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Capacity Demand based Multiobjective Optimal Small Cell Placement under Realistic Deployment Scenario

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***Abstract*—To address operator's capacity challenges, efficient demand driven deployment of 4G and 5G small cells considering multiple targets of the operator is very important. To that end, multiobjective optimized small cell planning methodology has recently been proposed. Yet, the method does not provide straightforward mechanism to consider operator's spatial capacity demand that can be obtained from operator's existing network capacity and data market targets. In this work, we present a capacity demand based multiobjective optimal small cell placement method and its performance analysis for exemplary service area of Addis Ababa. To formulate spatial capacity demand, we use spatial user and traffic distribution data from network management system of existing network. As an input for Matlab based network simulation multiobjective optimization, propagation is computed using deterministic ray tracing model over 3D building and terrain map of the service area. The multiobjective optimization is performed for network capacity and cost objectives in this work using a Genetic Algorithm. Results show that the multiobjective placement method presents optimal small cell topologies that meet operator's spatial capacity demand while optimizing aggregate network capacity and cost. The optimization reduced 185-network topology to 45-130 optimal network topologies while significantly improving network capacity. The capacity improvement shows significant user throughput improvement effect. For instance, the 130-topology provides 57% gain in 90%-ile user throughput compared to the not optimized 185-topology.**

Keywords— Small Cell Planning, Capacity Demand, NMS, Heterogeneous Network, Optimal Cell Placement, Multiobjecive optimization, Genetic Algorithm, LTE, LTE-advanced, 5G, Data Analytics.

I. INTRODUCTION

Penetration of mobile broadband services and corresponding data traffic has been significantly increasing in the last decade across the globe including Africa [1]. This is primarily driven by increased penetration of affordable smart user devices and various innovative video-centric data services.

To accommodate the corresponding increase in cellular network data traffic, mobile operators need to continuously enhance their cellular network capacity and for that various capacity enhancement techniques have been developed and standardized in the 4th and 5th generation (4G and 5G) mobile technology standards [2-5]. Therein, one key technology is network densification whereby density of cells is increased with the increasing data demand by deploying small cells such as picocell under the umbrella macro cell coverage [6]. Different densification scenarios are incorporated in Third Generation Partnership Project (3GPP) Long Term Evolution (LTE), LTE-Advanced and 5G New Radio (NR) radio access technology standards [4, 5].

The successful deployment of small cells by an operator requires optimal network plan that meets capacity demand of operator's service area [7]. The capacity demand is one key target set by the operator based on its existing network capacity exhaust challenges and data market target. Furthermore, operator's need to minimize network cost that is directly proportional with required number of small cells to meet the capacity demand. To tackle the network cost increase even small cell leasing has been proposed [8]. Other operator small cell planning considerations may include elimination of coverage holes in existing macro/micro cellular networks. Also, effective network load balancing is very important and have gained a lot of interest [9-11]. The densification of a network will increase its energy consumption and thus, energy efficiency of heterogeneous networks composed by macrocells and small cells have become a popular research item recently [11-13]. These challenges have inspired a rethink traditional planning approaches towards for novel approaches that are demand driven (considering spatiotemporal capacity demand variations) and accommodate simultaneous optimization of multiple targets [14].

To that end, [15] presents a multiobjective optimization methodology for small (2) cell planning framework and [16] considers an indoor small cell planning by applying deterministic ray-tracing modeling. Although these works provide a very good framework to optimize small cell placement by simultaneously considering multiple objectives of an operator, they lack straightforward (3) mechanism to incorporate capacity (4) demand of the operator that can be formulated from an operator's existing network capacity and its data market targets.

In this work we formulate a capacity demand based small cell placement within a hot spot area of Addis Ababa. The propagation characteristics is modeled over a 3D map by using a deterministic ray-tracing computation. The network layout is obtained by applying multiobjective optimization. The spatial capacity demand is obtained based on realistic spatial traffic and user distribution data that is collected from network management system (NMS) of the operator. We emphasize that all elements of the performance evaluation are realistic since we use a real macrocell network as a starting point and user distributions as well as service demand has been obtained from NMS. The propagation modeling is obtained by using the state-of-art ray tracing software [17].

Results show that without multiobjective optimization there is a need of a network topology with 185 small cells to meet capacity demand of the service area.

The rest of the paper is structured as follows. Section II provides system model. Section III presents the capacity demand based small cell placement method. Then, Section IV describes the exemplary service area of Addis Ababa and assumptions for the simulation campaign while Section V presents obtained performance results. Finally, Section VI forwards concluding remarks.

II. SYSTEM MODEL

For a given operator's network service area, we assume N_m LTE or LTE-Advanced existing macrocells and N_c small cell candidate locations. The candidate locations are formulated based on operator's capacity demand and N_o locations of them are selected using multiobjective optimization ($N_o \leq N_c$). Small cells are deployed in selected optimal locations in-band or out-of-band with respect to the operating band of the macrocells. Fig. 1 depicts illustrative network layout for two three-sector eNodeBs ($N_m = 6$) and four small cells ($N_o = 4$). User distribution within the service area is formulated based on raw network data from operator's existing network management system.

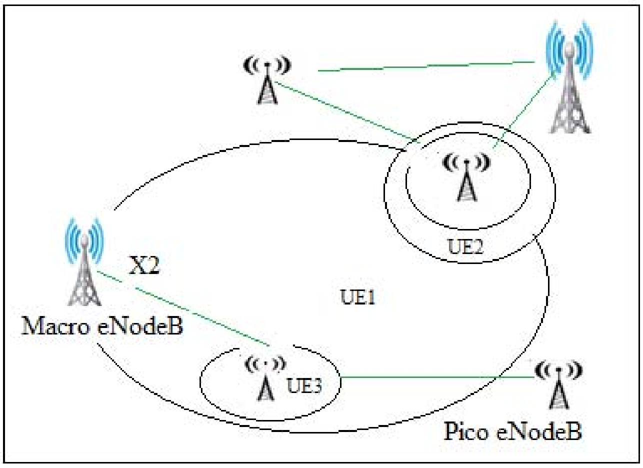

Figure 1 Heterogeneous network layout with 2 eNodeBs and 4 small cells

Then instantaneous downlink signal-to-interference-plus-noise-ratio (SINR) for i^{th} user in case of in-band small cell deployment at a given subframe can be computed as

$$SINR_i = \frac{\gamma_{io} P_{io}}{\sum_{j=1}^{N_m+N_a-1} \gamma_{ij} P_{ij} + P_n} , \tag{1}$$

where P_{ij} and γ_{ij} are average received power and channel power at i^{th} user from j^{th} cell. The o^{th} cell is serving macro or small cell for i^{th} user that is selected based on the best received power cell association method. P_n is noise power at the user. In case of out-of-band small cell deployment, user SINR is computed using (1) but considering only macro or small cells depending on the user's serving cell.

Average received power is computed considering average pathloss which itself computed using deterministic dominant path model based on building and terrain map of the service area [18]. Furthermore, cable loss and antenna gain are also included pathloss budget.

Mapping of SINR to spectral efficiency is performed using modified Shannon formula [19]:

$$S_i = n * BW_{eff} log_2(1 + \frac{SINR_i}{SINR_{eff}}), \tag{2}$$

where n is MIMO rank, BW_{eff} adjust for the system bandwidth efficiency and $SINR_{eff}$ adjust for the SINR implementation efficiency which value is obtained from detailed link-level simulation and curve fitting. Then user throughput is computed using $T_i = N_{PRBi} BW_{PRB} S_i$, where N_{PRBi} and BW_{PRB} are number of allocated PRBs for the user and bandwidth of a PRB, respectively. Available number of PRBs are limited and depends on available system bandwidth (i.e., the number of PRBs depends on the bandwidth configured). To achieve fair resource allocation among all users, we use proportional fair resource scheduling technique [20].

For N_u number of users in the network service area, the aggregate network capacity per subframe becomes

$$C = \sum_{i=1}^{N_u} T_i. \tag{3}$$

III. DEMAND DRIVEN SMALL CELL PLACEMENT METHODS

A. Capacity Demand based Placement

Small cell placement in the service area is performed based on straightforwardly calculated spatial capacity demand. The demand is the difference between target spatial capacity and currently existing spatial capacity. The target capacity is multiplication of the number of users and target user throughput set by the operator while existing capacity is obtained from existing live network busy hour traffic data. Spatial user and network traffic distribution are both obtained from operator's network management system. In this work, we leverage hourly data with 50m pixel resolution and collected over a month in the Bole area of Addis Ababa mobile network. From that data the peak hour monthly average user and traffic distribution is shown in Fig. 2.

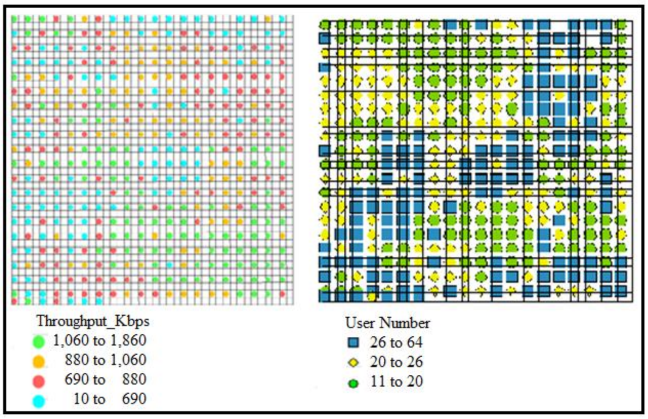

Figure 2 Monthly average traffic and user distribution of Bole area of Addis Ababa

Further details on the steps for small cell placement based on computed capacity demand are explained in Table 1.

TABLE I. CAPACITY DEMAND BASED SMALL CELL PLACEMENT

Input: User and traffic distribution, target user throughput and small cell capacity

1. Set target user throughput and small cell capacity
2. Compute target spatial capacity from user distribution and target user throughput for the service area
3. Compute existing spatial capacity from traffic distribution for the service area
4. Compute capacity demand subtracting existing capacity from target capacity
5. Calculate required number of small cells dividing the capacity demand by small cell capacity. We take the ceil of the result
6. Localize small cells optimally within the service area.

B. Multiobjective Optimization based Placement

Although the aforementioned capacity demand-based placement is straightforward, it does not consider radio propagation and network environment that significantly affects small cell spatial capacity distribution. Furthermore, it does not optimize required number of small cells to meet the capacity demand. To address these challenges, we apply multiobjective optimization based small cell placement where simultaneous capacity and network cost optimization is conducted over previously formulated small cell topology.

Let us assume that network topologies are indicated using a vector z of size N_c such that when k th cell is active, z(k)=1 otherwise z(k)=0. Then the number of small cells becomes

$$N_s = \sum_{k=1}^{N_c} z(k) \tag{4}$$

The multiobjective problem can be formulated as

$$\min_z f(z) = [N_s(z), -C(z)], \tag{5}$$

where network capacity is obtained from equation (3) for the topology defined by vector z. To solve the multiobjective problems in (4) and (5), evolutionary algorithms are effective metaheuristics since the mathematical structure of the objective functions does not feature convexity or continuity [21, 22]. As a result, we use the popular multiobjective evolutionary algorithm called non-dominated sorting genetic algorithm II [23, 24].

IV. DEPLOYMENT SCNEARIO AND NETWORK ASSUMPTIONS

For this work, we apply 2 km × 2 km network service area from Bole sub city of Addis Ababa. Its environment and network layout are shown in Fig. 3. As can be seen in the figure, the service area consists of 13 three sector eNodeBs (thus 39 macrocells) that serves various hot spots in the area. Moreover, the environment type is dense urban and includes 387 buildings with height varying from 10 m to 55 m.

As indicated in Section II, deterministic ray-tracing model called dominant path model is applied for propagation computation. The computation is performed using building and terrain maps of the service area.

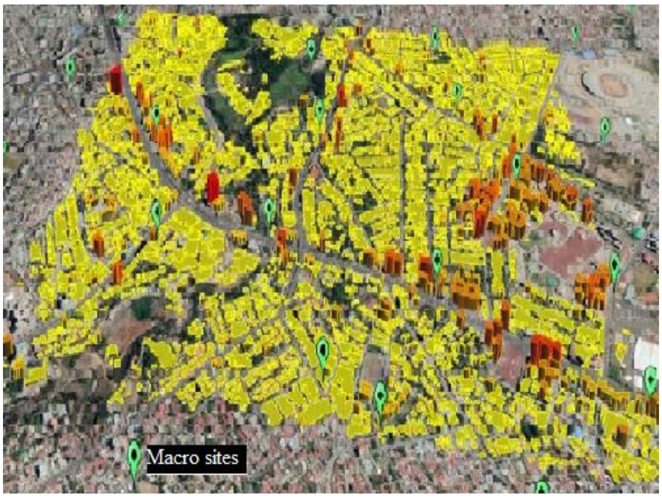

Figure 3 Service area from Bole district of Addis Ababa

To obtain performance results of the small cell placement method, simulation campaign is undertaken for parameter values and assumptions that are presented in Table 2.

TABLE II. SIMULATION ASSUMPTIONS AND VALUES FOR PARAMETERS

Parameter	**Macrocell**	**Small cell**
Transmission power	46dBm	30dBm
Antenna pattern	Huawei ADU451819	Omnidirectional
Antenna Gain	17dBi	5dBi
Antenna Height	From existing network	5m
Small cell type	In-band small cells	
UE and traffic distribution	From NMS	
Target user throughput and small cell capacity	4 Mbps and 60 Mbps	
UE height	1.5m	
UE antenna gain	0 dB	
UE noise figure	9 dB	
Cable loss	2 dB	
Carrier frequency	2 GHz	
Average pathloss	Dominant path model	
Shadow fading	Gaussian in dB scale with 8dB STD	
SINR to SE mapping	$\mathrm{SINR_{min}} = -10\mathrm{dB}, \mathrm{n} = 2, \mathrm{BW_{eff}} =$ $, \mathrm{SINR_{eff}} =, \mathrm{SE_{max}} = 7.7$ b/s/Hz	
System bandwidth	20 MHz	
Thermal noise density	-174 dBm/Hz	
Simulation	Radio propagation modeling (WinProp), System level simulation (Matlab), 5 m resolution	

V. RESULTS AND PERFORMANCE ANALYSIS

Based on user and traffic distribution of the service area (see Fig. 2), capacity demand based placement method provides 185 small cells with spatial distribution shown in Fig. 4. Comparing Fig. 4 and Fig. 2, we note that small cell distribution follows the user distribution that is an expected result when assuming a certain rate target to all users, is higher in areas where more number of users and less amount of existing traffic.

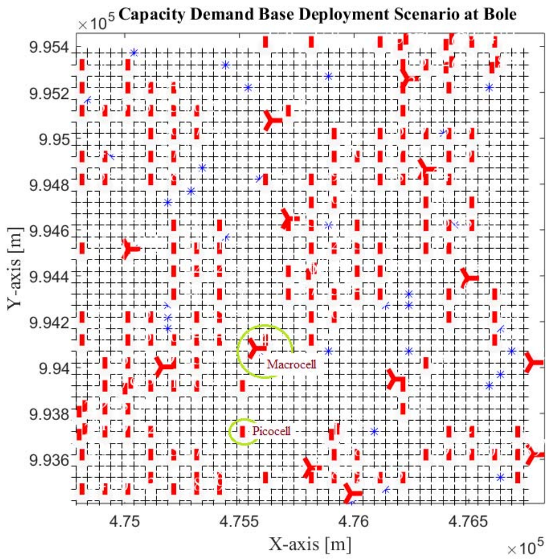

Figure 4 Small cell distribution obtained using the capacity demand based placement method

When the multiobjective optimization placement for maximizing network capacity and minimizing network cost is run over small cell spatial distribution in Fig. 4, we find optimal Pareto front result that is shown in Fig. 5. It shows how the aggregated network capacity grows with the number of small cells (between 45 to 130). It is found that the network capacity increases first slowly with additional small cells but starts to grow faster when the density of the small cells becomes high.

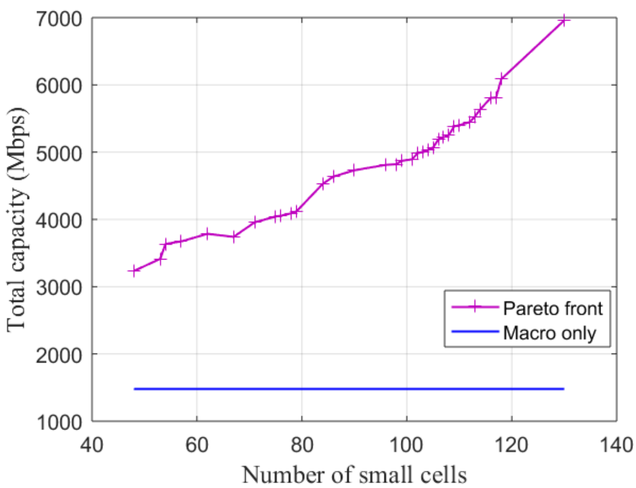

Figure 5 Optimal Pareto front from multiobjective optimization-based placement

User SINR and throughput results for the 130 small cells topology are depicted in Fig. 6 and Fig. 7, respectively. The SINR result show that after optimization, 10%-ile, 50%-ile and 90%-ile user SINRs are improved by 5 dB, 5.4 dB and 5.6 dB. These gains are mainly attributed to the interference reduction from reduced number of small cells and optimized topology selection.

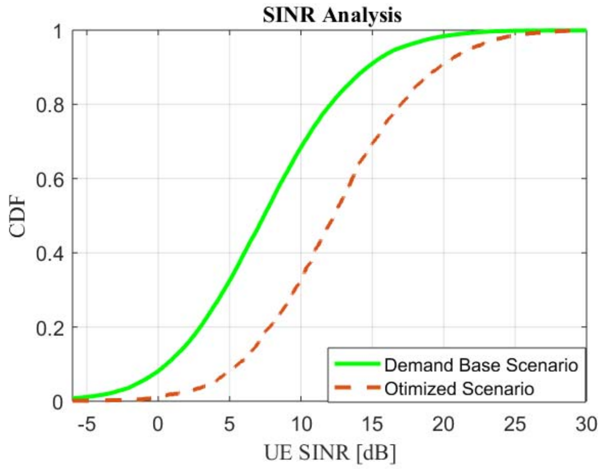

Figure 6 SINR result for 130 small cells topology

Similarly throughput result in Fig. 7 shows 12%, 33%, and 57% gains for 10%-ile, 50%-ile and 90%-ile user throughput. Yet, we can see that the 50%-ile throughput results is less than operator's target throughput.

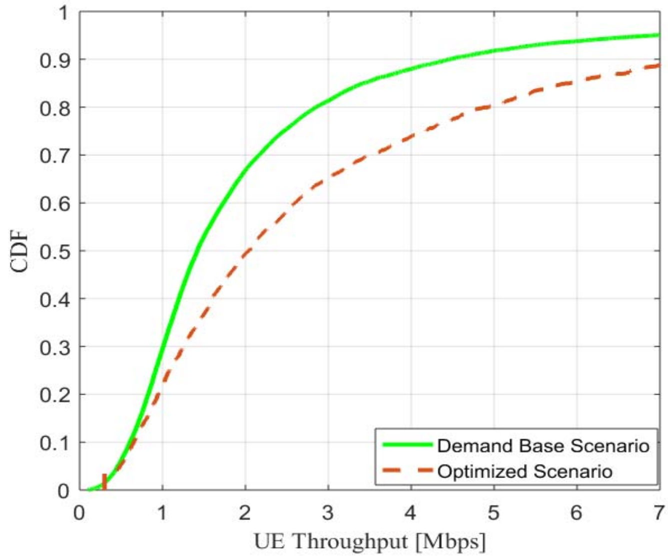

Figure 7 UE throughput result for topology with 130 small cells

VI. CONCLUSION

To meet the increasing high data rate demand, operators are expected to plan and deploy demand-driven dense and ultra-dense 4G and 5G networks considering their various network requirements including network capacity and cost. For that, literature has proposed novel multiobjective optimization small cell planning methodology. Although the method captures well simultaneous optimization need of operator's multiple targets, it does not straightforwardly incorporate operator spatial capacity demand that can be formulated based on operator's existing network capacity and its data market target. In this work, we have presented a capacity demand based multobjective optimal small cell placement method and its performance analysis. Results have showed that multiobjective optimal placement can be achieved considering operator's capacity demand while simultaneous optimizing different target. For network capacity and cost optimization, the method can present optimal network topologies that significantly reduces required number of small cells while improving network capacity. Significant user throughput improvement can also be attained from enhanced network capacity from the optimization.

Future research will consider advanced spatial capacity demand formulation; multiobjective optimization for requirements other than network cost and capacity; and other types of small cells including out-of-band ones and those operating in high bands (e.g. 28 GHz).

Acknowledgement

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