# Density-aware Mobile Networks: Opportunities and Challenges

Shahram Mollahasani[a,d], Alperen Eroğlu[a], Ilker Demirkol[b,*] and Ertan Onur[a,c]

[a] Department of Computer Engineering, METU, 06800, Ankara, Turkey
[b] Department of Mining, Industrial and ICT Engineering, Politècnica de Catalunya, 08242, Manresa, Barcelona, Spain
[c] Department of Computer Science, Stony Brook University, Stony Brook, NY 11794-2424
[d] School of Electrical Engineering and Computer Science, University of Ottawa, K1N 6N5, Ottawa, Canada

ARTICLE INFO

*Keywords*:
Density-aware mobile networks; Nomadic cells; Cellular networks; Density-adaptive protocols; Base station density

ABSTRACT

We experience a major paradigm shift in mobile networks. The infrastructure of cellular networks is becoming mobile since it is being densified also by using mobile and nomadic small cells to increase coverage and capacity. Furthermore, the innovative approaches such as green operation through sleep scheduling, user-controlled small cells, and dynamic end-to-end slicing will make the network topology and available resources highly dynamic. Therefore, the density of dynamic networks may vary in time and space from sparse to dense or vice versa. This paper advocated that on density-awareness is critical for dynamic mobile networks. Mobile cells, while bringing many benefits, introduce many unconventional challenges that we present in this paper. Novel techniques are needed for adapting network functions, communication protocols, and their parameters to the network density. Especially when cells on wheels or wings are considered, static and man-made configurations will waste valuable resources such as spectrum or energy if the density is not considered as an optimization parameter. In this paper, we evaluate the dynamicity of nomadic cells in density-aware mobile networks in a comprehensive and articulable way. The main challenges we may face by employing dynamic networks and how we can tackle these problems by using a density-oriented approach are discussed in detail. As a key concern in dynamic mobile networks, we treat the density of base stations, which is an indispensable performance parameter. For the applicability of such a parameter we present several potential density estimators. We epochally discuss the impact of density on coverage, interference, mobility management, scalability, capacity, caching, routing protocols, and energy consumption. Our findings illustrate that mobile cells bring more opportunities in addition to some challenges which can be solved, such as adapting mobile networks to base station density.

## 1. Introduction

The state of the art in a mobile cellular network has been the centrally-managed, stationary, and relatively inflexible architecture that was prosperous, albeit not scalable. The present-day networks have already reached the spectrum limitations. We have to densify cellular networks by spatial multiplexing and employ mobile or nomadic cells to overcome capacity limitations and coverage problems. However, increasing the number of mobile base stations (BSs) may cause severe interference and redundant coverage resulting in energy wastage [1]. Centralized configurations or real-time centralized monitoring are not applicable in this case due to the difficulties in acquiring global information about the dynamic network and computational complexity of the tasks. For example, optimization of network management and coordination usually require solving NP-hard problems.

The evolution and proliferation of the technologies bring along rapidly increasing users demands such as more bandwidth, a higher speed of the services with lower latency, and the internet anywhere [2]. To meet these requirements and to enhance the quality of service (QoS), 5G networks are introduced with a new network architecture and novel technologies to ensure low latency, higher bandwidth, and to support higher mobility rates. In order to increase the network capacity, the cell densification is presented as a promising solution. Densification, which is increasing the number of base stations, brings up the small cell paradigm. Moreover, future network architecture introduces novelties compared to the present network architecture such as cloud-based core network, virtualization, slicing, user-controlled or user-dependent base stations (such as Wi-Fi routers in homes or offices), moving base stations (drones, base stations on wings or wheels), and self-organization. Accomplishing all these enablers also poses many challenges in the dynamicity of the network [2, 3]. Specifically, due to the high flexibility of 5G networks' topology, the number of base stations can be impact directly by either reducing or sometimes by increasing in a specific area of the network. All these aspects lead to a dynamic infrastructure that is not predictable in advance [4, 5]. Herein, it should not be overlooked that the density of base stations is ever-changing. If this erratic parameter is not handled as an optimization parameter, it will negatively affect the network performance. For instance, in dynamic networks due to higher interference, insufficient coverage, massive power consumption, and higher mobility ratio, the limited network resources may not be used very efficiently [3]. Therefore, new solutions should consider the effective density of base stations to adapt the network performance to the highly dynamic structure.

As the network enlarges and becomes dynamic, its management and control become a symptomatic issue. Operator intervention requirements have to be drastically reduced

A preliminary version of this paper, `arXiv:1712.09104 [cs.NI]` is available at https://arxiv.org/abs/1712.09104.

*Corresponding author
ilker.demirkol@entel.upc.edu (I. Demirkol)
ORCID(s): 0000-0002-8026-5337 (I. Demirkol)

by employing self-organization. There is a research gap between state of the art and the ambition of achieving a self-organized, adaptive, and flexible networking architecture [6].

In this paper, we claim and illustrate that we need to answer the following open research questions arising from the dynamism of the future networks:

- How are the future networks different from the existing architectures?
- What is a density-aware dynamic mobile network?
- How does network density change?
- Why is the density of BSs critically important?
- Why must BSs density be considered as an optimization parameter?
- Why may the solutions without considering BSs density fail?
- How can the density of BSs be estimated?
- How can BSs density be used in network applications and communication stack?

Answering all of these questions is the aim of this paper.

In this paper, we elaborate one how dynamicity of BS density can affect other network parameters such as interference models, channel models, energy management models, mobility models, scalability of networks, antenna type selection, reliability of communications, latency, etc. We also show how the density of BSs can be employed as an optimization parameter for tackling challenges we will face in the next generations of mobile networks such as interference, modulation coding scheme adaptation, QoS, transmit power adaptation, dynamic backhauling, densification, scalability, etc. All in all, we can simply claim that cellular networks start resembling ad-hoc networks. A distributed, self-organizing, -healing, and -adapting network architecture is necessary. Based on this claim, the contributions and structure of this paper can be described as follows:

- The first contribution is that we present a new paradigm, which is density-aware dynamic mobile networks, into the forefront by exhibiting dynamic infrastructure covary with moving base stations in addition to stating the inadequacy of present architectures in Section 2.
- As the second contribution, a qualitative and novel analysis of network density is presented. Section 2.4 claims that the network density is a crucial parameter since it substantially influences the dynamic network performance. We classified and explained the density estimators in dynamic networks in Section 2.5.
- Challenges and enablers in density-aware mobile networks are extensively exposed by considering the dynamic topology in a mobile network as the third contribution. In Section 3, the opportunities that can be achieved by adapting the BS density in the current mobile and wireless networks are investigated in a comprehensive manner. We present an extensive list of research challenges in Section 3 by discussing them in detail.
- As the last contribution, we reveal how the density of base stations can be leveraged, and we illustrate the idea behind this paper, which is the density-adaptive solutions in Section 3. For example a novel aggregate-interference technique is presented to control the interference based on the density changes. Finally, the most prominent ideas are summarized and concluded in Section 4.

## 2. Why is Density-awareness Important?

In this section, we bring to the light future paradigm changes in mobile networks. We clearly explain what the definition of a density-aware mobile network is, and what its differences from the present networks are. We claim that the present architectures are inadequate. In these discussions, we encounter that the network infrastructure changes, which cause variations in the number of base stations in a specified area. Therefore, in density-aware dynamic networks, network density will change incessantly. This section qualitatively analyzes the impact of BSs density on the performance of dynamic networks, and discusses density estimator algorithms and categorize them based on their features.

### 2.1. Paradigm Changes in Mobile Communications

One of the significant paradigm shifts happens in the control domain of operators. In the past, network operators used to plan, dimension, and install BSs. Before and after the launch of the BSs, optimization was plausible. Performance monitoring, failure mitigation, and corrections were carried out by the network operator within the lifetime of a BS. However, this scheme will change substantially in future mobile networks, and operators will partially lose their control on cell deployment, as we will explain in this paper.

Another paradigm change is in the infrastructure of mobile networks. In the past, we used to assume that locations of the user equipment (UE) were stochastic, and the network infrastructure was stationary. In the future, BSs may also be mobile yielding a random infrastructure; e.g., drones may provide service to blind spots [7, 8, 9]. We present some example scenarios where the density of UEs and also BSs may change in a dynamic fashion in Figure 1. The figure illustrates how cells on wings or wheels may change the infrastructure of mobile networks. Because of mobility and many other factors that we present in this paper, the infrastructure of mobile networks start resembling ad hoc networks in terms of their dynamism. As a consequence, the density of BSs unpredictably change. As can be seen in these scenarios, the density of users may increase suddenly because of some emergency situation such as a car accident or a sports event. As we can see on the left-hand side of Figure 1, the

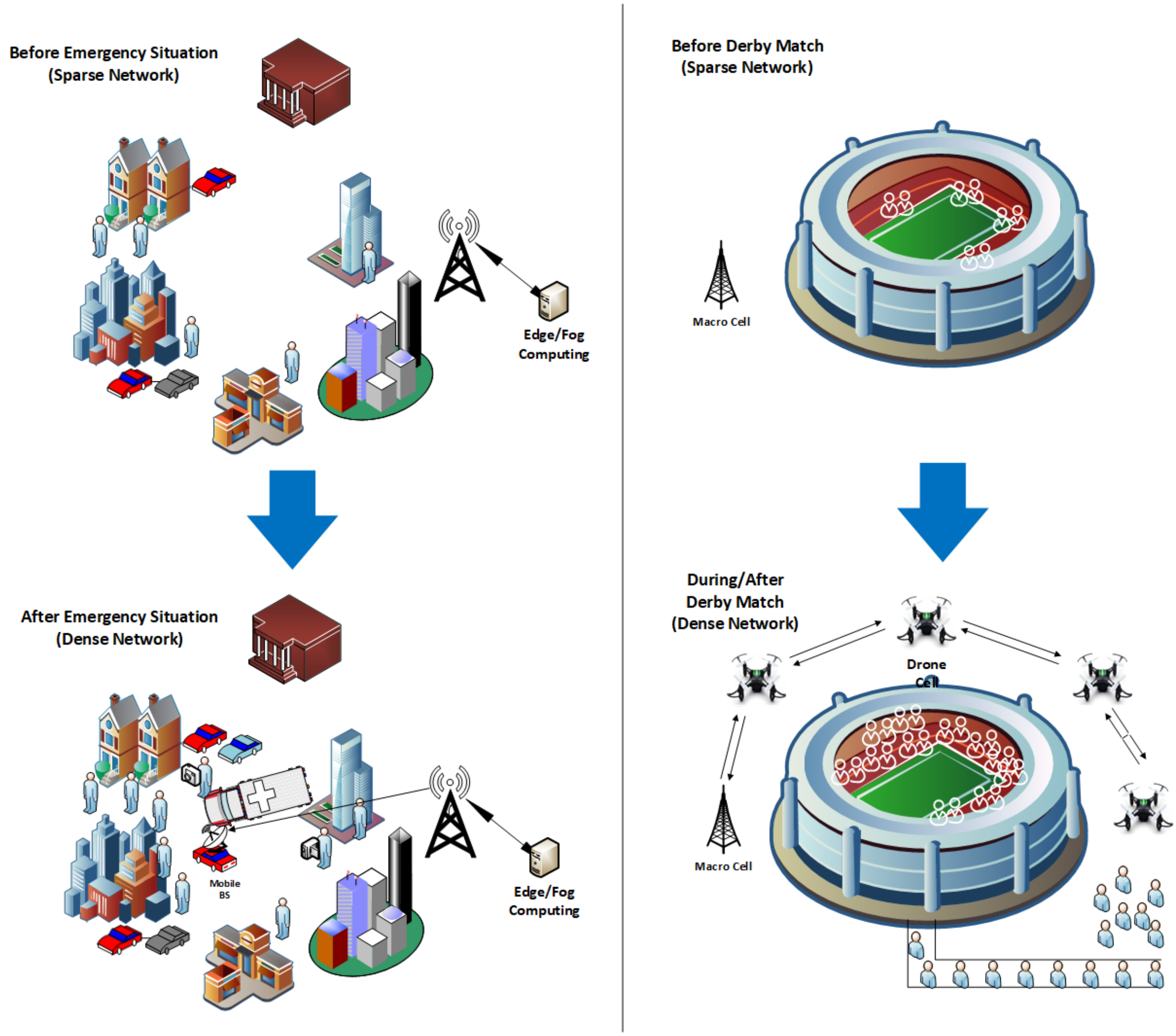



**Figure 1:** Two application scenarios of mobile BSs in future networks are presented.

area seems sparse initially. However, after the car accident, the density of users increases dramatically. Therefore, mobile or nomadic BSs are deployed in the area to maintain the QoS in terms of coverage and/or capacity. In emergency scenarios, pre-deployment planning may not be possible [9]. Communication services are of critical importance for public protection and disaster recovery. Man-made or natural disasters such as earthquakes may disrupt communication services that are currently provided by stationary infrastructures. Employing drone BSs can be a viable approach for establishing a communication infrastructure in affected areas and for providing coverage in blind spots. Drone BSs can also be used for gathering data from rural fields where no communication infrastructure exists. For instance, drone cells may act as mobile sinks in applications of the Internet of Things and in massive machine type communication scenarios [10].

Dynamic topology means that the number of base stations and the number of user equipment in a given area are always changing. This change is a run-time variation which is not foreseeable in advance. In order to meet the requirements while users' demands are increasing, the number of base stations serving them should be increased. At this point, if the density of base stations in a dynamic network increases, then some problems such as interference or redundant energy consumption will come up [11]. Thus, dynamic network solutions should consider the network density as a performance optimization parameter. If we consider the density of base stations, the resources will then be utilized more effectively, and the QoS can be enhanced.

As another scenario, a derby football match can be given. Some flying BSs such as drones may provide coverage and enhance QoS during the event, as presented on the right-hand side of Figure 1. Before the event and after the event, the user density in the stadium will be low. However, it will be substantially higher during the match. Instead of incurring the cost of deploying stationary cells inside or nomadic cells around the stadium, cells on wings may be employed on the stadium to satisfy the QoS requirements of users by getting closer to UEs. Depending on the user density, additional BSs can be dynamically deployed, which in turn changes the network density.

## 2.2. Why Does Infrastructure Become Dynamic?

Mobile cells have a huge potential to be employed in future networks. In addition to cells' mobility [12] [13], factors which make a network dynamic are as follows:

- User-controlled BSs (e.g., femtocells bought and controlled by end-users): When BSs are deployed in customer premises (such as homes), users may turn them on or off depending on consumption requirements [14].

- Green operation (e.g., sleep scheduling of BSs): BSs may employ duty-cycling for energy conservation. Depending on the employed duty-cycling scheme, the effective density of BSs will be different over periods of time [15].

- Incremental deployment: Gradual deployment of BSs will change the network density throughout the deployment time [16].

- Loss of control and failures in the topology: Deterministic and pre-planning deployment are not prominent anymore. The operator may have to comply with the constraints imposed by the urban structure strictly. Consequently, the deployment can be considered to be stochastic [17].

- Support for various verticals (e.g., automotive, health), multi-tenancy, and various scenarios (e.g., megacities versus low average revenue per user (low-ARPU) regions or sporadic events such as Olympics) by dynamic network slicing [18].

The mobile network infrastructure will become stochastic, and the location of small cells cannot be pre-planned with the introduction of mobile cells. Considering the scenarios described above and shown in Figure 1, we can list the major advantages of employing mobile or nomadic cells as follows:

- Mobile cells may be rapidly deployed to mitigate coverage holes without introducing site-acquisition costs [19].

- Drone cells may facilitate ubiquitous coverage in rural areas [20].

- Mobility of drones cells can be inline with the mobility of the end-users providing a better approach for group mobility, lowering the mobility management costs [21].

- Mobile cells, together with edge/fog computing, may bring processing power closer to the end-users, which can decrease the power consumption and provide a higher data rate by obtaining high signal-to-noise-plus-interference-ratio (SINR) [22].

- Broadcast data rates can be improved, especially for the UEs located at cell edges [23].

## 2.3. Why Will The Present Architectures Fail?

It is not possible today for present mobile communication networks to address these paradigm changes because of their shortages and limitations [24, 25, 26]:

- Inflexible architecture, static and manual configurations: When the infrastructure is dynamic, it is clear that the static configurations will waste resources. Manual configurations make the network inflexible to the dynamism in the topology and are subject to severe human errors. Softwarized networks cast light onto these problems.

- Lack of common control functions and interfaces: Real-time and holistic management is almost impossible because of vendor lock-in and vendor-dedicated hardware and software components requiring trained/expert administrators. Softwarization and virtualization of the networks may help solve this problem.

- Limited backhauling capacity: By considering the capacity of current fronthaul, backbone, and backhaul in the network architecture, a limited amount of data can be transferred among network entities. To fulfill the requirements of the aforementioned paradigm changes by overcoming the above limitations, heterogeneous networks consisting of mobile, nomadic, or stationary small cells can be a feasible approach. Integrated access backhaul may help solve this problem by transferring traffic from backhaul links into relays, which provides a flexible node deployment for capacity and coverage expansion.

- Connection-centric, but not context-aware network: Due to the high variance of traffic demands in time and space, we need content-delivery based services for the next generation of mobile networks. However, the current connection-based networks are not designed to cope with such a high traffic load or to provide communication and content services in the correct time and location for UEs. Therefore, the ability to manage information context for achieving broader insight over network conditions, including traffic, the density of nodes, and mobility of network elements, is mandatory for future networks, which is not achievable within current networks.

- High latency: In the current network architecture, generally user applications, such as video streaming and websites, can cope with the latency through the implementation of caching techniques in the network model. However, future connected devices such as autonomous cars, remotely-controlled robots, health monitoring equipment, drone cells, and automation systems, due to their critical applications and real-time data, cannot tolerate high latency during their communications.

**Table 1**
The qualitative discussion of the impact of the density regime on network performance.

| | Sparse ($\lambda < \lambda_c$) | Phase Transition | Dense ($\lambda > \lambda_c$) | References |
|---|---|---|---|---|
| **Network capacity** | low | maximum | below maximum | [27, 28, 29, 30] |
| **Inter-cell Interference** | low | to be managed | high | [31, 32] |
| **End-to-end throughput** | low | maximum | below maximum | [33, 34, 35] |
| **Coverage** | patchy | resource-efficient | redundant | [34, 36, 37] |
| **Mobility management** | disruptive | optimal | high cost | [34, 36, 37] |
| **Number of relay base stations** | few | minimal | large | [38, 39, 40] |
| **Possibility of multi-path routing** | none | very low | high | [38, 39, 40] |
| **Redundancy assisted topology control** | N/A | possible | possible | [41, 42] |
| **Resilience to failures** | N/A | low | high | [43, 44] |
| **Energy consumption** | low | optimum | high | [45, 46] |
| **Spectral efficiency** | low | maximum | below maximum | [47, 48] |
| **CAPEX and OPEX** | low | optimal | high | [49, 50] |

## 2.4. Impact Analysis of Base Station Density

A qualitative analysis of the impact of BS density on various mobile network parameters and performance measures is shown in Table 1. The analysis is based on the following simple scenario. Assume a set of homogeneous BSs are incrementally and randomly deployed in a field-of-interest. Suppose BSs are initially deployed sparsely, and service can only be given in a cluster of isolated coverage areas. As the density of BSs ($\lambda$) gradually increases (e.g., more and more BSs are deployed), isolated clusters merge and produce a huge cluster at a critical density ($\lambda_c$). At this stage, the global topology (macroscopic properties) of the network changes, and this phenomenon is called phase transition.

The macro-behavior of the system below and above the critical density $\lambda_c$ is considerably different. The coverage area as an important component in the network consists of active BSs in the dense networking regime where $\lambda > \lambda_c$. Whereas, the network is partitioned, and there exist coverage holes in the sparse networking regime where $\lambda < \lambda_c$. The macroscopic behavior of the network changes from disrupted networking (i.e., isolated coverage areas having large capacity) to degraded performance (full coverage with high interference) as the density increases. In this transition, at some density slightly larger than $\lambda_c$, resource-efficient operation of the network is possible. Therefore, the performance of the network is largely dependent on its topology that can be represented as a graph.

In graphs, a phase transition is a concept where the probability of the presence of a feature in a graph jumps from zero to one rapidly at a threshold value of the controllable parameter. The left- and right-hand sides of the threshold can be considered as static and chaotic regions. The region around the threshold is referred to as the phase transition region where innovations occur in a resource-efficient fashion.

Take transmit power adaptation as an example. At a critical threshold of the transmit power, the connectivity of the network jumps from disconnected to highly-connected state [51]. A level of transmit power less than the threshold causes a disconnected network, and the network is dysfunctional. Whereas, increasing the transmit power beyond the threshold causes a fully-connected network while increasing the interference and wasting resources. Operating at the critical threshold facilitates resource-efficient networking.

Similar phase transitions can be observed in many network design problems that are NP-hard such as drone cell placement [52]. The complexity of such problems in the phase transition region surges. The centralized solutions of such problems do not scale in large networks. The network has to configure itself locally for using resources efficiently through cell selection [53], service time maximization [54], or bandwidth allocation [55].

The macro-behavior of the system at different density levels (below and above the critical density $\lambda_c$) is described in Table I. As the density of small cells increases, the coverage and capacity will grow due to a high level of spatial multiplexing. On the other hand, as the density of a network increases, the capacity will eventually converge due to interference in dense networks [27, 28, 29, 30]. Although, the total network capacity will be low in sparse networks due to the coverage holes and partitioning, the received inter-cell interference will be reduced due to the low amount of interference. On the other hand, in dense networks where the cells are located very close to each other, the amount of inter-cell interference is high. This can be managed by optimizing the density of active BSs [31, 32]. The densification of networks in fact can provide more available channels and increase throughput [33, 34, 35]. Moreover, the cost of mobility management escalates in dense networks due to the very high number of handovers. Whereas, in sparse networks, the mobility support would be disruptive due to patchy coverage [34, 36, 37]. Concurrent multi-path transfer, multi-homing and utilization of relay BSs also become infeasible in sparse networks due to possible coverage holes in the network [38, 39, 40]. Topology control by exploiting redundancy in dense networks is possible, which can be useful in flexible networks [41, 42]. For instance, sleep scheduling of BSs can be employed considering the load in the network. The same fact also increases the resilience of the network to failures in dense networks [43, 44]. The amount of energy consumption will increase by deploy-

**Table 2**
Approaches for estimating density of nodes in a network.

| Category | Requirement | Advantages | Disadvantages | References |
|---|---|---|---|---|
| **Location-based** | The coordinates of devices, location pre-awareness (e.g., GPS) | Ease of integration | Extra energy consumption, errors in GPS measurement | [61, 62, 63, 64] |
| **Neighborhood-based** | Monitoring and analyzing traffic, beaconing and neighbor discovery | Existing functions in a stack can be employed | Not scalable, limited to transmission range, accuracy depends on traffic | [5, 65, 66, 67, 68, 69] |
| **Power-based** | Received signal strength or SINR measurements | Ease of integration, no other auxiliary function, or monitoring traffic of network | Sensitive to channel characteristics that may not be uniform in a field | [58, 70, 71, 72] |

ing more BSs. Therefore, the optimal density of BSs ($\lambda_c$) is vital for enhancing energy efficiency in networks [45, 46]. Spectral efficiency (SE) will improve until the density of BSs reaches to its critical level ($\lambda_c$) and will dramatically degrade by over-deployment of BSs, due to the growth of the overall received interference in the network [47, 48]. Moreover, although when density of BSs is below $\lambda_c$, the capital expenditure (CAPEX) and operational expenditure (OPEX) can be low due to the sparsity of BSs, it can not satisfy the minimum QoS requirement in the network. However, when the number of BSs per unit area is around $\lambda_c$, although the cost of implementation and maintenance may increase, we can satisfy all UEs QoS requirements with the minimum cost [49, 50].

In dynamic dense networks, collisions over random access channels, high congestion levels, and inconstant capacities may be the significant challenges [56]; whereas in sparse networks, partitioning is the key challenge [57]. Dynamic networks have to collaborate locally for coverage preservation, mobility management, interference control, and efficient resource allocation. However, the state-of-the-art architectures do not rely on localized cooperation. For carrying out those tasks in a density-adaptive fashion, BSs have to discover their neighborhood or estimate the density in an incessantly changing topology. Edge computing can be a valuable technology towards this aim by providing a higher-level perspective and having more processing power with respect to BSs; it can collect and evaluate the required data for density measurements from BSs (such as received signal strength (RSS), channel quality indicator (CQI), SINR, etc.) and provide more accurate results [58, 59].

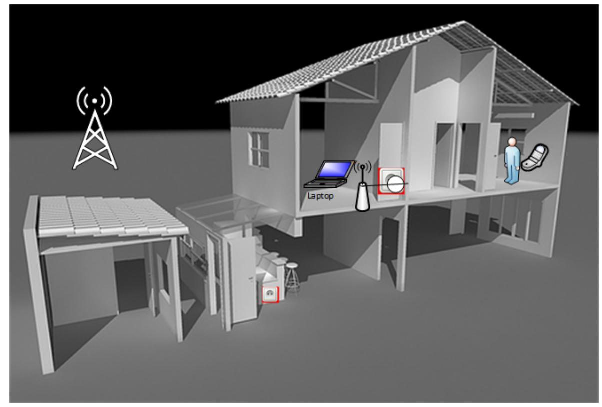
As the cells become sporadic and their size changes, the mobility management will be more cumbersome. When large cells are employed, paging costs are lower since the destination terminal is searched in fewer cells. When the cell sizes become small, paging consumes valuable in-band resources since a large number of cells are paged, considering a constant location area mapping. Therefore, real-time decentralized management of cell sizes and coverage may have an adverse impact on mobility management [60].

## 2.5. How Can the BS Density be Estimated?

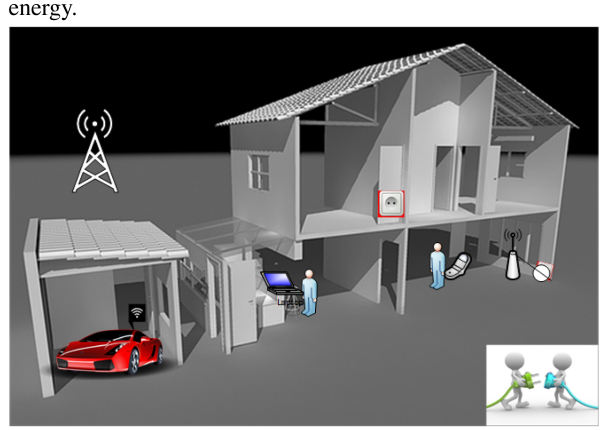
As explained in the previous sections, the control of the BS density is important for an efficient network operation. An important question is then how to estimate the BS density. The network density is highly correlated with the location of BSs, the neighborhood structure, the quality of received signals from other BSs or user equipment, and population data [73]. We can roughly categorize the network density estimation approaches as shown in Table 2. Location-based estimators employ auxiliary positioning systems such as global positioning system (GPS) that consume extra energy [61, 62, 63, 64]. Neighborhood-based estimators, which are not scalable and suffer from inaccurate results, infer density from a census on packet traffic [5, 65, 66, 67, 68, 69]. Power-based estimators combine the merits of location- and neighborhood-based estimators [70, 58, 71, 72], although RSS is not a robust distance estimator. While some of these approaches are designed for ad hoc networks, they can generally be employed in any wireless network with minor modifications.

In cellular networks, the spatial distribution of BSs is vital for the analysis of connectivity, coverage, and performance [69]. The proper adjustment of spatial distribution and configuration of cells in simulators produce credible models which are important for capacity planning. In [69], the information of BS location obtained from different operators in Germany is used to find out the utility and restrictions of population data as a base for similar cellular deployments, and it is shown that the density of the network is highly correlated to population data. They also figure out that relatively populated areas can be considered as a reasonable co-variate to model large-scale deployments. This study validates that predicting the number of BSs per unit area based on the population density is sensible only for the small areas with partially populated areas. Proposing accurate density estimators is an open research challenge with huge potential in stochastic geometry, especially for non-uniform deployments [74].

To summarize, current mobile networks, due to their limited backhauling capacity, static and manual configurations, have a limited flexibility to cope with the dynamicity in future networks. However, the density-awareness in future network architecture is essential because BSs may also be mobile, such as the drone cells, yielding a random infrastructure. Therefore, dynamic network solutions should consider the network density as a performance optimization parameter for enhancing the utilization in the resources, and for improving the network QoS. To do so, we need an appropriate density estimator for adapting network parameters such as the modulation techniques, antenna types, and transmit power to the estimated BS density in a dynamic fashion. In the following, we evaluate the potential difficulties we may encounter in dynamic mobile networks in addition to potential solutions to mitigate these difficulties.




(a) Initially, the femto BS is operational on the first floor and users, instead of using outdoor BS, connect to the mobile network through the femto BS that can enhance QoS and conserve energy.



(b) The household decides to move the access point to the ground floor which causes an uncontrolled BS failure for some time.

**Figure 2:** A scenario where the household is able to change the location of a femto-cell deployed inside the house.

## 3. Challenges and Opportunities

Various opportunities and challenges are accompanied by the future 5G networks [75, 76]. Table 3 categorizes and summarizes these challenges by featuring the enabler technologies or solutions. Since a feature of dynamic mobile networks may provide an opportunity together with some research challenges, we analyze research challenges and its possible solutions by discussing benefits and enablers specifically. In this section, by considering the density-awareness perspective, we introduce possible solutions for specified challenges, which we will face in the next generations of networks.

### 3.1. Densification

In order to satisfy 5G networks requirements, including higher data rate for a massive number of network entities, densification is introduced as a key feature to enhance the system capacity requirements as stated in [77, 78, 79, 80]. By densifying the mobile networks through employing small cells, higher SINR can be achieved, which can provide a higher data rate for individual UEs and reduce the latency in the network [81]. One of the major drawbacks of small cells is limited coverage area they provide due to their low power functionalities. Moreover, small cells can also provide service for a low number of UEs due to their limited resources [3, 80]. Therefore, we need to tackle these problems by employing density-adaptive algorithms, which can optimize the density of BSs in order to prevent coverage holes in the network while UEs can achieve higher throughput by connecting to BSs with higher capacity and lower load. Many research studies consider and manifest that small cells resemble random ad hoc networks, which is a well-known observation [2]. In such dense networks the area spectral efficiency is directly susceptible to base station density, as stated in [2].

### 3.2. Quality of Service and Experience

Channel quality may vary in time and frequency. In millimeter-wave (mmWave) band small cells, gNBs are equipped with multi-user, multiple input, multiple output (mu-MIMO) antennas, and user mobility is low, one may assume dynamic channels (due to the high attenuation level in mmWave band) while the channel quality does not vary considerably in time [82]. In this case, user multiplexing over different carriers is a smarter option compared to time-domain channel scheduling. Depending on the physical layer dynamics, the radio link control has to support segmentation and concatenation of the frames. This is a clear requirement for a cross-layer design. Moreover, multi-homing techniques can also be employed for enhancing QoS [83], hence schedulers also have to deal with the reliability of connections and cross-link interference management, which can increase the processing load in the network. Wireless signals are considerably attenuated while penetrating inside the buildings in mobile networks. The attenuation substantially decreases the SINR, and consequently, the achievable data rates. Instead of outdoor deployments, indoor small cells may employ lower power levels and provide higher data rates compared to outdoor BSs. This scheme reduces energy consumption, improves the quality of experience (QoE), employs the spectrum efficiently, facilitates the use of licensed bands for home networking, lowers the level of electromagnetic radiations, minimizes the costs for the mobile opera-

**Table 3**
The challenges of dynamic mobile networks and some of the existing enabling technologies that can be employed to address these challenges.

| **Challenges** | **Solutions** | **References** |
|---|---|---|
| Densification | Small cells, density-adaptive algorithms, coverage preservation techniques | [2, 3, 77, 78, 79, 80] |
| Quality of service and experience | Small cells, multi-homing in user plane, MEC, mu-MIMO, | [74, 82, 83] |
| Modulation techniques | Density aware small cells, cyclic-prefix insertion, adaptive MCS | [84, 85, 86, 87] |
| Ubiquitous coverage and connectivity | Cells on wings or wheels, network densification, D2D, relaying, ad hoc networks of BSs (MANET, FANET), NTN | [88, 89, 90] |
| Mobility management of cells | Multi-homing, group mobility support by mobile cells, MEC, lightweight-EPC, motion and deployment planning, DTN, virtual cell | [49, 91, 92, 93, 94] |
| Reliable communication | Multi-homed protocols, dual-connectivity, fault tolerance techniques, MEC | [95, 96, 97, 98, 99, 100] |
| Scalability | Distributing management and resource allocation, inter-numerology interference management NFV, SDN, C-RAN, NTN | [101, 102] |
| Antenna Type Selection | Directional, Omnidirectional, MIMO | [103, 104] |
| Dynamic (in-band) backhauling | Mobile or nomadic cells, mu-MIMO, IAB | [105, 106] |
| Low latency | Distributed and collaborative caching, D2D, mobile cells | [107, 108, 109, 110, 111, 112] |
| Energy efficiency and green operations | Small cells, MEC, sleep scheduling, cell zooming | [59, 80] |
| Management of dynamic architecture | SDN and NFV, slicing, orchestration, self-organizing and self-healing functions, density- and dynamics-aware protocols, antenna directivity, tilt or antenna count, MEC | [46, 47, 113, 114, 115, 116, 117] |
| Transmit power adaptation | MEC, cell-zooming techniques | [46, 118] |
| Interference management | MEC, density- and interference-aware protocols, e-ICIC | [65, 119, 120, 121, 122, 123, 124] |

tor and provides true ubiquity and coverage for subscribers. However, operators lose their control over BS deployment. As an example, there is an indoor Femto BS deployed in a house, as shown in Figure 2a, the location of the Femto BS which is changed based on user decision. Furthermore, this deployment change causes uncontrollable interference to neighboring houses after the BS becomes operational at its new location. Therefore, by implementing adaptive density algorithms, the density of active BSs can be estimated frequently by leveraging multi-access edge computing (MEC) utility in order to maintain and enhance QoS (higher throughput, lower delay, interference, outage and etc.) in future networks. In [74], the BS distribution for different cities are modeled, and they claim the proposed model can be used to prevent coverage holes and interference in the network.

### 3.3. Modulation Techniques

In the next generation of mobile networks, by employing multi-carrier modulation, we can immune our system to fading due to the simultaneous transmission of data over multiple paths (multipath fading), which can also prevent cross-link interference during communication among cells. However, when multi-carrier modulation is employed, simultaneous transmission over sub-carriers may lead to greater deviations in instantaneous signal power and push amplifiers into the non-linear regions. This phenomenon leads to a larger amount of power consumption and dramatically increases the costs of amplifiers. Moreover, frequency selectivity fading will lead to higher bit error rates and degrade the quality of the channel [84]. In order to cope with these problems, density aware small cells are adequate candidates since the terminal-to-base distances in small cells are shorter, which can reduce the average transmit power and cost of amplifiers. Typically, less frequency selectivity is experienced in small cells [85]. Additionally, to combat frequency selectivity, cyclic-prefix insertion can be employed in multi-carrier modulation, and the length of the prefix depends on the channel delay spread, which can be affected by BSs density variations. Therefore, cyclic-prefix can be adapted to the network density to prevent inter-symbol interference in the network [125]. Moreover, choosing an appropriate modulation coding scheme (MCS) is vital for satisfying 5G networks' requirements, such as ultra-reliable low-latency communications (URLLC) and enhanced mobile broadband (eMBB). Because, in URLLC communication signals need to be interpretable quickly, which require lower MCS, while in eMMB communications, a high number of bits need to be coded for each transmission to achieve high throughput in the network. Therefore, MCS in the future networks needs to be tuned not only by considering the received SINR value (like LTE) but

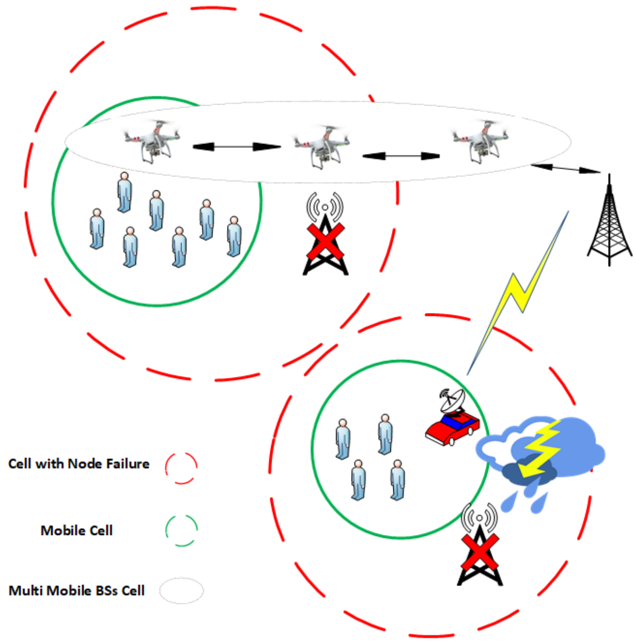



**Figure 3:** Mobile or stationary BSs may form an ad hoc infrastructure to backhaul traffic to the core network; for example, when a stationary BS fails as we exemplify here.

also it needs to be adapted to the BSs density [86, 87].

### 3.4. Ubiquitous Coverage and Connectivity

In future networks, UEs have different requirements and expect to receive service everywhere. Therefore, future networks need to be equipped with a flexible network coverage and topology. The topology and coverage of the dynamic networks must be controlled since it significantly impacts the performance in terms of capacity, delay, and resilience of the network under node and link failures. The topology depends on many controllable parameters and uncontrollable factors. Interference, attenuation, environmental parameters such as obstructions, especially for mmWaves, multipath propagation effects, fading, and noise, can be considered as uncontrollable factors which impact the link quality, and consequently the topology. These uncontrollable factors produce time- and space-variant links that are not predictable in advance. Cell mobility or presence may or may not be a controllable parameter that may sporadically cause blind spots or redundant coverage. The transmit power, antenna directivity, tilt, or antennae count are the controllable parameters that can be used to change the network topology as required to make the network adaptive to density changes. Topology and coverage control decisions should be given autonomously based on the estimated density by BSs or by a MEC entity. MEC entities have a broader perspective over network topology in comparison to BSs facilitating decentralized optimizations. For instance, in [58, 59], authors by adapting the transmit power of BSs to the network density, managed to enhance the network capacity and increase the throughput while coverage holes are prevented . Future networks guarantee the ubiquitous connectivity in case of a disaster, which causes a dysfunction of the network infrastructure [88]. At this point, with the help of device-to-device communication (D2D) and integrated access-backhaul (IAB) opportunity, BSs can form an ad hoc network. They establish a dynamic infrastructure to backhaul traffic to the core of the network as we show in Figure 3 in case of a network failure to sustain communication and enhance reliability through mobile BSs in the network [88, 89]. As claimed in [89, 90], in D2D communications, an optimal threshold value for density of BSs is required to enhance the network performance.

### 3.5. Mobility Management of Cells

In stationary networks, coverage is restricted to the range of BSs. However, by employing mobile BSs, network infrastructure will also be dynamic, which can enhance the network capacity, throughput, and coverage in future networks [34, 126]. For instance, flying BSs can form an ad hoc network and establish a dynamic infrastructure to backhaul traffic to the core network, as we show in Figure 3 in case of a network failure to sustain communication and enhance reliability through mobile BSs in the network. Although the implementation costs, maintenance, and the battery requirements of drone networks currently are a considerable challenge, the availability of cheap commodity hardware in the future presents a new avenue for provisioning such networks [50]. In particular, with the advent of Google's Sky Bender[1] and Facebook's Internet drone[2], drone empowered small cell networks (DSCNs) can be considered as a solution in future networks. Due to lower computational requirements and light payload, implementing drone cells can provide a lower CAPEX (in comparison with stationary BSs) and OPEX (with respect to energy consumption and maintenance) for network operators [49]. Due to the BSs' mobility, not only the users but also the BSs have to be tracked, and their locations have to be registered. Motion and deployment planning, handover management, and new (dynamic) location area concepts are required and can be considered as open research challenges. Even when the users are stationary, handovers may be necessary when the BSs move. One of the promising solutions for maintaining QoS in dynamic mobile networks and reducing handovers is employing a user-centric mechanism such as virtual cells where UEs can be connected to more than one BS [91]. In dense deployments, UEs may camp on multiple base stations simultaneously, and dual-connectivity, concurrent multi-path transfer or multi-homing may be possible. At this point, accurate estimation of location plays a vital role in cooperative mobile BSs. In current networks, location estimation methods such as the GPS are mainly used to calculate the coordinates of nomadic communication terminals and usually is sufficient to determine nodes' locations. In case GPS is not available, by employing proximity-based techniques or beacon nodes,

[1] https://www.theguardian.com/technology/2016/jan/29/project-skybender-google-drone-tests-internet-spaceport-virgin-galactic

[2] https://www.theguardian.com/technology/2017/jul/02/facebook-drone-aquila-internet-test-flight-arizona

we can estimate the nodes' coordination. Due to various mobility models of cells on wings or wheels, we need a highly accurate location estimator with a small delay. GPS has 10 to 15 m error in location estimation. The location information can be received with one second, which may not be applicable when multiple mobile BSs is emloyed, since it can cause a collision among them under fast mobility or affect the channel conditions among them. To reduce the estimation error, assisted or differential GPS (AGPS or DGPS) can be used that can enhance the accuracy of estimation for about 10 cm by employing ground-based reference points [92, 93]. To estimate location faster by equipping UAVs with an inertial measurement unit (IMU), which can be calibrated by the help of GPS, the location of mobile BSs can be retrieved faster and with higher accuracy [94].

### 3.6. Reliable Communication

Requirements for reliable end-to-end communication, availability of resources, lasting connectivity, and seamless handover can be addressed by employing multi-homed transport protocols and dual-connectivity not only in the control plane but also in the user/data plane. Multi-homing and dual-connectivity in the user plane ease the mobility management burden [95, 96]. In dense deployments, UEs may camp on multiple BSs at the same time. Reliable end-to-end communication requirements can then be addressed by employing multi-homed transport protocols not only in the control plane but also in the user/data plane. Cell discovery, security, access scenarios have to be tackled in dynamic networks when multi-homing is employed. Future dense networks have various types of wireless technologies such as LTE-Advanced, LTE, 3G, WiMAX, Satellite, WiFi, ZigBee, and Bluetooth. In these networks, tablets, IP-Cameras, laptops, sensors, smartphones, game devices, wearable devices, and other IP-enabled devices located on buses, aircraft, trains, satellites, etc. define a different application and user requirements. With the evolution of densification and mobility, which is the binding nature of the future networks, in addition to dynamically changing user preferences and QoS requirements, some challenges may arise, such as availability of resources, fault tolerance, lasting connectivity, and seamless handover [97, 98]. These developments in wireless communication systems equip users to concurrently receive content through multiple radio access technologies (RAT) for homogeneous or heterogeneous network environments. To do so, having a powerful and fast (low delay) processing unit such as MEC close to BSs can enhance the interface selection accuracy within a short time. Multi-homed protocols meet these requirements that can be implemented in the network communication stack. Multi-homing can use multiple network paths simultaneously to provide the lasting connectivity and the reliability of user requirements [99]. As demonstrated in [98], the transport layer multi-homed protocol has a better solution in order to provide reliable handover and connectivity. However, as we presented in Figure 2 and Figure 3, the density of BSs may fluctuate during each time slot. Therefore, future multi-homed algorithms need to consider the density of active BSs into their models to provide a reliable communication path in the network [100].

### 3.7. Scalability

In one-cell frequency reuse, the same time-frequency resources can be reused in neighboring cells. To increase the network capacity, operators can employ IAB, where the same radio technology standard is used for backhaul and access communications [101]. Although this approach eases network deployment and increases spectral efficiency, it may also cause significant variations in SINR due to a high amount of interference. Enhanced inter-cell interference control (e-ICIC) is a solution to this problem that has to be density-adaptive since BS topology changes in dynamic networks and the type received interference will be dynamically changed as it is shown in Figure 4. In the next generations of mobile networks, to fulfill the UEs requirement, different numerologies need to be employed [127]. However, by using mobile BSs, cells with different numerologies can travel in the network, which can cause Inter-Numerology Interference (INI) among cells [102]. Therefore, future interference cancellation models need to consider the variation of BSs numerologies with respect to the density of active BSs in time and space. In non-terrestrial networks (NTN), airborne or space-borne BSs are used for transmission. NTN may require delay-tolerant networking (DTN) protocols. When backhauling is not possible, mobile BSs may have to manage the functions of the core network themselves. Lightweight evolving packet core (lightweight-EPC) and DTN may have to be considered for BSs on wheels or wings. Furthermore, location area planning cannot be stationary anymore since the infrastructure becomes dynamic. Interference management models will be affected by mobile BSs since the cell layout will dynamically change by the movement of BSs. In such networks, the dynamicity of frequency reuse is high and cannot be handled by current interference management models. Therefore, adaptive interference management and resource allocation models for dynamic networks with mobile BSs are needed.

### 3.8. Antenna Type Selection

The antenna structure is another vital constraint for an efficient dynamic network. In a dynamic network, in case of using a more powerful radio signal to transmit data to longer destinations, although the coverage range is expanded, the link variation and loss can also increase too. Choosing an appropriate antenna type is another parameter that can affect the QoS in the dynamic networks. On the one hand, because BSs' locations can change frequently, by choosing omnidirectional antennas, there is no need to access nodes' locations, which can ease the communication in the network [103]. On the other hand, directional antennas can transmit signals to a more considerable distance in comparison with omnidirectional antennas, which can reduce hope count and latency in the network. The capacity of the network can also be enhanced by using directional antennas, which have higher spatial reusability with respect to the omnidirectional antennas. However, for moving topologies using directional

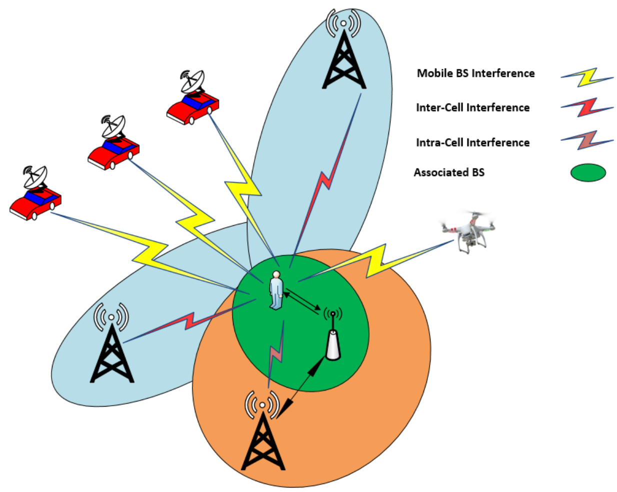



**Figure 4:** Different interference sources [foreseen] in dynamic networks.

antennas can be challenging [104]. Therefore, choosing an appropriate antenna in the dynamic networks is another important constraint which is needed to be evaluated for the future networks. By employing density-adaptive algorithms, the number of antennas by considering density of active BSs can be optimized. By using beam-forming techniques, density of BSs can be optimized in a way that interference is reduced, and overall system throughput is enhanced.

### 3.9. Dynamic (in-band) Backhauling

By introducing mobile BSs for future networks, channel models have to be revised. For cells on wings, air-to-ground, ground-to-air and air-to-air, channels have to be studied and modeled accordingly. The mobility of BSs can cause new challenges such as reflections from the ground (for drone cells), variations of drone attitude, considering changes in weather conditions for different altitude, environmental clutter, interference from other BSs in three dimensions (possibly four including time), and jamming by hostiles. All these additional constraints have to be evaluated in the channel modeling of BSs [128, 129, 130]. With the help of mobile BSs, there is a considerable potential for relay BS where nomadic nodes can be used to reduce the congestion in backhaul-links and provide higher capacity and faster communication in the network. Moreover, in-band (converged access/backhaul) or out-of-band relaying can be employed. The trade-offs between these approaches need to be evaluated [131]. Additionally, in 5G networks for increasing the network capacity, and provide reliable, secure, and lasting services, mmWave and massive multiple-input multiple-output (MIMO) can be considered as a solution [105]. This paradigm shift is analyzed in [106], in terms of network secrecy and network connection outage by demonstrating how base station density, mmWave small cells, and mu-MIMO affect each other through analytic models considering the base station density. They prove that if base station density is higher, then mu-MIMO-enabled networks along with mmWave small cells, dramatically decreases the network outage probability. Therefore, due to dynamicity of mobile BSs, employing the density of BSs in channels' models play a vital role for achieving accurate and adaptive models in the next generation mobile networks.

### 3.10. Low Latency

Due to the tremendous pace of increasing multimedia services, current network link capacity and bandwidth cannot satisfy the growth of users' demands. As it is mentioned previously, one of the main concerns in the dynamic networks is reducing the delay and response time in the network [107]. For instance, in delay-sensitive applications such as reconnaissance, packets need to be delivered within a specific delay bound. When multiple mobile BSs (such as drone BSs) are deployed together to provide coverage, communication delay among those BSs needs to be low to avoid any collisions among them. However, current protocols that are developed for mobile ad-hoc networks (MANETs) may not be applicable to flying ad-hoc networks (FANETs) of BSs [108]. To achieve this goal, network operators, by applying mobile content caching in the intermediate network infrastructures, reduce duplicate data and response time in the network [109, 110]. However, one of the main issues of caching in the dynamic network is to decide where the appropriate place for caching is [111]. In the current networks, by implementing caching toward the network edge, the amount of redundant data and delay can be reduced significantly. However, due to the mobility of infrastructures in the dynamic network, future networks need to be equipped with content-centric networking (CCN) architecture [112]. The main concern in CCN is to distribute caching in every network infrastructure, even to UEs, which can ease the data access and reduce the response time in the dynamic networks. When UEs request particular data in CCN, an interest packet will be transmitted to its neighbors, and the requested data can be delivered from the caching store of any node in the network. If the requested data is not available at neighbors, routers propagate interest packet in the network and push the cached data toward the requester. However, due to the universal distribution of caches in the network, cooperative policies need to consider diversity, freshness, number of replications, and their locations in the network topology. Moreover, by employing density of BSs as an optimization parameter in routing and caching techniques, the amount of time required for transmitting the cached data to the destination can be reduced by optimizing number of active BSs. The size of required cached dataset in the network can also be optimized which can decrease the transmission load and bandwidth needed in the network.

### 3.11. Energy Efficiency and Green Operations

Small cells may reduce $CO_2$-equivalent gas emissions per second. However, in ultra-dense networks, the total sum may not be negligible. Furthermore, the new dimension of energy efficiency research will be trying to reduce the power consumed for the mobility of BSs. Energy consumption, $CO_2$-equivalent gas emissions, and the impact of the battery-driven operation of mobile BSs have to be carefully investigated. By increasing the density of small cells, and maximizing the energy efficiency, BS density needs to be adapted and optimized by considering the overall network condition. On the other hand, the network needs to be smart enough to maintain QoS when the density of base stations dynamically changes [80]. For instance, by turning off a BS in a heterogeneous network, its traffic load needs to be adaptively handled by its neighbor cells to prevent coverage holes in the network. In [59], authors introduced a density-adaptive algorithm which can jointly enhance energy efficiency by adapting the density of BSs to network condition while coverage and throughput are enhanced by adapting BSs' transmit power to the effective density of BSs.

### 3.12. Management of Dynamic Architecture

Software-defined networking (SDN) and network function virtualization (NFV) are two distinct concepts that may help implement dynamic networks [113]. The integration of SDN and NFV can be used to optimize resource allocation in the network, while centralized and stationary resource allocation may waste valuable resources [114]. Through mobile edge computing, hybrid approaches may be developed. End-to-end slicing will significantly be more complicated than the present approaches since to-be-solved optimization problems morph with a higher frequency [115, 116, 132]. One should also not forget the scalability requirements. End-to-end slicing and limited computation resources' sharing are important challenges of the future networks. Cloud radio access network (C-RAN) is a novel mobile network architecture with joining the processing resources of the base-band unit in a pool, and virtualizing base-band units with the help of SDN and NFV [115]. C-RAN enables the aliasing of the limited computation resources, and can not be used from the other nodes in traditional radio access network (RAN) architecture on demand. For enhancing interference management and reduce the power consumption, C-RAN can dynamically allocate radio resource heads (RRHs) by considering the network condition. In future networks, the enabling of such a feature introduces the concept of cloudification. Techniques such as coordinated multipoint (CoMP), carrier aggregation, and MEC, and their hybrid approaches may be developed for the enhancement of the joint resource usage at centralized baseband units.

Self-organizing networks (SONs) have many functions (such as energy efficiency (EE), coverage and capacity optimization (CCO), mobility load balancing (MLB), etc.), which can enable BSs to adapt themselves automatically to the network condition. However, these functions may conflict with each other if the density of BSs is not considered. For instance, by increasing EE without considering BSs' density, CCO functionality may negatively be affected due to the reduction of SE in the network. In order to increase SE to its maximum level, BSs' density needs to be optimized [47]. Moreover, SE will be increased when the density of BSs is optimized, and in case of over-deployment SE will be degraded drastically [47]. Therefore, by optimizing the density of BSs, EE and CCO can be enhanced simultaneously. In [117], authors present an energy-efficient mechanism by considering the density of BSs and controlling the transmit powers for a dynamic SON. As it is shown in [46], by evaluating the density of BSs, a threshold value for the minimum received SINR in each cell can be obtained, which is used for optimizing coverage, energy consumption and SE in the network. Thus, by employing the density of BSs in SON, the possible conflicts among SONs' functions will be prevented.

### 3.13. Transmit Power Adaptation

Optimizing downlink power allocation is another critical parameter that plays a vital role in enhancing throughput and user satisfaction in the network. On the one hand, if the power is excessively allocated in BSs' downlink channel, it can cause interference among neighboring cell, which can reduce the QoS and throughput in the network. On the other hand, degrading too much the downlink power can cause coverage holes and reduce the throughput in the network. Therefore, the downlink transmission power needs to be chosen wisely, and it needs to be adapted to the density of BSs in dynamic networks. In [46], by employing MEC in the network architecture, the minimum required received SINR for maintaining QoS in the network with respect to the density of active BSs is calculated. The obtained value will be transferred to BSs, and BSs adapt their transmit power in a distributed manner to reduce the interference in the network while the overall throughput is enhanced. For density-aware mobile networks, cell zooming is a key concept regarding with preserving coverage, controlling network outage, and improving the energy efficiency [118]. Adapting transmit power based on the effective density of base stations is one of the dynamic solutions for cell zooming. To control the network coverage and outage, changing the transmit power of each base station depending on the base station density can be a handy solution as clearly illustrated in [118]. We conduct a Monte Carlo simulations by leveraging the outage and transmit power models proposed in [118] to clearly observe the impact of the network density on the network outage and the transmit power of base stations. The simulation parameters are presented in Table 4. In our simulations, we randomly deployed a set of base stations and user equipment as a three-dimensional network. In each run, a UE is randomly selected as a reference point, and received signal strength values are collected by this UE from its closest base station. If the collected RSS value is less than a threshold value, this run is considered as an outage. We compute the ratio of simulation runs that yields outage to the total number of runs as the outage probability. The simulation results are compared with the provided analytic model for the network outage based on the actual density. As can be seen in Figure 5, the density of BSs needs to be higher for the network with lower transmit power to achieve the same outage probability in two networks equipped with BSs that have different transmit power levels (10 $mW$ and 20 $mW$). Additionally, as we explained in Table 1, when BS density reaches the transition phase, increasing the density of BSs will not enhance the outage probability anymore, and it can increase the inter-

**Table 4**
The nomenclature for symbols, notations, values and units of the simulations' parameters.

| Parameter | Default Value | Units | Ref |
|---|---|---|---|
| Actual density, $\lambda$ | [0.001,0.003] | nodes/$m^3$ | [118] |
| Path-loss exp. $\gamma$ | $1.5 \leqslant \gamma \leqslant 2$ | | [133] |
| Reference distance, $r_0$, | 1 | $m$ | [70] |
| Transmit power, $P_t$ | [10,100] | $mW$ | [59] |
| Simulated outage probability, $P_O$ | [0,1] | | [118] |
| Nearest neighbor index, $k.n$ | 6 | | [118] |
| radius, $R$ | 300 | $m$ | [118] |
| $K$ | $-40.046$ | $dB$ | [118] |

ference and the energy consumption in the network. As can be seen in Figure 5, to achieve the same outage probability in case of different transmit power levels, the density of BSs in the network with lower transmit power needs to be higher. Therefore, by considering density-aware approaches, we can reach an adaptive and flexible model for dynamic networks where BS density and BS transmit power can be varied in each time slot.

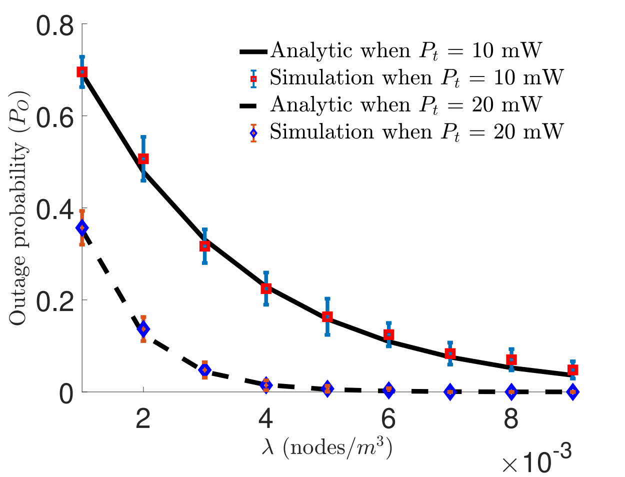



**Figure 5:** Impact of BSs density ($\lambda$) (nodes/m$^3$) on the probability of network outage ($P_O$) when the transmit power of base stations ($P_t$) is changing.

### 3.14. Interference Management

In future networks, high-speed and ubiquitous connectivity will be a leading demand that can be satisfied by densification. Network densification provides higher capacity by performing spatial reuse and less congestion with offloading. However, interference, depending on the spatial distribution of base stations, will be a significant problem to be tackled [121]. Density-aware interference management will increase link capacity and spectral efficiency in dynamic networks [122].

In 4G mobile networks, if a UE is located at cell edges, it can receive signals from multiple contiguous cells. Inter-cell interference may originate from various types of BSs. Different UEs can also interfere with each other, as shown in Figure 4. What will be of notable importance is the interference from nomadic or mobile cells in future networks. In Figure 4, we present a scenario where a cell on wheels (mobile BS) interferes with a UE. This type of interference is the most challenging if centralized solutions are to be employed [122, 123, 124].

Mobile operators may control interference at three levels: at the RAN, between RAN and UE, and within UE.

In coordinated multi-point operation, BSs have to synchronize with each other over the X2 interface (the signaling interface which is used between eNodeBs) to transmit the same information to edge terminals. In this case, inter-cell interference becomes a constructive phenomenon which is regarded and processed by the terminals using techniques to combat multipath fading [120]. With this approach, the broadcast is increased more in small cells in comparison to macro cells.

Network density is used as an optimization parameter in [65] to enhance network capacity. Authors consider the expected link rate, which depends on both user association and interference distribution, as a function of network density. Interference and network throughput models based on BSs' density are also presented to clarify the trade-off between the density of BSs and network throughput or interference. By densification, network throughput will increase until the BSs' density reaches a threshold. Crossing the threshold degrades throughput because of the high acceleration of interference and increases service disruption due to large numbers of handovers. High link capacities or high SINRs do not always guarantee high throughput in a network. Under congestion, the performance can become low. That is why a UE may not connect to a BS even when it provides the highest RSS. It is shown that a robust and optimized network density estimator is an essential requirement for maximizing the network capacity [65].

Different or the same frequency bands can be used by femtocells as macro cells do. However, employing co-channel femtocells results in inter-cell interference with their adjacent macro cells, which can reduce the performance of cell-edge UEs. An adaptive solution is presented in [119] for reducing the downlink interference caused by femtocells. That solution exploits the orthogonal fractional frequency reuse (FFR) for radio resource allocation and FFR resource hopping based on the femto-BS density and locations. If the density of femto-BSs near the macro BS is high, then femto-BSs should use orthogonal sub-channels based on the FFR method proposed. If the density of femto-BSs is low, they should choose a sub-channel randomly for a while and then hop to other sub-channels. However, such an approach is not sufficient to avoid inter-macro-cell interference in the case of high femto-BS density. The analysis of the impact of the femto-BS density shows that the density of femto-BSs should be considered to successfully combat interference [119].

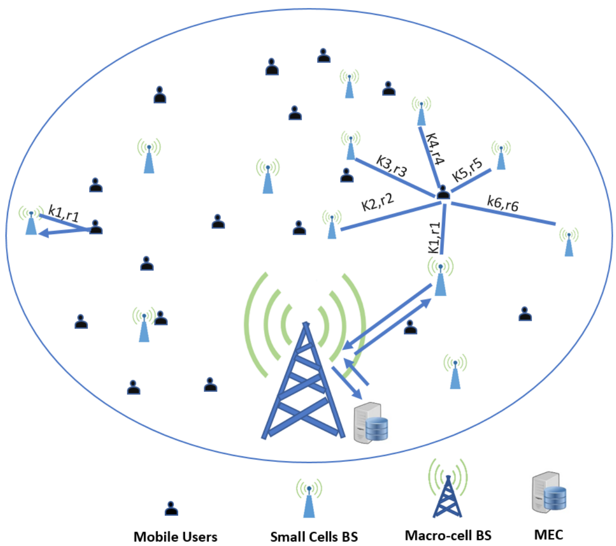
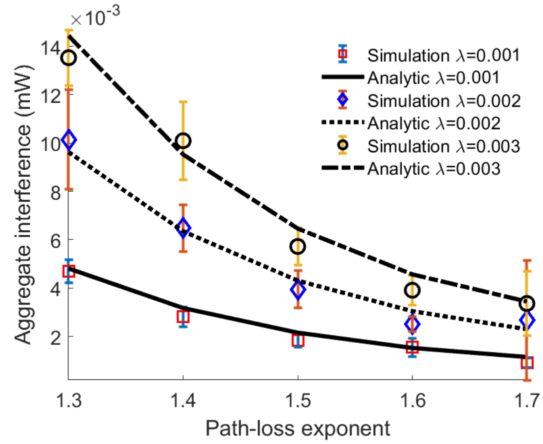
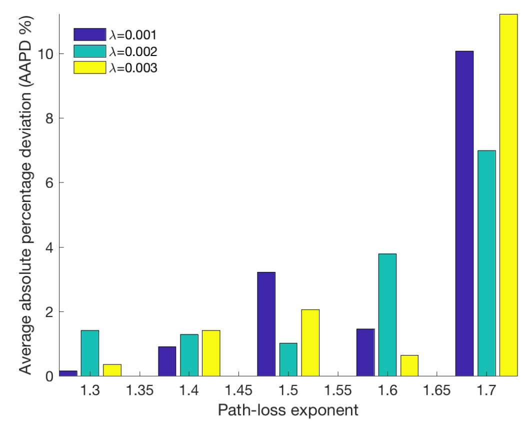



**Figure 6:** A cellular network scenario including a set of base stations, user equipment and a macro-cell for backhauling.




(a) Aggregate interference (mW)




(b) AAPD (%)

**Figure 7:** Impact of path loss exponent $\gamma$ and density $\lambda$ on aggregate interference from all nodes.

As a simple back-of-the-envelop calculation, we consider a network where the base stations are randomly deployed with an effective density of $\lambda$ nodes/m$^2$ in a two-dimensional Euclidean space as illustrated in Figure 6. This corresponds to the 2-D Poisson point process. The joint probability density function (PDF) of random distances from a randomly selected reference point up to the $n^{\text{th}}$ nearest neighbor is given in [134] as $f_{\mathbf{R_n}}(r_1, r_2, \ldots, r_n) = e^{-\lambda\pi r_n^2}(2\pi\lambda)^n \prod_{i=1}^{n} r_i$. We consider the simple path-loss model; the received signal power by a randomly positioned user equipment from the $k^{\text{th}}$ nearest base station that is $r_k$ meters away is $x_k = K\left(r_0/r_k\right)^{\gamma}$, where $\gamma$ is the path-loss exponent, $K$ accounts for the attenuation factor at $r_0$, the impact of non-distance-related factors and the transmission power. The mean of the received interference power from the closest $n$ base stations to a randomly located UE is then

$$\mu_n = \frac{2K(\pi\lambda)^{\gamma/2}\Gamma(n+1-\frac{\gamma}{2})}{(2-\gamma)\Gamma(n)}, \qquad (1)$$

where $\Gamma(.)$ is the Euler gamma function and $\gamma < 2$. Unfortunately, we could not derive a closed-form formula for the PDF of the aggregate interference in this formulation. In large scale networks, the aggregate interference from a huge number of interferers approaches to

$$\mu_n = \frac{2Kn(\pi\lambda/n)^{\gamma/2}}{(2-\gamma)}, \qquad (2)$$

by using Stirling's approximation of the quotient of gamma functions. We present aggregate interference in Figure 7 that are validated by Monte-Carlo simulations implemented in Matlab. In the simulations, a set of base stations are uniform randomly deployed in a circular field with the chosen density. As shown in Figure 6, the processing power of BSs can be enhanced by equipping the network with MECs. For instance, in this scenario the density of BSs can also be obtained by a density estimator model (as also explained in Section 2.5) deployed in MEC [58]. The simulation parameters are presented in Table 4. The downlink received signal strength for a randomly located UE is computed following the simple-path loss model. We fix $K = -40.046$ dB including the transmit power. Figure 7a depicts that for the same path-loss exponent, when the density of BSs decreases, aggregated interference also diminishes because of lower received power. When the network conditions such as channel quality are harsh, we can deploy more base stations to enhance the QoS. Aggregate interference grows up by increasing the density, as shown in Figure 7a. The convergence is only possible when $\gamma < 2$. As the path-loss exponent increases, the aggregate interference will drop as expected.

The average absolute percentage deviation (AAPD %) of the analytic aggregate interference results from those of the simulations are shown in Figure 7b. As the path loss exponent goes to 2, the AAPD values increases and gets closer to 10%-15% range. Since this model leverages the average received signal strength, the accuracy of the results is subject to the positions of the nodes, and the topology. If the user is near to the middle, then the accuracy of the results will be higher. However, if the user or the nodes at the corner of the topology, then the accuracy of the results will degrade. These results provide us an intuition about how UE's downlink capacity changes as the density of the network increases. Practical issues such as shadowing, fading, transmit power adaptation have to be addressed for dense networks to draw adequate conclusions.

All in all, one size protocols that are statically configured will not fit all scenarios in dynamic networks. Robust interference management, coverage control and SON techniques that take mobile cells into account have to be developed. Such approaches may increase the cost of control. Backhauling from cells on wheels or wings to the infrastructure may increase the load on and the cost of transport networks. Traffic from mobile cells may overload the whole system if not controlled. Topology control and resource allocation become a very important challenge that cannot be easily addressed with the present inflexible management planes.

## 4. Conclusion

With the invent of mobile BSs such as drone cells, not only the user's devices but also the elements in the infrastructure of the network has also become mobile, introducing many novel and not-addressed challenges. A flexible and density-adaptive mobile communications architecture is required. However, there is a significant research gap between state of the art and the ambition of achieving a self-organized, adaptive, and flexible networking architecture. In this paper, we present this gap by presenting the paradigm changes in mobile communications and the consequences thereof. The existing architectures have severe limitations and shortages to be able to address the introduced paradigm changes. We stress in this paper that density-aware and -adaptive networking is crucial in future networks by presenting a qualitative and quantitative analysis of the impact of density on network performance. We also categorized different density estimators to illustrate how the density of BSs can be obtained in dynamic networks. We investigate opportunities can be achieved, and challenges can be faced by adapting the density of BSs in the current mobile and wireless networks to maintaining and improving quality of service and experience, latency, energy efficiency, resource management, interference management, mobility management, etc. in a comprehensive manner. We also evaluate how the density of BSs can be leveraged in the density adaptive solutions by providing a novel aggregate interference technique that can control the interference based on the density changes in dynamic networks. With the light of the comprehensive analysis and results for the density-aware and -adaptive solutions, the density can be as an opportune and a practical solution which should be considered in network communication stack to increase the network performance in addition to reducing the energy consumption and resource wastage at run-time.

## Acknowledgements

This work was supported by TÜBİTAK, Project 215E127. Dr. Onur is partially supported by the Fubright Academic Research Scholarship.

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Shahram Mollahasani received his BSc degree in computer hardware engineering from IAU, Kashan, Iran in 2010, the MSc degree in computer engineering from EMU, Famagusta, Cyprus in 2013 and his PhD degree in computer engineering at METU, Ankara, Turkey in 2019. He is currently working as a PostDoc at university of Ottawa, Canada. His research interests are in the area of wireless communications, green networks, 5G mobile networks, and AI-enabled networks. He is a member of the Wireless systems, Networks and Cybersecurity Laboratory (WINSLab) at METU and Networked Systems and Communications Research (NETCORE) Laboratory at university of Ottawa. He is a member of IEEE.

Alperen Eroğlu received his BSc degree at the department of electronics and computer education as the valedictorian of the department from Fırat University, Elazığ, Turkey in 2009, and the MSc degree in computer engineering from METU, Ankara, Turkey in 2015. During the MSc, he researched and studied in the fields of robotics, artificial intelligence, software engineering, system architecture and modeling, embedded systems, wireless sensor networks, computer networks. He accomplished his MSc studies in the field of wireless sensor networks. He is currently a PhD student in the department of computer engineering at METU. He has been working as a research and teaching assistant at METU. His research interests are in the area of 5G mobile networks, Internet of Things, computer and wireless networks. He is a member of the Wireless systems, Networks and Cybersecurity Laboratory (WINSLab). He is a member of IEEE.

Ilker Demirkol, *IEEE Senior Member*, is a Ramon y Cajal Research Professor in Network Engineering Dept. at the Universitat Politecnica de Catalunya. His research focus is on communication protocol development and performance evaluation of wireless networks. He received his BS, MS, and PhD degrees in Computer Engineering from Bogazici University, Istanbul, Turkey. He has held several positions both in academia and industry, such as Network Engineer, System and Database Consultant. He is the recipient of the Best Paper Award in IEEE ICC'13 and Best Mentor Award at U. of Rochester, NY, in 2010.

Ertan Onur received his BSc degree in computer engineering from Ege University, Izmir, Turkey in 1997, and the MSc and PhD degrees in computer engineering from Bogazici University, Istanbul, Turkey in 2001 and 2007, respectively. During the MSc and PhD degrees, he worked as a project leader at Global Bilgi, Istanbul and as an R&D project manager at Argela Technologies, Istanbul. He developed and managed many commercial telecommunications applications. After obtaining his PhD degree, he worked as an assistant professor at Delft University of Technology, the Netherlands. From 2014 on, he is with METU, Turkey. He was the editor/convenor of the Personal Networks Group of Ecma International Standardization Body. Dr. Onur's research interests are in the area of computer and wireless networks and their security. He is the founder of the Wireless systems, Networks and Cybersecurity Laboratory (WINSLab). Dr. Onur is presently a visiting Fulbright scholar at the Department of Computer Science, Stony Brook University, NY. He is a member of IEEE.