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Published in:
Proceedings of the 22nd Conference of Open Innovations Association FRUCT, FRUCT 2018

DOI:
10.23919/FRUCT.2018.8468304

Published: 19/09/2018

Document Version
Publisher's PDF, also known as Version of record

A Planning and Optimization Framework for Hybrid Ultra-Dense Network Topologies

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***Abstract*—The deployment of small cells has been a critical upgrade in fourth-generation mobile networks as they provide macrocell traffic offloading gains, improved spectrum reuse and reduce coverage holes. The need for small cells will be even more critical in fifth-generation networks due to the introduction of higher spectrum bands, which necessitate denser network deployments to support larger traffic volumes per unit area. A network densification scenario envisioned for evolved fourth and fifth generation networks is the deployment of ultra-dense networks with small cell site densities exceeding 90 sites/km^2 (or inter-site distances of less than 112 m). The careful planning and optimization of ultra-dense networks topologies have been known to significantly improve the achievable performance compared to completely random (unplanned) ultra-dense network deployments by various third-party stakeholders (e.g. homeowners). However, these well-planned and optimized ultra-dense network deployments are difficult to realize in practice due to various constraints, such as limited or no access to preferred optimum small cell site locations in a given service area. The hybrid ultra-dense network topologies provide an interesting trade-off, whereby, an ultra-dense network may constitute a combination of operator optimized small cell deployments that are complemented by random small cell deployments by third-parties. In this study, an ultra-dense network multiobjective optimization framework and post-deployment power optimization approach are developed for realization and performance comparison of random, optimized and hybrid ultra-dense network topologies in a realistic urban case study area. The results of the case study demonstrate how simple transmit power optimization enable hybrid ultra-dense network topologies to achieve performance almost comparable to optimized topologies whilst also providing the convenience benefits of random small cell deployments.**

I. Introduction

In wireless telecommunications market, demand for data rate has been increasing dramatically. It is projected that average data consumption will reach 1 GB data usage per day and therefore 20-50 GB/month average monthly usage by 2020 [1]. Moreover, the number of connected devices will be 28 billion by 2021 [2]. Furthermore, mobile subscriber growth will be 5%-15% for each year over the next decade and one million new mobile broadband subscribers will be added to the wireless networks every day until the end of 2022 [3]. These data provide insights to observe that number of users and data consumption have been increasing expeditiously. From this perspective, it can be understood that wireless networks have to be continuously upgraded to meet these evolving capacity requirements.

A. Capacity enhancement methods

Capacity enhancement could be achieved by three different techniques. These techniques can be given as follows: the increased spectrum resources, the increased spectral efficiency, and the increased network densification. These techniques support network operators with different amount of capacity gains; however, increased network densification has contributed to network capacity more than other techniques [4], [5].

5G will be the next standard that is expected to be widely adopted beyond 2020. Actually, the main target of this standard is to provide 1000x fold increase in the capacity [6]. In order to provide the unprecedented increase in capacity, 5G mobile standard will require the introduction of Ultra-Dense Networks (UDNs) [7]. The UDNs are considered dense network deployments whose site densities exceed 90 sites/km^2 or inter-site distance (ISD) is less than 112 m [1].

Ultra-densification of the networks will be enabled by deployment of small cells to complement existing macrocells. Small cells offer big advantages with their easy installation process, compact design and cheap prices. Nowadays, small cell is a term that refers to the low-power and compact small cells (e.g. picocells, femtocells) or network extensions (e.g. relay) that are used to enhance the capacity and coverage in data traffic hotspots or rural areas [8].

B. Network densification approaches

In order to densify the wireless networks, network operators could deploy small cells in target service areas. The typical objective of the operator-deployed small cells would be to enhance the capacity and coverage in the areas, such as transport hubs, hospitals, and shopping malls.

In addition to operator-deployed small cells, end users or other third-parties may deploy small cells in their homes, offices, and enterprises to boost capacity and enhance indoor coverage [9]. This end user-led deployments would result in random topologies with selection small cell deployment locations being completely decoupled from operator's networking planning considerations. From an operator-perspective these user-deployed small cells have the benefit of saving the operator the required considerable monetary and time investment for site acquisition, backhauling and powering that comes with increased densification [10]. However, the unplanned nature of random topologies would result in relatively poor performances compared to operator optimized topologies.

The hybrid UDN topologies provide an interesting trade-off between optimized and random topologies, whereby, the UDN may constitute a combination of operator optimized small cell deployments that is complemented by random small cell deployments by end-users and other third-parties. The adoption of such hybrid deployment approaches enables the operator to leverage the benefits of random deployment whilst enhancing system performance through optimizing the topology of a subset of the small cell sites. Actually, these hybrid topologies create a network planning and optimization problem that is of interest from both research and practical perspective. Thus, the corresponding research problem addressed in this paper can be stated as follow: investigating a planning and optimization framework for hybrid topologies that could provide results to analyze the performance of hybrid topologies with pre-defined network performance metrics (e.g., cell-edge performance).

C. Contribution and organization of study

In this study, a multiobjective optimization framework is given to address a case where network operators leverage the benefits of both optimized UDNs and randomly deployed topologies in the same service area. Therefore, the main focus of this study is to investigate the performance of hybrid UDN topologies with different predefined performance metrics.

To investigate the performance benefits of hybrid topologies, fully optimized and random topologies are also produced in the same service area for the bench-marking purpose. A realistic case scenario is considered for the system performance comparisons between hybrid, optimized and random topologies. Furthermore, an approach for post-deployment transmit power optimization is introduced to further enhance the performance of sub-optimum hybrid and random topologies.

The paper is organized as follows: Section II introduces the system model and performance metrics. An optimization framework for small cell locations and transmit power optimization is presented in Section III. The case study is introduced in Chapter IV. In Chapter V, simulation results and discussion are given. Finally, conclusions are drawn in Section VI.

II. System model and performance metrics

A. System model

The goal of the study is to plan a UDN that is composed of small cells in a service area $\mathcal{A}$. The service area is divided into the A small area elements which are also known as pixels. The average received power is assumed to be constant within the whole pixel area, hence the pixel resolution provides a trade-off between computation complexity and accuracy of the simulations.

In this study, the wireless system is considered as OFDMA (Orthogonal Frequency Division Multiple Access) downlink with system bandwidth B. The considered service area has a maximum of L predefined candidate small cell locations. Each candidate location represents a possible location for placement of a small cell with maximum transmit power P_{max}.

The RF propagation path loss matrix can be represented by matrix $\mathcal{L} \in \mathbb{R}^{A \times L}$, whereby, $\mathcal{L}(a, l)$ represents the path loss between the a^{th} pixel and the small cell deployed in the l^{th} candidate location. The selection of serving small cell in each pixel is based on maximum received signal power in that pixel. To that end, the received signal power at the a^{th} pixel of signal from the small cell deployed at the l^{th} candidate location is given by:

$$P_{rx}(a, l) = (P_{max} - \mathcal{L}(a, l)) \cdot x(l) \tag{1}$$

where the vector $\mathbf{x} \in \{0, 1\}^L$ indicates whether a small cell is deployed at the l^{th} candidate location. If the small cell is deployed at the candidate location, then $\mathbf{x}(l) = 1$, otherwise, $\mathbf{x}(l) = 0$. Actually, $\mathbf{x}$ could be considered to refer to the network topology since it represents the actual cellular layout and therefore the main network planning variable.

The average SINR at a^{th} pixel each pixel is given by

$$\gamma(a) = \frac{P_{rx}(a, l) - \mathcal{F}(a, l)}{\sum\limits_{i=1, l \neq l^*}^{L} P_{rx}(a, l) + \sigma^2} \tag{2}$$

where σ^2 is the noise power, l^* is the serving cell for that pixel and $\mathcal{F}(a, l)$ is the fast fading between the a^{th} pixel and the small cell deployed in the l^{th} candidate location. Subsequently, the of throughput $\tau(a)$ achievable in the a^{th} pixel is obtained through mapping the SINR results using a modified Shannon formula [11]

$$\tau(a) = \begin{cases} B(a) \cdot B_{eff} \cdot log_2(1 + \frac{\gamma(a)}{SINR_{eff}}), & \text{if } \gamma \geq \gamma_{min}. \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

where $B(a)$ is bandwidth allocated at a^{th} pixel, γ_{min} is the minimum required SINR, and the constants $SINR_{eff}$ and B_{eff} are effective SINR and effective bandwidth values used to adjust the model to account for realistic implementation inefficiencies [11].

B. Performance metrics for network planning

In order to achieve the best solutions in wireless system design, different metrics are taken into consideration. Generally, the goal of network operators is to maximize capacity and coverage in a service area. Moreover, network operators are also willing to minimize their costs. In order to reduce costs, they could use less number of small cells in their service areas. On the other hand, with more small cells, more capacity and coverage could be provided with careful wireless planning. This situation creates a trade-off for network operators.

In order to characterize this the trade-off in simulations, three different metrics are considered in this study. In addition to these three metrics, another metric used for power optimization is created. These metrics and their explanations are given as follows:

- *Number of small cells (f1):* This metrics represents the number of small cells in the wireless system design. More small cells can provide more capacity and coverage; however, more small cells increase the costs of the network operators.
- *Network capacity (f2):* This metric represents total aggregate throughput in a wireless system.

- *Cell-edge performance (f3):* This metric represents performance in cell-edge areas which are the weakest places of the wireless networks.
- *Pixel SINR 5^{th} percentile (f4):* This metric represents the 5^{th} percentile of all pixel SINR values. It is used in order to investigate the power optimization.

(f1), *(f2)* and *(f3)* are used in the simulations in order to investigate the performances of different topologies. *(f4)* is used in simulations in order to investigate the performance of proposed power optimization method.

In addition to those metrics, fairness in achievable throughput is also considered in this study using the Jain's fairness index given.

$$J(t_1, t_2, ..., t_N) = \frac{(\sum_{i=1}^{N} t_i)^2}{n \cdot (\sum_{i=1}^{N} t_i^2)} \tag{4}$$

where t_i represents throughput of the i^{th} user out N users. Jain's fairness index result in ranges of $\frac{1}{N}$ to 1. Fairness of system is maximized when each user has the same data rate.

III. Optimization framework

Network operators deploy small cells in order to achieve maximized capacity and coverage in target service areas. To find locations of small cells that maximize capacity and coverage in a target service area, network operators investigate target service area to find possible small cells locations. However, the large number of small cell locations in the UDNs would complicate investigation for network operators. Thus, optimization algorithms could be used to find optimal locations of small cells.

In this study, targets of the network operators are considered as aggregate capacity *(f2)* and cell edge performance *(f3)*. If the goal of the network operator is to maximize aggregate capacity *(f2)* of target service area, network operators could use *(f2)* to design wireless networks. On the other hand, cell edge performance *(f3)* may have priority in wireless system design. Therefore, cell-edge performance metric *(f3)* could be selected to design wireless systems. Thus, two different wireless network design optimization problems are considered in this study.

Generally speaking, denser wireless networks can provide more capacity because of high-frequency reuse. On the other hand, the large number of small cells increases costs of wireless systems. In this regard, network operators should maximize capacity in their wireless system while minimizing the number of small cells. Therefore, network capacity metric *(f2)* or cell-edge performance metric *(f3)* could be optimized with the number of small cells *(f1)*. As it can be seen, there can be a trade-off between *(f1)* and *(f2)* or *(f1)* and *(f3)* metrics. This trade-off creates multidimensional optimization and it is called multiobjective optimization [12].

In order to find the trade-off between number of small cells *(f1)* and aggregate capacity *(f2)*, following multiobjective optimization problem is proposed as follows:

$$minimize f = [f1, -f2] \tag{5}$$

For number of small cells *(f1)* and cell-edge performance *(f3)*, the topologies featuring the best trade-off between *(f1)* and *(f3)* could be found by proposed formulation as follows:

$$minimize f = [f1, -f3], \tag{6}$$

In addition to multiobjective optimization, single objective optimization is also used in order to optimize transmit power levels of the small cells. The purpose of power optimization is to maximize SINR values of pixels. Thus, it can be formulated as follows:

$$minimize f = [-f4], \tag{7}$$

(5), (6) and (7) are combinatorial problems belonging to NP-Complete class. In this study, search space of optimization is a set of $2^C - 1$, where C is the number of candidate locations in target service area. Even for the small number of the set, search space can be extremely huge. For example, if the number of the set is 15, the number of network topologies is more than $32 * 10^4$. Therefore, it complicates the simulations. Furthermore, because of mathematical structure of *(f2)* and *(f3)*, search space is highly non-linear and full of discontinuities. Therefore, to solve the (5) and (6), a Multiobjective evolutionary algorithm (MOEA) [13], Non-dominated Sorting Genetic Algorithm II (NSGA-II) [14] is used.

In order to solve (7), Genetic Algorithm (GA) is used in this study. To conceptualize how transmit power optimization is investigated, the flow diagram of transmit power optimization is given in Fig. 1. Power optimization is investigated by considering the 5^{th} percentile of all pixel values. It means that 5^{th} percentile of all pixel values (13974 Pixel SINR values) is optimized in order to maximize the pixel SINR values. In order to maximize 5^{th} percentile of all pixel values, *(f4)* metric is used in the single objective optimization.

As shown in Fig. 1, to investigate the optimum transmit power levels, small cell locations are predefined. Thus, small cell locations do not change with the single objective optimization but transmit power levels of small cells change. After calculating the SINR values of each pixel, 5^{th} percentile of all SINR values is found. Then, this value is used for the input of single objective optimization. According to this value, the simulation may end or continue.

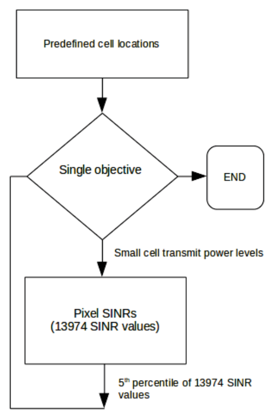

Fig. 1. Flow chart of transmit power optimization

IV. Case study

A. Deployment area

Network densification in the future will have several challenges for network operators since network densification will be hard in highly populated areas. 90% of population growth is expected in Asia and Africa by 2050 [15]. In addition to that, these areas already have high population density in the range of 40000 – 200000 $people/km^2$. Therefore, these areas would be the main target of the UDNs. On the other hand, these areas will also suffer from limited infrastructure in terms of the energy, backhauling and site acquisition [16].

As stated earlier, small cells in the UDNs can be deployed by network operators or by users. Deployment by network operators will be done with information about locations of small cells. It means that network operator will have information about locations and other features of small cells. On the other hand, deployment by users cannot be known by network operators since users can deploy their small cells anywhere. Actually, it is possible to detect locations of user-deployed small cells from network operator side; however, network operators still do not know the decisions of the users. Therefore, this type of deployment will lead to random network topologies where network operators will not have certain decisions about locations of small cells.

In order to study different UDN settlements, static service level simulator is developed. The main purpose of the simulator is to find optimum topologies depending on performance metrics given in section III. The simulator also investigates performance differences of random, optimized and hybrid topologies.

In order to contextualize UDN planning and optimization framework, a real case UDN scenario in a highly populated area is considered. In this study, Hanna Nassif ward in Dar es Salaam, Tanzania is assumed as a place where the UDN is deployed. The population density in Hanna Nassif is approximately 40000 $people/km^2$. In $1km^2$ areas of Hanna Nassif includes almost 3000 buildings which their heights are in the range of 3-6 m. Their topographical difference is approximately 19 m. Three-dimensional (3D) representation of UDN deployment scenario is given Fig. 2.

In case area, there are totally 368 candidate locations for small cells. These candidate locations are represented with white-dots in the Fig. 2. Small cells are all located at rooftop level.

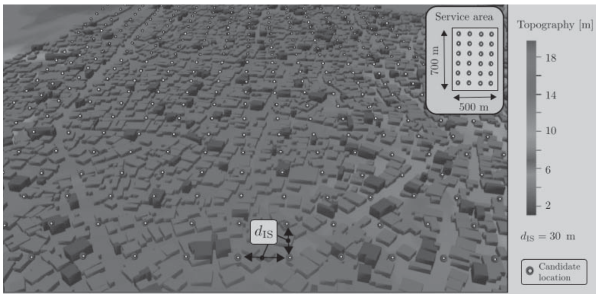

Fig. 2. Planning case deployment scenario [9]

The reason to choose the rooftop small cells is to improve outdoor coverage. Small cells located at rooftop level provides LOS conditions for high-capacity wireless backhauling [17]. Furthermore, the rooftop is a good place for different technologies such as energy harvesting from alternative energy resources such as wind and solar [18].

B. Simulation approaches

In order to investigate different network topologies, a static simulator is developed by considering real wireless networks. In real wireless networks, there are different parameters to consider in details. The parameters used in this study are given in Table II. Simulations could be run in any environment such as local computers and computer clusters. However, to shorten the simulation time, Triton [19] which is Aalto University high performance computing cluster was used. The approaches for three different topologies are given in flow diagrams in Fig. 3. Moreover, the flow diagram of the system level simulator is given in Fig. 4.

In order to obtain optimized topologies, NSGA-II algorithm is used. Actually, NSGA-II algorithm in this study optimizes the locations of the small cells. It means that NSGA-II searches for the optimal candidate locations for the certain number of small cells depending on the user distribution. In this sense, NSGA-II provides the optimal solutions that enhance particular performance metrics.

To investigate the performance of random topologies, 1000 random and different topologies are created. For example, if the purpose is to deploy 140 cells in target service area, 1000 different topologies, which each consists of 140 cells, are created.

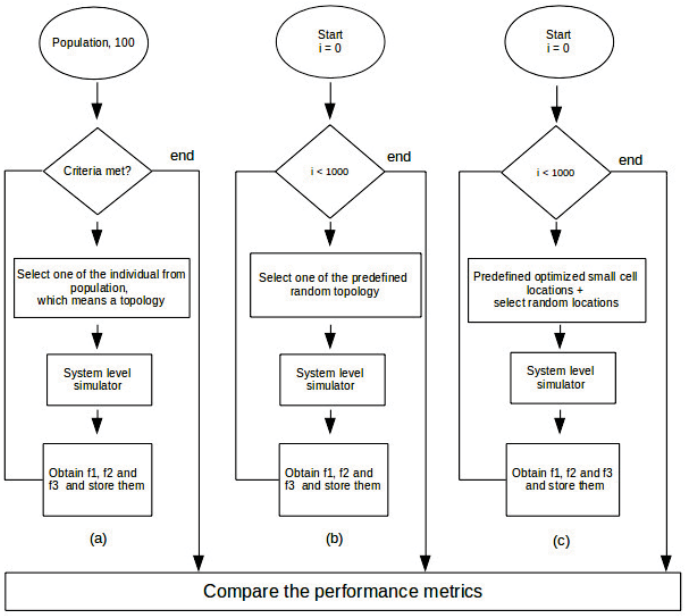

Fig. 3. (a) Flow diagram of optimization of small cell locations, (b) Flow diagram for random topologies investigation, (c) Flow diagram of hybrid topologies investigation

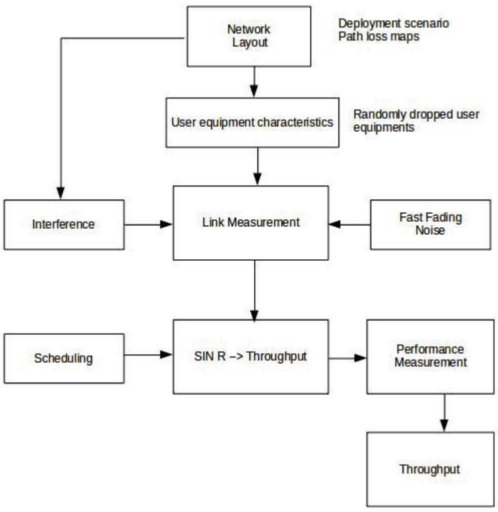

Fig. 4. System level simulator block diagram

Hybrid topologies are combinations of random and opti-mized topologies. In order to investigate the performance of hybrid topologies, 1000 different topologies that consist of both optimized and random topologies are created. Actually, there is a proportionality for hybrid topologies. For example, if the target is to deploy 140 cells, 60 optimized cell locations and 80 random cell locations can be created. In addition, 100 optimized cell locations and 40 random cell locations can also be chosen. In Table I, hybrid topologies investigated in this study are given.

C. Key Parameters and Assumptions

Two different spatial traffic distribution (STD) cases are considered in this study and these are uniform STD and non-uniform STD cases. As mentioned in Section 2, service demand by users is uniformly distributed over the service area in uniform STD case. Non-uniform STD implies that service demand is more likely to be found in certain areas. Actually, non-uniform STD case could be found in real wireless net-works and uniform STD case could be a reference for non-uniform STD case in terms of performance comparisons.

TABLE I: Topology types

Random	completely random small cell locations for uniform STD/ non-uniform STD
Optimized	optimized small cell locations for uniform STD/ non-uniform STD
Hybrid1	consists of 40 optimized small cell loca-tions and 100 random small cell locations for uniform STD/ non-uniform STD
Hybrid2	consists of 70 optimized small cell loca-tions and 70 random small cell locations for uniform STD/ non-uniform STD
Hybrid3	consists of 100 optimized small cell loca-tions and 40 random small cell locations for uniform STD/ non-uniform STD

In order to investigate performances of different topologies, randomly created 400 users are dropped on the network layout in one snapshot. Actually, each user is associated with pixels, which each has 5x5 m^2 in network layout. To increase the statistical quality of the study, 400 users are dropped on the network layout 3000 times. It means that 3000 snapshots are used in static system level simulator.

On the other hand, in terms of transmit power optimization, only one snapshot is used. It means that there is only one topology and transmit power levels of small cells in this is optimized. Only one optimized topology is obtained by results of optimized topologies. Random topologies are created randomly for only one snapshot. In order to create a hybrid topology, different combinations of random and optimized topologies are used.

TABLE II. SIMULATION PARAMETERS

Parameter	**Values/Assumptions**
Deployment Scenario	Outdoor small cells deploy-ment
Carrier Freq./ Bandwidths	Carrier Freq : 2600 MHz, BW : 10 MHz
Simulations	Radio propagation modeling (WinProp) [20], Static system level simulations (Matlab), 5 m resolution
SINR-throughput mapping	SINRmin (dB) -10 BWeff 0.42 SINReff 1.1 Smax (b/s/Hz) 7.67
Transmit Power	30 dBm
Transmiter Gain	0 dBi
Receiver Gain	0 dBi
Antenna Height	7 m
Antenna Patterns	Isotropic
Number of small cells	368 candidate locations, number of SC changes for topologies
Location	Deployed on the rooftop
UE height/location	UEs dropped in whole area (both indoor and outdoor), height is not considered
Number of UEs	400
Number of Monte Carlo Iterations 3000	
Fast fading	Rayleigh Fading, number of paths is 10
Buildings	Heights 3 to 6 m Penetration loss: 20 dB
Cell association	Cell association: maximum received signal strength wins. Fast Fading is not considered in the cell association
Scheduling	Round Robin
Population for optimizations	100 for topology optimiza-tion, 1000 for power opti-mization

It should be noted that each topology is same during the simulation time of transmit power optimization. One snapshot is used to reduce the time complexity of the simulations. Moreover, there is no UE dropped on the network layout in the transmit power optimization phase. Thus, just working on the pixel SINR values is possible with only one snapshot.

V. SIMULATION RESULTS AND DISCUSSION

A. *Optimized topologies*

In Fig. 5, optimized topologies are compared in terms of cell edge performance. It can be seen that non-uniform STD case has better performance than uniform STD case. Actually, it can be really expected from the results. After optimizing the network layout, NSGA-II selects candidate locations which are close to UEs. In this regard, non-uniform STD case has more concentrated users in small areas as compared to uniform STD case. Therefore, with the same number of small cells, it is quite possible that non-uniform STD has much better cell edge performance.

In Fig. 6, aggregate capacity comparison of non-uniform and uniform STD cases are given. In this figure, it can be seen that non-uniform STD case has better performance with the low number of small cells while uniform STD case has better performance with high number of small cells. From this point, it can said that uniform STD case has almost same characteristic of non-uniform STD case after the certain amount of small cells. It means that uniform STD case with the high number of small cells reaches almost same small density/m^2 density of non-uniform STD case and after some points, it becomes better than non-uniform STD case.

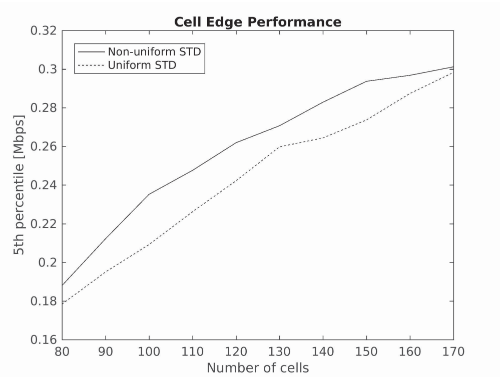

Fig. 5. Cell edge performance of optimized topologies

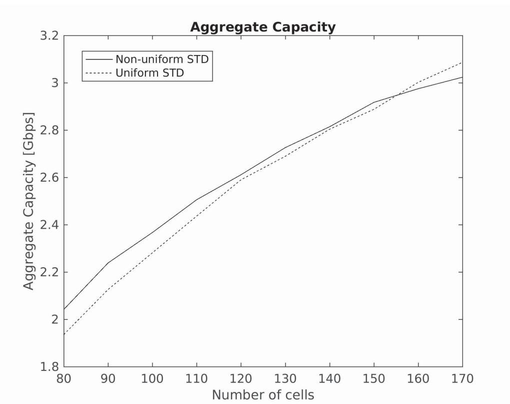

Fig. 6. Aggregate capacity performance of optimized topologies

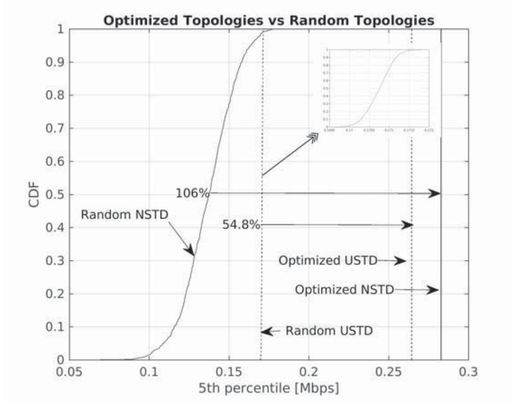

Fig. 7. Cell edge performance comparison of random topologies and optimizedtopologies

B. *Optimized vs random topologies*

In Fig. 7, cell edge performance comparison of random and optimized topologies is given. In this figure, it can be seen that optimized topologies have much better performance as compared to random topologies. In addition, optimization in non-uniform STD case increases cell edge performance by 106% while optimization in uniform STD case increases cell edge performance by 54.8%. Note that comparison between random and optimized topologies is done by considering the median value of random topologies CDF and cell edge value of optimized topology which has 140 small cells. From these results, it can be seen that non-uniform STD case has more advantages in terms of optimization. Actually, this situation is the result of traffic distribution. In random topologies, locations of small cells are selected without information of user distribution. As stated earlier, UEs in non-uniform STD case are mostly in the certain areas while UEs in uniform STD case are distributed uniformly over the network layout. Therefore, it could be expected that performance of random topology non-uniform STD case should be worse than random topology uniform STD case. On the other hand, after optimization, performance increase in non-uniform STD case is more than another uniform STD case.

In Fig. 8, the aggregate capacity performance of random and optimized topologies is shown. In this figure, optimized topologies have more performance as compared to random topologies. Note that comparison between random and optimized topologies is done by considering the median value of random topologies CDF and aggregate capacity value of optimized topology which has 140 small cells. Moreover, similar to figure 17, increase in non-uniform STD case is more than the increase in uniform STD case. It should be noted that optimized topologies in Fig. 8 are optimized by NSGA-II in terms of aggregate capacity. It means that performance metric is used for optimization. Therefore, optimized topologies of and optimized topologies of could be different from each other.

Fairness is another criterion that has been taken into consideration. In Fig. 9, it can be concluded that network optimization increases the fairness of the network layout.

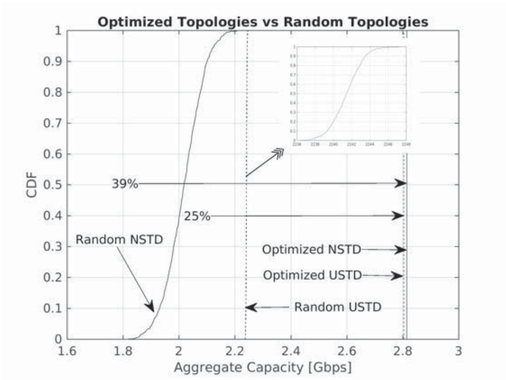

Fig. 8. Aggregate capacity performance comparison of random topologiesand optimized topologies

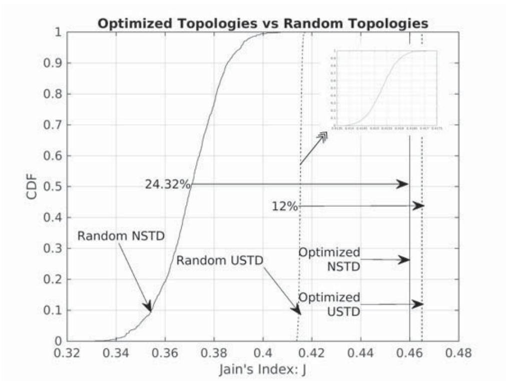

Fig. 9. Fairness comparison of random topologies and optimized topologies

C. Hybrid topologies

In Fig. 10, 11 and 12, performances of all topologies are shown. In terms of metric performances, it can be easily seen that random topologies are the worst topologies while optimized topologies are the best topologies. It can be an expected result because optimized topologies are the ones which are optimized by taking user traffic distribution into account. Moreover, random topologies are random in nature; therefore, random topologies are the worst topologies in terms of performances and fairness. Furthermore, performances of hybrid topologies are between random and optimized topologies. However, each hybrid topology has different performance. This situation is the result of the proportionality of random and optimized topologies. It can be said that if the number of optimized small cell locations in hybrid topologies is larger than the number of random small cell locations in hybrid topologies, then performance increases.

In Fig. 10, cell edge performances of all topologies are given. In terms of hybrid topologies, uniform STD case is better in hybrid1 and hybrid2. On the other hand, hybrid3 has better results for non-uniform STD case. As explained before, non-uniform STD cases consist of UEs that are populated in certain areas. Hence, if there are more random small cell locations in hybrid topology, uniform-STD case creates better performance. Another important thing to observe from this figure is that the changes in non-uniform STD cases are more than uniform STD cases in terms of the hybrid topologies. For example, increase from hybrid1 to hybrid2 is much larger for non-uniform STD case.

In Fig. 11, aggregate capacity performances of all topologies are given. Actually, in all topologies, uniform STD cases have more performance than non-uniform STD cases. Furthermore, more optimized small cell locations increase aggregate capacity performances.

In terms of fairness, it can seen that non-uniform cases are more favorable with the optimized small cell locations. It means that fairness of non-uniform STD cases increases faster than uniform STD cases when the number of optimized small cell locations increases in the hybrid proportionality. This situation can be seen in Fig. 12.

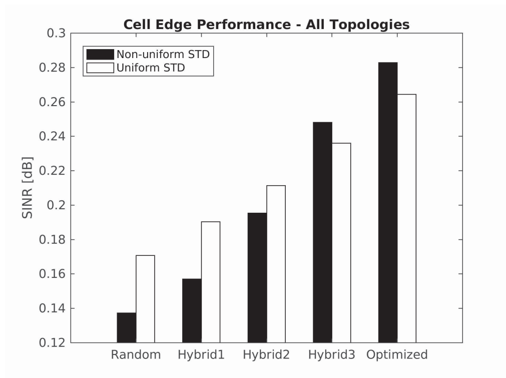

Fig. 10. Cell edge performance comparison of all topologies

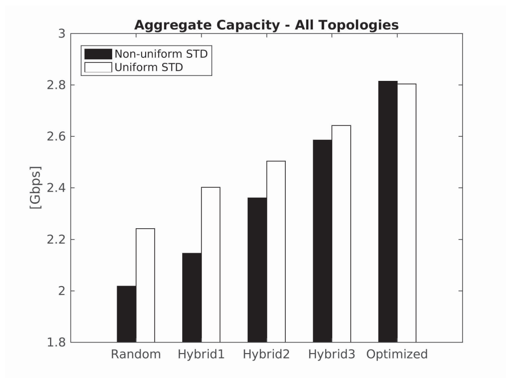

Fig. 11. Aggregate capacity performance comparison of all topologies

D. Transmit power optimization

1) Random Topologies: In order to evaluate the transmit power optimization for random topologies, random 140 cells are taken into consideration. For the evaluations, the same topology is used with both full transmit power levels (30 dBm) and optimized transmit power levels. In order to understand if power optimization works well, Fig. 13 should be checked.

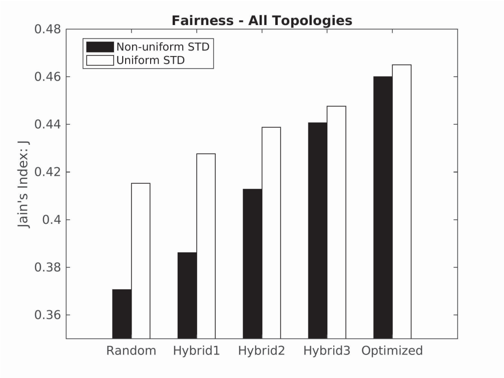

Fig. 12. Fairness comparison of all topologies

In Fig. 13, cumulative distribution function of all pixel SINR values is given. After power optimization, SINR values of pixels are increased. Therefore, this shows that power optimization works well for random topologies.

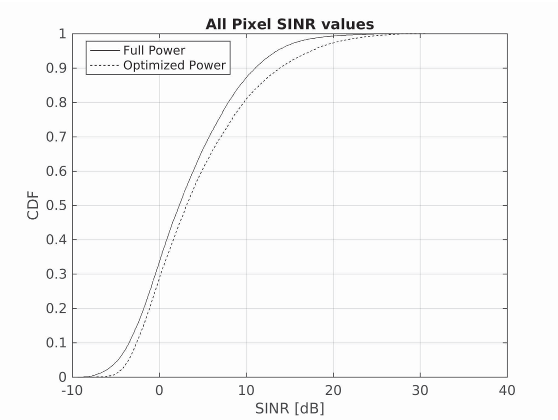

Fig. 13. CDF of pixel SINR values for random 140 cells

So far, it has been seen that SINR values could be increased by power optimization. As stated, if pixel SINR values are increased, SINR values of UEs can also be increased. In Fig. 14, UE SINR values are given. From this figure, it can be seen that optimized transmit power increases the SINR values of UEs. Thus, it can be assumed that throughput values of UEs are also increased because of increase in SINR values. On the other hand, some of the small cells are switched off after power optimization. Therefore, total bandwidth in the service area is reduced.

Throughput values of UEs are given in Fig. 15. According to Fig. 15, throughput values of UEs are not increased. It means that throughput values of UEs are decreased with power optimization. In wireless telecommunications, bandwidth has a crucial role in terms of data rate. Each cell serves some number of UEs and therefore bandwidth of each cell is shared between its served UEs. Even though SINR values could be increased, the number of resources or bandwidth cannot be shared in the same way after power optimization.

In Fig. 16, number of UEs for each cell is given by bar plots. (a) represents full power case and (b) represents optimized power case. It can be seen that UEs are distributed more equally in (a) as compared to (b). Since some cells are switched off by power optimization, their own loads are transferred to one of the other active cells. Therefore, with new transmit power levels, the bandwidth of active cells is shared among more UEs. Because of that, UEs obtain fewer resources as compared to full power case and this reduces the throughput of UEs. From this perspective, traditional serving cell selection procedure cannot be the effective solution for this study. Thus, load balancing could be considered in a way where estimated available throughput per link is used instead of link quality estimation [21]. In this regard, it can be said that load balancing could be studied after power optimization; however, it is not in the content of this study.

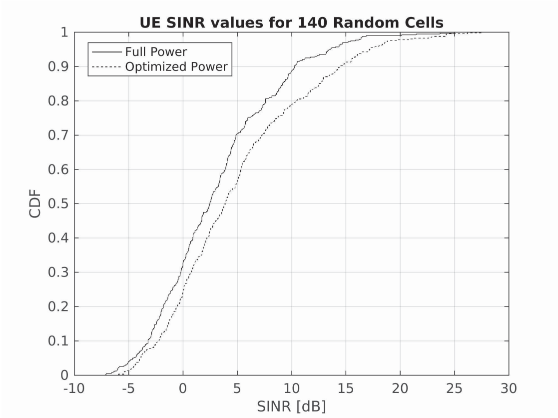

Fig. 14. SINR values of UEs for non-uniform STD case-only for one snapshot

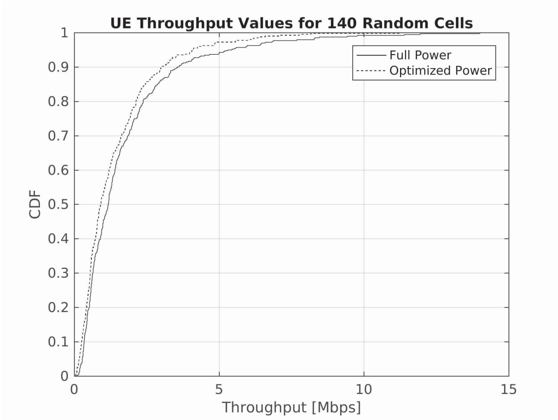

Fig. 15. Throughput values of UEs for non-uniform STD case-only for one snapshot

2) Hybrid Topologies: In Fig. 17, it can be seen that power optimization increases median of pixel SINR values. However, increases for different hybrid topologies are different from each other. For example, hybrid1 has more increase as compared to hybrid2 since there are more random small cell locations in hybrid1. It means that when there are less optimized small cell locations, the impact of power optimization is higher. From this figure, it can be understood that if there are more optimized small cell locations in hybrid topologies, there may not be any changes after power optimization. Indeed, after power optimization, transmit power levels of hybrid3 is still same as in the full transmit power case.

In Fig. 18, it can be seen that throughput of UEs is reduced as expected since some of the small cells are switched off after power optimization. Therefore, although SINR values of pixels are increased with power optimization, throughput values of UEs is dropped because of resource sharing.

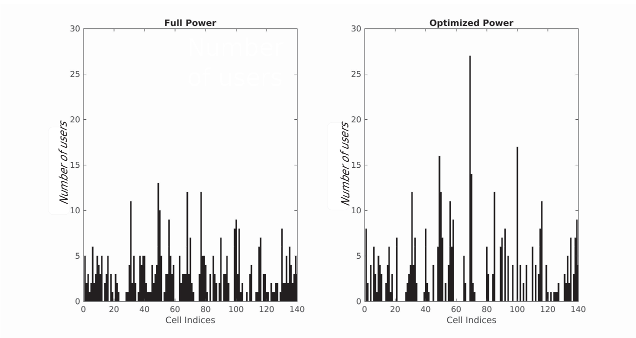

Fig. 16. UE association through small cells

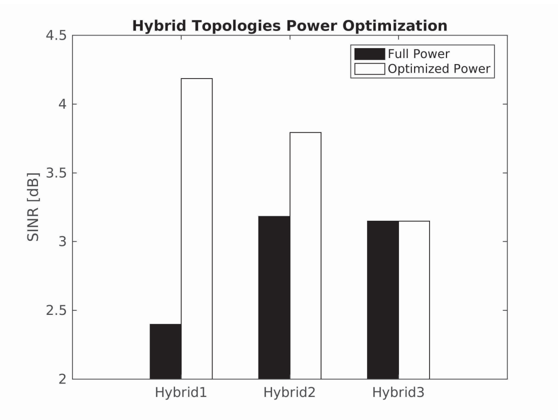

Fig. 17. Median SINR values of pixels after hybrid power optimization

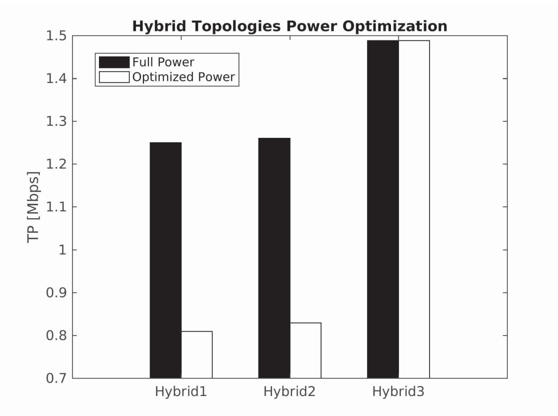

Fig. 18. Median throughput values of UEs after hybrid power optimization-only one snapshot

VI. Conclusions

In this study, a planning and optimization framework for hybrid UDN topologies is presented. In order to optimize different metrics, NSGA-II algorithm is used in a system level static simulator. The results confirmed that optimized network topologies provided much better performance results compared to both hybrid and random topologies, whereas, the hybrid topologies outperformed the random topologies. Moreover, the performance gap between hybrid and random topologies increased as the fraction of optimized site locations increased in hybrid topologies.

The performance increasingly dense deployments are interference limited. Therefore, the use of small cell transmit power optimization provides significant performance gains due to SINR improvements. In this study, pixel SINR values are used as an input for transmit power optimization algorithm. According to the results, post-deployment power optimization increases SINR performance for both random and hybrid topologies, with the performance of hybrid topologies approaching that of optimized topologies.

However, power optimization does not increase the throughput values of UEs in the simulations since some of the small cells are switched off in order to have better SINR values in the network layout. Therefore, since the best received signal power case is used in user association, most of UEs connect to same small cells. This situation reduces bandwidth per user although SINR of UEs is increased. Hence, load balancing can be a good topic for further study in this context.

Also of interest would be comparative performance studies of deployments at different spectrum band, in particular, the 5 GHz unlicensed band and the 28 GHz candidate 5G band. The difference in RF propagation characteristics between the 28 GHz and the 2.6 GHz band considered in this study may provide some interesting outcomes in terms of hybrid and optimized topologies. Moreover, the trade-off between the improved propagation at 2.6 GHz versus the larger spectrum resources available at 28 GHz also creates further interesting problems for topology optimization and load balancing with multi-band small cell deployments.

Acknowledgment

The work was partially supported by the EIT DIGITAL project HII-ACTIVE.

Hanna Nassif GIS data was kindly provided by Prof. R. Sliuzas of ITC-Faculty of Geo-Information Science Earth Observation, University of Twente.

References

[1] Ultra dense network (UDN) white paper *Nokia Solutions and Neworks Oy.* 2016, June. Web: https://resources.nokia.com/asset/200295

[2] Cellular Networks for Massive IoT white paper *Ericsson* 2016. Web: https://www.ericsson.com/assets/local/publications/white-papers/wp_iot.pdf

[3] Ericsson. (2017) Ericsson Mobility Report, Web:https://www.ericsson.com/assets/local/mobility-report/documents/2017/ericsson-mobility-report-june-2017.pdf

[4] D. López-Pérez, M. Ding, H. Claussen and A. H. Jafari, "Towards 1 Gbps/UE in cellular systems: understanding Ultra-Dense Small Cell Deployments", *in IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2078-2101, Fourthquarter 2015.

[5] Viavi. (2015) Optimizing Small Cells and the Heterogeneous Network (HetNet) white paper. Web: https://www.viavisolutions.com/es-mx/literature/optimizing-small-cells-and-heterogeneous-network-hetnet-white-paper-en.pdf

[6] Q. C. Li, H. Niu, A. T. Papathanassiou and G. Wu, "5G Network Capacity: Key Elements and Technologies" *in IEEE Vehicular Technology Magazine*, vol. 9, no. 1, pp. 71-78, March 2014.

[7] M. Kamel, W. Hamouda and A. Youssef, ”Ultra-dense networks: a survey”, *in IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2522-2545, Fourthquarter 2016.

[8] Small Cell Forum (SCF). (2012, February) Small cells – what is the big idea? Small Cell Forum. Last accessed 25/10/2016. Web: http://scf.io/

[9] D. G. González, E. Mutafungwa, B. Haile, J. Hämäläinen, H. Poveda, “A planning and optimization framework for ultra dense cellular deployments”, *Mobile Information Systems*, March 2017.

[10] ”Neighborhood small cells for hyper-dense deployments: Taking hetnets to the next level”*Qualcomm, Tech. Rep., February 2013.* Web: https://www.qualcomm.com

[11] P. Mogensen, W. Na, I. Z. Kovacs, F. Frederiksen, A. Pokhariyal, K. I. Pedersen, T. Kolding, K. Hugl and M. Kuusela, ”LTE Capacity Compared to the Shannon Bound”, *in Proc. 2007 IEEE 65th Vehicular Technology Conference - VTC2007-Spring*, April 2007, pp. 1234–1238.

[12] Y. Sawaragi, I. Hirotaka, and T. Tanino, *Theory of Multiobjective Optimization*, 1st ed. Academic Press., 1985.

[13] C. A. Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-objective Problems, 2nd ed. Springer: Genetic and Evolutionary Computation Series*, 2007.

[14] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II” *IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182–197, Apr 2002.*

[15] UN, ”World urbanization prospects: The 2014 revision, highlights,” United Nations, Department of Economic and Social Affairs, Population Division, UN Report ST/ESA/SER.A/352, 2014. Web: https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf

[16] GSMA, ”The mobile economy Africa 2016”, 2016. Web: http://www.gsma.com/mobileeconomy/africa/

[17] P. Amin, N. S. Kibret, E. Mutafungwa, B. B. Haile, J. Hämäläinen, and J. K. Nurminen, ”Performance study for off-grid self-backhauled small cells in dense informal settlements”, *in Proc. 2014 IEEE 25 th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, Sept 2014, pp. 1652–1657.

[18] Y. Mao, Y. Luo, J. Zhang, and K. B. Letaief, ”Energy harvesting small cell networks: feasibility, deployment, and operation,” *IEEE Communications Magazine*, vol. 53, no. 6, pp. 94–101, June 2015.

[19] Aalto Triton. Online resource. http://science-it.aalto.fi/for-triton-users/

[20] Altair.Winprop overview. Online resource. http://www.altairhyperworks.com/product/FEKO/WinProp

[21] Nokia. (2016) Ten key rules of 5G deployment white paper. Available: www.nokia.com