellular access network; and also increases the power efficiency despite an increase in power consumption. However, the homogenous unoptimised MIMO configuration model from literature results in reduced power efficiency especially when the actual traffic demand is considered, as the MIMO order increases.

3 Proposed 5G heterogeneous network system model

A 3D geographical service area, G, is considered for BS deployment. Our model aims to exploit both heterogeneous BS types/models (macro, micro and pico cells), MIMO multi-antenna transmission and CRE to increase network capacity in more infrastructure (CAPEX) and energy-efficient network manner. Notations used are defined in Nomenclature.

A $(m \times n)$ MIMO configuration means the BS has m transmit antennas and the user (UE) equipment has n antennas for signal reception. For this work $m = n$. Each site i is defined by three variables: (a) its 3D coordinates $i_{x,y,z}$; (b) its site acquisition cost v_i; and (c) backhaul cost b_i. It is assumed that small cell candidate sites and BSs are by a given ratio less expensive compared to macro sites and BSs. The notations x and $\hat{x}$ are used for macro and small cell BSs, respectively.

3.1 BS models and configurations

- In each candidate macro site $m \in M$, we assume that operators can deploy an omnidirectional macro BS operating in one of $|O|$ MIMO antenna *configurations* with a transmission power level $p^m \in P$. We assume that all RF chains of BSs $m \in M$ operate at the same power level p^m. MIMO spatial multiplexing is assumed to increase system capacity [18]. Thus, the capacity of the BS to handle traffic is increased as the number of RF chains increases, however, this also increases the energy consumption of the BS and also the equipment cost. While in each small cell site $s \in S$, one of $|\hat{N}|$ *models* for small cell BSs can be deployed, operating in one of $|O|$ MIMO antenna *configurations* at transmission power level $p^s \in P$. Each small cell *model* represents a different *type* of small cell BS with a different power consumption profile, communication range (i.e. maximum transmit power) and equipment cost.

3.2 Coverage and traffic model

- Let $p_{r(d,k,i)}$ be the received downlink power by UE i from antenna k of BS d, which can be computed using the Hata propagation model [19]. To model signal coverage of a service area, we define a set, C, of dense and uniformly distributed points over G that should receive a signal power from at least one BS above a given threshold, Q. The percentage of C that is covered defines the degree of coverage of the network, which should be maximised

$$\Upsilon_{c,d} = \begin{cases} 1 & \text{if point } c \ (c \in C) \text{ is covered by BS } d \\ 0 & \text{otherwise} \end{cases}. \quad (1)$$

- Furthermore, we model the expected traffic demand distribution by a set U of demand points distributed across the service area where every demand point, $u, u \in U$, has a minimum data demand, R_u, that must be provided by the deployed network in addition to its coverage requirement, Q. *Demand points aggregate data traffic demand from UEs in a small area*.

3.3 Cell association

LTE-advanced allows coordinated multi-BS data transmission, however, in this work, it is assumed a UE can only be linked to one and consequently receive data from one BS at a time. However, it is assumed that UEs receive data simultaneously from all RF chains of their serving BS when MIMO is used. Let the binary matrix $\boldsymbol{a}$ represent the UE to BS associations such that $a_{(d,i)}$ determines if the UE is associated to BS d where the variable is 1 if it does or 0 otherwise. Traditionally, a UE i is associated to a BS S_i from which it receives the strongest downlink power, according to (2)

$$S_i = \arg\max_{d} \left(p_{r(d,i)}\right) \quad \forall d \in D \Big| p_{r(d,i)} \geq Q \quad (2)$$

$$S_i = \arg\max_{d} \left(\hat{\beta}_d \, p_{r(d,i)}\right) \Big| p_{r(d,i)} \geq Q \, . \quad (3)$$

However, due to the very small transmission power of small cells compared to macro BSs, small cell biasing is defined for small cell networks. The use of small cell biasing allows small cell BSs to attract more UEs. In this work, it is assumed that only small cell BSs utilise biasing consequently bias $\hat{\beta}$ value for a macro BS is zero. Computing the optimal bias values for small cells is a challenging optimisation task that is part of the proposed 5G problem [20]. Consequently (2) is modified to (3) by adding a *bias* to the received pilot power.

3.4 Network capacity

The network capacity defines the traffic handling capability of the network and is closely related to the individual load of the BSs. Overloaded BSs will provide connected UEs with poor QoS. A BS d is stable if its *load* (ρ^d) is less than or equal to one and is defined by (4). Based on the average *load* of deployed BSs, we consider maximising the percentage of satisfied UEs, i.e. on the average, the number of UEs that receive their minimum data requirement, given by (6)

$$\rho^d = \max\left(0.1, \sum_{i}^{|U|} a_{(d,i)} \frac{R_u}{\partial A^d \, \mathrm{BW} \, \omega^u}\right) \quad (4)$$

$$\omega^u = \min \left(\delta \log_2 1 + \epsilon \, \mathrm{SINR}^u, \omega^{\max}\right) \quad (5)$$

$$\tau = \left(\frac{\sum_d^{|D|} (1/\rho^d)}{|U|}\right) \cdot 100. \quad (6)$$

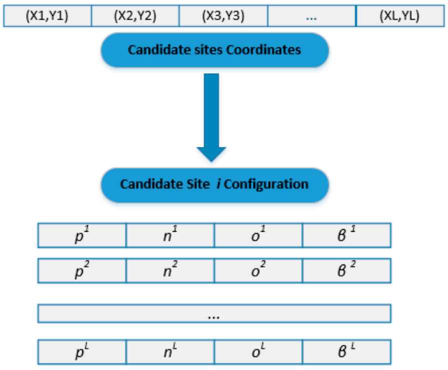

Fig. 1 *Solution representation*

3.5 Network power consumption

Minimising the power consumption of cellular networks is highly desired since energy bills account for a significant percentage of operational cost. We incorporate a detailed energy consumption model from [21], not described here for space limitation. The power consumption of the network is a function of the number, *type*/*model*, transmission power and *load* of the deployed BSs and also the number of RF chains employed for each BS (i.e. the MIMO order). Given the BS model *(n)*, the MIMO antenna *configuration* (*o*), the BS transmit power *(p)* and load (ρ^d) let the power consumption of BS d be given by $E^d = E(o, n, p, \rho^d)$.

4 Proposed 5G problem model

The objective of the proposed optimisation problem is to find the optimal number, locations, *types*, transmission powers (p), small cell *bias* vector ($\hat{\beta}$) and the number of RF antenna chains of BSs that maximises the network capacity while minimising CAPEX and energy consumption cost, subject to the coverage constraint. The following decision variables are introduced:

$$x_i, \hat{x}_i = \begin{cases} 1, & \text{if a BS is deployed in site } i \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

$$z_{in}, \hat{z}_{in} = \begin{cases} 1, & \text{if a BS of model } n \text{ is deployed in site } i \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$$k_{io}, \hat{k}_{io} = \begin{cases} 1, & \text{if antenna configuration } o \text{ is deployed in site } i \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

The objectives are thus

$$\text{Capacity:} \quad \max_{x, \hat{x}, \hat{\beta}, p, z} \tau \tag{10}$$

$$\mathrm{C1} = \sum_{m \in M} \sum_{n \in N} \sum_{o \in O} x_m\left(e_{(m,n,o)} \cdot k_{mo} \cdot z_{mn} + (v_m + b_m)\right) \tag{11}$$

$$\mathrm{C2} = \sum_{m \in S} \sum_{n \in \hat{N}} \sum_{o \in O} \hat{x}_m\left(\hat{e}_{(m,n,o)} \cdot \hat{z}_{mn} \hat{k}_{mo} + (v_m + b_m)\right) \tag{12}$$

$$\text{CAPEX:} \quad \min_{x, \hat{x}, z, \hat{z}} \mathrm{C1} + \mathrm{C2} \tag{13}$$

$$\text{Power:} \quad \min_{x, \hat{x}, \hat{\beta}, p, z} \sum_{m \in M} x_m E^m + \sum_{m \in S} \hat{x}_m E^m \tag{14}$$

Subject to

$$\sum_{i=1}^{|D|} \sum_{c=1}^{|C|} \Upsilon_{dc} \geq (1 - \mathrm{Cov})C \tag{15}$$

$$\sum_{i=1}^{|O|} k_{do} \leq 1 \quad \forall d \tag{16}$$

$$\sum_{i=1}^{|N|} z_{dn} \leq 1 \quad \forall d \tag{17}$$

$$\sum_{i=1}^{|D|} a_{iu} \leq 1 \tag{18}$$

$$a_{iu} \leq x_i \Upsilon_{iu} \quad \forall i, u. \tag{19}$$

The above optimisation problem aims to design a high capacity but cost-efficient cellular access network by exploiting heterogeneous BS types, MIMO multi antenna transmission and CRE. The optimisation problem has three objectives; to maximise the capacity of the network (10), to minimise CAPEX given in (13) and to minimise energy consumption (12). Equation (15) states that the coverage of the network over the service area must be greater than or equal to the given threshold, *Cov*. Constraints (16) and (17) state that only one *type* and *configuration* of the BS can be deployed at any site while (18) and (19) enforce that a UE can only be associated to one BS at a time and that a UE can only associate to a BS that has been deployed, respectively. The BS transmit power and small cell biasing constraints (not shown) take the general form of (16) and (17).

5 5G BS optimisation using meta-heuristics

The high dimensions and large search space of the proposed 5G optimisation problem makes it infeasible to use exact methods to find the 'optimal solution' in a practical time, especially for large problem instances. For example, a scenario with merely '30' candidate BS sites and '5' BS *configurations* will have a gigantic search space of 5^{30}. This motivates the application of meta-heuristic algorithms. Meta-heuristic algorithms, if applied correctly and fine-tuned, can overcome the large search space of the problem to find *good* approximate solutions to the problem or even optimal ones in some cases. However, they do not guarantee on the optimality. The successful application of Meta-heuristic algorithms in 5G cellular architecture depends on novel solution representation, the design of efficient search operators, tuning and comparisons between different algorithms, and incorporation of problem-specific knowledge.

We introduce the term '*cell plan*' which is used to describe a candidate solution to the optimisation problem.

5.1 Solution representation

The solution representation is a critical issue for applying any meta-heuristic algorithm to solve an optimisation problem. The solution representation should allow every point in the search space to be reached. We propose an integer matrix representation where the configuration of every candidate site is represented by an integer vector as shown in Fig. 1.

The integer matrix represents the configurations of an arbitrary cell plan for which the cost and performance implications are computed using a fitness function. The matrix has the same number of rows as the total number of BS sites (L), such that the configuration for the ith candidate site is given by the ith row of the matrix. At this stage of our work, we consider four configurations per site; the power level/deployment status (p), the type of BS deployed (n), the antenna transmission set up (o) and the bias value (β) for small cell BSs.

5.2 Fitness function

The fitness function (or fitness) returns a quantitative assessment of the quality of a candidate cell plan with respect to the design objectives. We propose the following fitness function to be maximised:

$$\Delta\text{Cov} = \text{Coverage target} - \text{Achieved coverage}$$
$$\Delta\text{Cov} = \max(0, \Delta\text{Cov})$$
$$\text{Capacity} = \min(\text{Capacity target}, \text{Achieved capacity})$$

$$F_1 = \left(\frac{\text{Capacity}}{\text{cost}^{1/\propto}}\right) \tag{20}$$

$$F_2 = K^{\Delta\text{Cov}} \tag{21}$$

$$F = \left(\frac{F_1}{F_2}\right). \tag{22}$$

The fitness function in (22) adopts a strategy where cell/network plans that do not meet the coverage performance target of the network are penalised in the search process by the result of (21). '*cost*' can either be energy consumption given by (12) or the CAPEX (13). α (alpha) is a parameter for adjusting the ratio of importance between the desired system *QoS* performance (in this case capacity) and cost of the system, and is an integer between 1 and 20.

Figs. 2 and 3 show the observed impact of the alpha parameter on the capacity and energy efficiency of the optimal cell pan returned. Simply, it can be observed that higher values of α increasingly favour the network capacity performance over cost. To achieve higher capacity more BS nodes or antennas are required which in turn lowers the energy efficiency of the network as the network capacity approaches 100%. A detailed analysis of the parameter is out of the scope of this work.

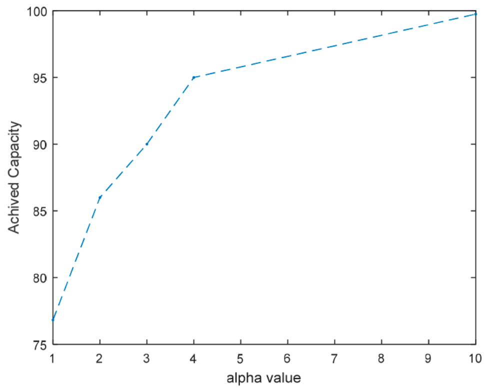

Fig. 2 *Impact of alpha on capacity achieved by the optimal cell plan*

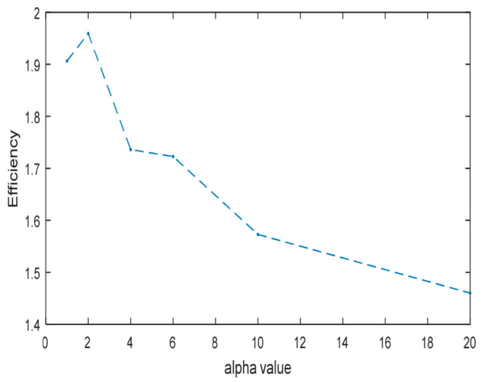

Fig. 3 *Impact of alpha on energy efficiency of optimal cell plan*

Table 1 Base station parameters

Parameter	Macro BS	Micro BS	Pico BS
max. cell radius, km	0.9	0.26	0.08
pmax, dBm	46	39	22
power config, dBm	46, 42.1, 39.8	39, 36.3	22
antenna gain, dB	18	12	7
bias config., dBm	NA	0, 1, 2, 3, 4	0, 1, 2, 3, 4
MIMO config.		1 × 1 to 4 × 4	

6 Results

In this section, we evaluate the proposed 5G network-planning model that jointly optimises the BS type and their MIMO setups. We also discuss some important results observed. We consider a 16 km^2 (4 km × 4 km) area with no existing BSs. All BSs are assumed to use omnidirectional antennas. It is assumed that macro and small cells use separate 5 MHz bandwidth at 2 GHz frequency range as such no inter tier interference is assumed, however, there is inter-cell interference between cells of the same type. Other interference scenarios can also be assumed. Table 1 contains the parameters used for the simulation. We assume 2000 demand points, each with a data demand of 5 Mps. We employ a simulated annealing (SA) meta-heuristic as outlined in Algorithm 1 (see Fig. 4) to tackle the 5G deployment problem. The SA is a probabilistic meta-heuristic technique for approximating the global optimum of a search space. The SA maintains a temperature value that decreases in each iteration by a constant cooling rate. The temperature is used to compute the probability for accepting a worse solution as a method for escaping local optima solutions (see [22]). The optimal parameters for the SA were set through experimentation.

6.1 What's the benefit of the proposed 5G optimisation framework?

To evaluate the cost efficiency benefit of our proposed 5G BS deployment optimisation problem, where the heterogeneous BSs, small CRE bias and MIMO spatial multiplexing antenna setup *configurations* are *jointly* exploited (optimised) during BS deployment, we compare against the state of the art station deployment model in literature for planning a heterogeneous cellular access network [16], the Heterogeneous BS with *fixed homogenous* antenna transmission setup model. In this model, the BS antenna transmission setup is assumed to be *fixed homogenously* per BS and only the type, power, number and locations of BSs are optimised. Under this model, we consider the influence of different setups for MIMO spatial multiplexing per deployed BS on meeting the demand of the traffic scenario. The power consumption of the cell plan is considered as the cost factor during the optimisation; however, the infrastructural cost (i.e. CAPEX, e.g. equipment, site acquisition, backhaul) is also reported. The service area coverage requirement is set to 99%. All results are averaged over 25 runs of a SA algorithm. The 'set up' is the MIMO antenna *configuration* assumed.

Table 2 shows the performance of the proposed 5G deployment framework against the *fixed homogenous* antenna transmission set up framework used in the literature. The influence of MIMO on the result of network planning is also shown. The power efficiency metric is computed using (20) with $\alpha = 2$, and is scaled to the [0, 1] range. α is set to 2 to bias towards higher capacity solutions as a key requirement of 5G. In the table, capacity is defined as the average *Shannon* throughput (capacity) seen by the demand points, considering the available bandwidth, the capacity demand distribution across the coverage areas of the deployed BSs and the Signal to noise ratios. The *Shannon* capacity defines the maximum theoretical rate at which data bits can be transmitted across the link with acceptable error probability from any BS to a demand point, and is computed by (5). The *Shannon* capacity is important to comment on the networks instantaneous data transfer capacity as opposed to (6), which focuses on the number satisfied UE demand. It can be clearly observed from Table 2 that the highest throughput capacity (150 Mbs) is achieved when the highest (of all the scenarios considered) MIMO set up is utilised homogenously per BS (Alg 'D'). However, it can also be seen that this algorithm also has the highest power consumption, which is used to power the extra antennas. It can also be observed that all the scenarios that use MIMO (B, C, D) have higher power efficiency than the baseline Alg 'A' without MIMO. However, it is observed that the power efficiency does not increase consistently by deploying higher-order MIMO transmission *homogenously* across the BSs. Finally, it can be seen that power efficiency is best improved (by 38%) when the proposed *joint* MIMO and Heterogeneous BS planning framework is used, with only a 3% drop in *Shannon* throughput from Alg 'D' with the highest *Shannon* throughput. This can be attributed to increased flexibility introduced by the proposed framework in terms of possible network *configurations*.

```
Input:  T0 : Starting temperature
        Iter: Number of iterations
        Λ: The cooling rate
        T = T0
Let x = random solution using Fig.1
For i = 1 to Iter
      Let f = fitness of x using (22)
      Make a small change to x to make
      x'
      Let f' = fitness of x' using
               (22)
      If f' is worse than f Then
        Let p =exp(-(Δfitness)/T)
        If p < rand(0,1) Then
                   Reject change
                   (keep x and f)
        Else
                   Accept change
                   (keep x' and f')
        End If
      Else
            Let x = x'
      End If
      Let T = Tλ
End For
Output: The solution x
```

Fig. 4 *Algorithm 1: Outline for SA algorithm for 5G BS deployment*

Table 2 Performance of the proposed 5G deployment framework and Influence of MIMO (Cap: Capacity, E: Energy consumption, #BS: Number of base stations, PE: Power efficiency)

Alg	BS trans setup	Cap, bit/s	Power, W	PE ($\alpha = 2$)
A (baseline)	1 × 1	3.50×10^{07}	83.02	0.00
B	2 × 2	7.20×10^{07}	151.28	0.43
C	3 × 3	1.10×10^{08}	371.41	0.40
D	4 × 4	1.50×10^{08}	542.71	0.56
Proposed	**optimised**	$\mathbf{1.45 \times 10^{08}}$	**312.60**	**0.94**

Bold values indicates of the just for emphasis.

However, our problem model also increases the size of the problem search space due to an increase in the number of network *configurations*.

A second empirical simulation is done using (6) as the capacity metric which considers the *actual* demanded traffic to compute the percentage of demand points that received their demanded capacity based on the BSs *loads*. A total of 2000 demands points, each with a fixed capacity requirement of 5 Mbs is randomly distributed on the service are. The objective is to minimise the cost (energy or CAPEX) of the network to handle the demanded capacity for all demand points and provide the required coverage. The candidate site cost for macro sites is randomly set between 7 and 15, their backhaul cost is set to 5 per deployed BS, the equipment cost is computed by *MIMO order* × (0.1 × *backhaul cost*). Similarly, the site cost of small cell candidate sites is set randomly between 1.5 and 3, while their backhaul is set to 0.3 × *backhaul of macro BS*. Their equipment cost is set in the same manner as above. These values were set after consulting an industry domain expert familiar with the cost structure of mobile networks. A similar power consumption trend to Table 2 is observed in Table 3. Increasing the number of transmit antennas used to configure the BSs (MIMO) also increases the power consumption mainly due to power consumed by the extra amplifiers required to power them. However, a different trend in power efficiency is observed compared to Table 2 where Shannon's throughput was used as the capacity metric. It is observed that the power efficiency of the deployed network decreases (from the baseline scenario) as the MIMO order increases when using the *Heterogeneous BS* with fixed homogenous antenna transmission setup network planning model (i.e. Alg B to D), despite the reduction in the total number of BS sites deployed. This can be attributed to the inflexibility of this model, which always deploys high capacity BSs across the service area to meet the demanded capacity even in areas that may not require that level of capacity increase. In contrast, the proposed 5G deployment framework introduces flexibility in the network design process by making the MIMO antenna transmission set up and CRE per deployed BS additional decision variables of the network planning algorithm. The benefit of the proposed framework can be observed in Table 3, which achieves the highest power efficiency of all the algorithms considered. In comparison, to Alg 'A' (which achieves the second-best power efficiency) and Alg 'D' (which uses the lowest number of candidate sites), the proposed framework deploys 49 less BS sites than Alg 'A' and consumes about 7740 less Watts compared to Alg 'D' while still achieving a 100% capacity.

In Table 4, the CAPEX cost (as given by (13)) is considered as the cost component during the network optimisation. It can be observed that the use of MIMO decreases the total CAPEX cost and thus maximises the CAPEX efficiency. This savings arises from the reduced cost associated with the deployment of new BS

Table 3 Performance of the proposed 5G deployment framework taking into account demanded traffic (PE: Power Efficiency ($\alpha = 1$))

Alg	Trans setup	Cap, %	Power, W	#BS	PE
A(baseline)	1 × 1	100	7348.3	127	0.81
B	2 × 2	100	9596.2	75	0.42
C	3 × 3	100	12,284	60	0.14
D	4 × 4	100	14,336	47	0.00
Proposed	**optimised**	**100**	**6595.8**	**78**	**1.00**

Bold values indicates of the just for emphasis.

Table 4 CAPEX comparison (Back: Backhaul cost, Site: Site acquisition cost, Equip: Equipment Cost, #BS: Number of BSs)

Alg	#BS	Equip	Back	Site	Total
A	127	26.8	267.5	491	785.3
B	75	39.3	196.5	388	623.8
C	60	53.3	177.5	357	587.8
D	47	64.6	161.5	306	532.1
Prop.	**50**	**54.6**	**162.5**	**307**	**524.1**

Bold values indicates of the just for emphasis.

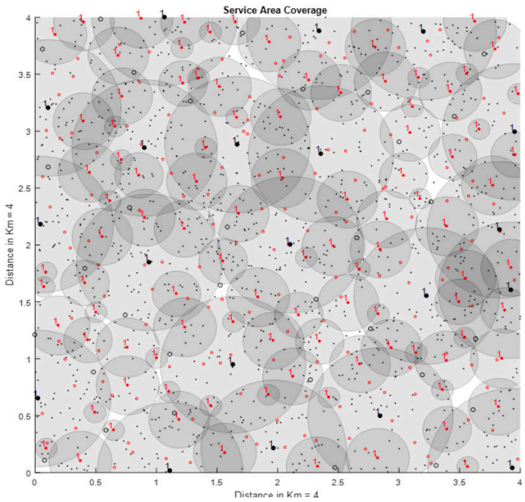

Fig. 5 *Optimal cell plan result of Alg ‘A’ (1 × 1)*

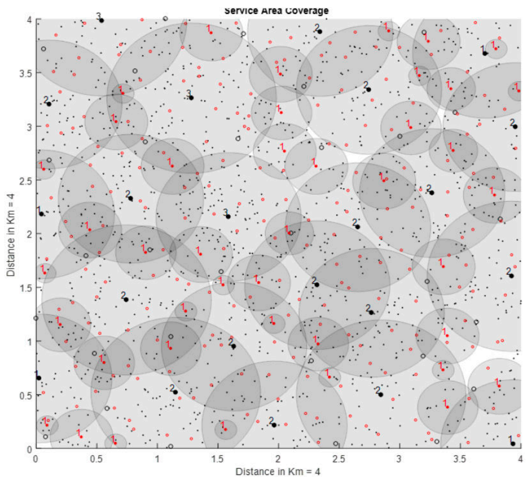

Fig. 6 *Optimal cell plan result of proposed model*

sites and backhauling. This further characterises the influence of MIMO on the CAPEX deployment outcome. Alg ‘A’ employs the traditional cellular transmission (without MIMO) and consequently, a higher number of BSs are needed to achieve the same capacity target. Since for each of these BSs, the mobile network operator incurs a cost for site acquisition and backhaul, this significantly increases CAPEX even with when low-cost small cell BSs are exploited. Another interesting observation is the impact of MIMO on the equipment cost. It can be observed that as the MIMO order increases; higher equipment cost is incurred (see Figs. 5 and 6). The proposed 5G framework can be seen to improve (by 8 units) the CAPEX cost over Alg ‘D’ (which achieves the second-best CAPEX cost reduction) in comparison to the baseline Alg, ‘A’. These results show the cost flexibility introduced by the proposed 5G framework that decides if it is more cost-efficient to deploy a new BS, the type of BS or if it better to employ more antennas on existing BSs.

7 Conclusion

In this work, we have proposed and evaluated an optimisation framework for planning 5G access network planning where the MIMO, cell range bias *configurations* as well as BS types are *jointly* optimised. This is in contrast to a state-of-the-art model in literature that assumes a *fixed* MIMO and CRE *configuration* across BSs. From simulations, it is observed that the use of MIMO sizably increases the throughput capacity of a heterogeneous cellular access network; and also increases the power efficiency despite an increase in power consumption. However, the *fixed* MIMO *configuration* model from literature results in reduced power efficiency especially when the actual traffic demand is considered, as the MIMO order increases. Furthermore, it observed that there is a sizable reduction in the number of deployed candidate sites when higher MIMO order BSs are deployed. Results presented show that the design flexibility introduced by the proposed 5G framework increases cost-efficiency of the network design task in terms of both power and CAPEX efficiency. The results also show the effectiveness and versatility of meta-heuristic algorithms for deploying and operating cost-efficient 5G networks, which we intend to study extensively in future work.

In Fig. 5 all BSs are deployed with a single antenna, consequently, the cell plan returned has a high BS density in order to provide the demanded capacity.

In the cell plan shown in Fig. 6, the MIMO setup per BS is not fixed homogenously since it is included as a decision variable in the proposed 5G planning model. This is in contrast to existing network planning models from literature that assume a fixed homogenous MIMO transmission setup across the BSs. For example, as determined by the network planning algorithm, some BSs use 3 × 3 configurations others are deployed with 1 × 1 and 2 × 2 configurations. A visual decrease in the number of sites can also be clearly observed compared to Fig. 5 as a consequence of MIMO.

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