USER-IN-THE-LOOP FOR HETHETNETS WITH BACKHAUL CAPACITY CONSTRAINTS

MEISAM MIRAHSAN, RAINER SCHOENEN, HALIM YANIKOMEROGLU, GAMINI SENARATH, NGỌC-DŨNG ĐÀO

ABSTRACT

A popular method to model heterogeneous networks is the use of two independent homogeneous Poisson point processes to locate UEs and BSs with unlimited backhaul capacity. Despite the analytical tractability, this approach is far from accurate. First, the distribution of UEs in real scenarios is neither homogeneous nor independent of BSs. Besides, the assumption of unlimited capacity for backhaul connections is optimistic, especially in the future 5G HetNets with small cells. In this article, we propose a novel modeling approach for heterogeneous networks with heterogeneous spatial traffic distribution (HetHetNets). Specifically, in the proposed model, a particular ratio of UEs are collocated with the BSs while the rest of UEs are independently and homogeneously distributed in the network. Moreover, the proposed model presumes backhaul connections with constrained capacity. We study the impact of this more realistic network modeling on the effectiveness of the spatial user-in-the-loop (UIL) schemes in HetHetNets. Spatial UIL assumes that (some) UEs can be influenced by the operator to move in the network. Finally, we propose a new objective for the UIL mechanism that takes into account the impact of the BS loads and the backhaul capacities on the network performance.

Meisam Mirahsan and Halim Yanikomeroglu are with Carleton University.

Rainer Schoenen is with HAW University.

Gamini Senarath and Ngọc-Dũng Đào are with Huawei.

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INTRODUCTION AND MOTIVATION

The spatial distribution of wireless user equipments (UEs), the wireless access network, and the backhaul network can be viewed as three layers of heterogeneous wireless cellular networks with heterogeneous traffic distribution (HetHetNets). The spatial distribution of UEs constitutes the network traffic demand characteristic. Meanwhile, the access connection between UEs and the base stations (BSs), and the backhaul connection between the BSs and the core IP network constitute the network supply capacity.

The distributions of the wireless traffic demand and wireless capacity supply do not necessarily match in the wireless cellular networks, in either the time domain or the space domain. Commonly, some locations (times) of the network are overloaded while other locations (times) are underloaded. The problem with this lack of match is twofold:

1 In the overloaded parts of the network, the available resources must be shared to serve excessive amounts of demand, which leads to low data rates per user.

2 In the underloaded parts of the network, the unused resources are wasted. The root cause of this problem is that the idle network capacity and idle resources cannot be reserved in underloaded locations (times) to be transferred to the overloaded locations (times).

In a wireless cellular network with ideal backhaul connections, the lack of capacity is mainly due to the access connection limitation, that is, the wireless access problem and low channel quality between UEs and BSs. However, in the envisioned 5G networks with small cells deployed in residential and office buildings, the assumption of ideal backhaul is more optimistic than realistic, especially considering the fact that a main portion of the small cells (i.e., femtocells) will be deployed by customers rather than service providers. Recently, there has been increasing interest in the literature in the study of limited backhaul capacities in future 5G HetNets [1].

Figure 1 illustrates an example HetHetNet comprising macrocells, picocells, and femtocells with different backhaul capacities. In the networks with limited backhaul capacity, the UE rate limit will be a consequence of limited backhaul in addition to the wireless access connection limit. The backhaul connections in this article are assumed to be wired. However, the proposed model in this article is applicable to HetHetNets with wireless backhaul connections.

One solution to the problem of mismatch between supply distribution and demand distribution is to bring the wireless traffic demand and wireless capacity supply together in the time and space domains. Predictive resource manage-

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ment and user location tracking [2], and optimized small-cell BS deployment in traffic hotspots, are among mechanisms that try to bring wireless capacity supply to wireless traffic demand location and time. On the other hand, user-in-the-loop (UIL) [3], defined below, is a relatively new and significantly effective method of bringing traffic demand to the time and location of wireless capacity supply (traffic shaping).

The UIL concept aims to influence the user behavior (which can be viewed as "layer 8" in OSI network models) in a wireless network in order to obtain better spectral efficiency by convincing users to move from one location to a better one or avoid traffic congestion by postponing session traffic out of busy hours. Indeed, UIL extends the past assumption of the user being only a traffic generating and consuming black box (in nature similar to the noise input into a system). Instead, the system-theoretic framework allows control input into the user block on which the user receives suggestions and incentives (and eventually penalties) in order to convince him/her to diverge from the default behavior (which is uncontrolled, i.e., open loop) so that the traffic can be shaped [3].

Indeed, complementing the engineering for the growth of the supply side, the engineering for the control of the demand side is referred to as UIL and is motivated here. UIL proposes dynamic pricing based on a user's behavior and willingness to adapt to network situations, compared to current static pricing policies. Results from a survey that measures how willing a user is to respond to such control are also presented in [3]. We describe the UIL in details.

In order to study the performance of wireless cellular networks under heterogeneous traffic distribution and limited backhaul assumption, and to capture and measure the impact of various methods (e.g., UIL) on the network performance, the first step is to model the traffic demand and capacity supply in the time and space domains.

Traffic demand modeling in the time domain has been well investigated in the literature. Traditionally, in voice-only networks, homogeneous Poisson process models were accurate enough to model traffic in time. After the emergence of different applications, such as video and data with variable data rate demands, the Poisson model failed to capture the traffic statistics; as a result, various heterogeneous (super-Poisson) traffic models based on the hidden Markov model (HMM), Markov modulated Poisson process (MMPP) [4], and other stochastic methods have been proposed in the literature and used for performance analysis.

Similarly, in the space domain, a popular approach to modeling and analysis of the supply and demand in HetNets has been the use of two independent Poisson point processes (PPPs) for the locations of BSs and UEs [5]. Despite analytical tractability, this popular approach has a major shortcoming: although the PPP model may be fitting for BS locations, it is less adequate for UE locations, mainly due to the fact that the model is not adjustable (tunable) to represent the amount of heterogeneity (non-uniformity) in UE locations. There is still relatively

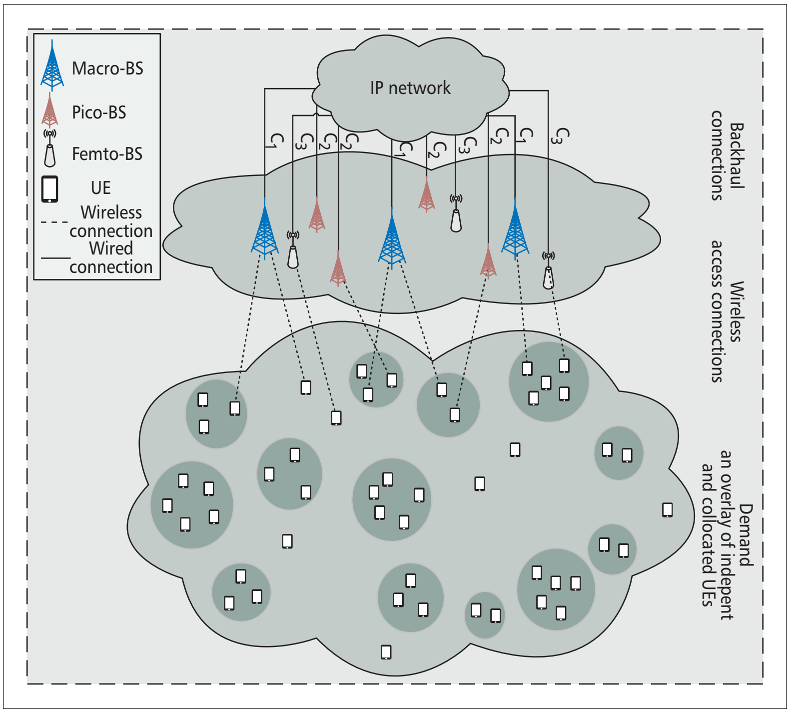

Figure 1. In the envisioned 5G HetHetNets, the assumption of backhaul connections with unlimited capacity is very optimistic. In particular, the envisioned femtocells and picocells might have backhaul connections with constrained capacity. In this figure, a sample three-tier HetHetNet with macrocells, picocells, and femtocells, which have different backhaul capacities, is demonstrated.

little literature that takes into account the heterogeneous spatial distribution of the traffic demand in wireless cellular networks [6–8].

The goals and main contributions of this article are summarized as follows:

- We introduce a novel HetHetNet model, that is, an adaptive spatial traffic model with adjustable heterogeneity to capture the characteristics of wireless demand distribution in wireless heterogeneous cellular networks.
- We study the impact of more realistic heterogeneous (non-uniform) spatial traffic demand distribution on the efficiency of the UIL method in HetHetNets with backhaul capacity limitation.
- We propose a new objective for the UIL mechanism that takes into account the impact of the BS load and the backhaul capacity on the network performance.

The remainder of this article is organized as follows. The spatial traffic modeling and network modeling are described. The basic UIL is reviewed. The new UIL method involving BS load and backhaul capacity is introduced. The simulation parameters and results are presented, and present conclusions and remarks.

Modeling HetHetNets

Although PPP modeling leads to analytical tractability [9, 10], a more realistic model results in more accurate understanding of network performance. The concept of user distribution is directly related to the network performance in wireless networks in general and wireless cellular

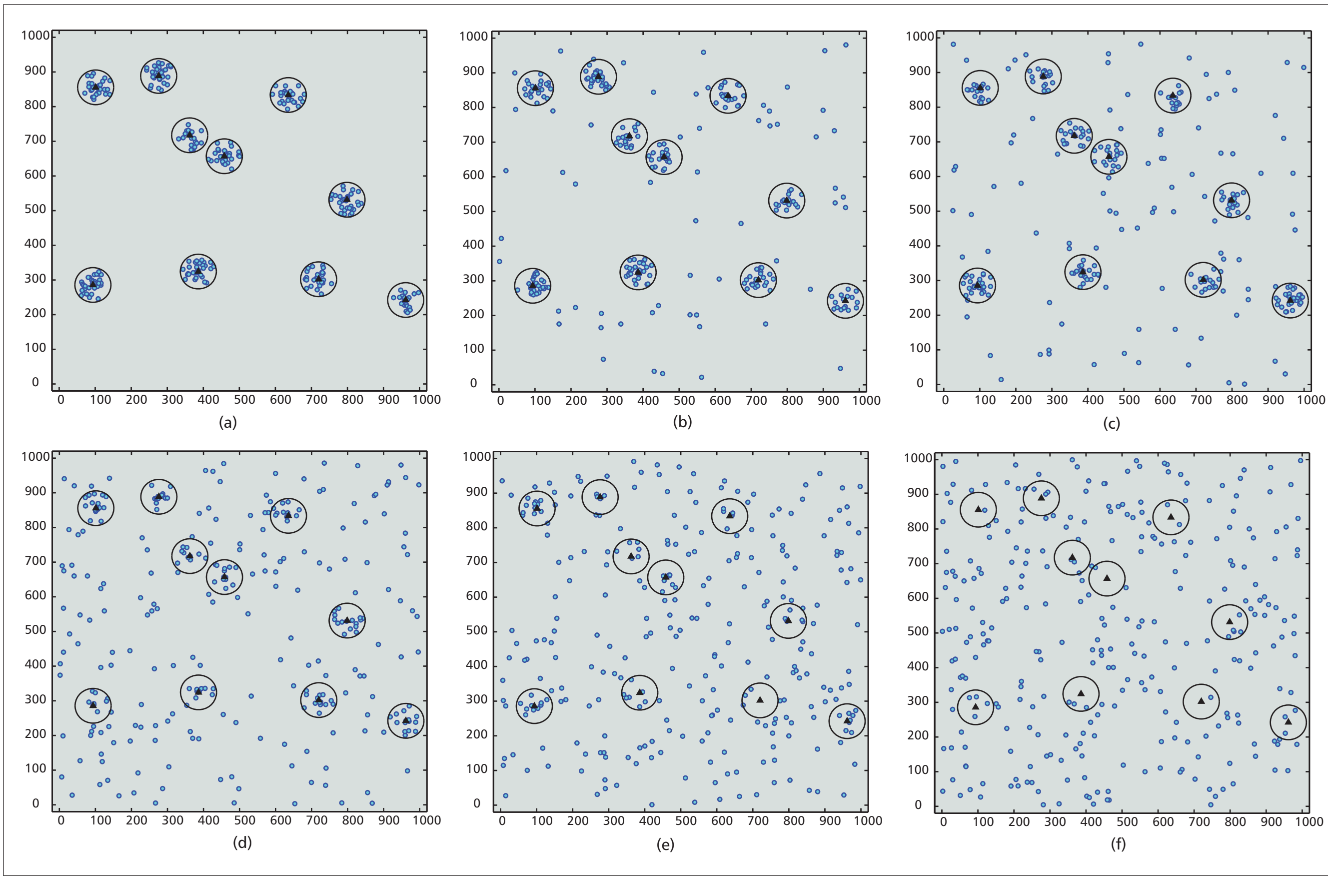

Figure 2. Various UE distributions with different clustering properties are illustrated in a 1000 m × 1000 m network. Black triangles denote the BSs and small dots denote the UEs. Starting from a pure Matern point process a), the ratio of independent UEs increases and the CoV decreases until a homogeneous PPP (f) with no clusters is reached with CoV = 1. The number of BSs is 10, and the Matern cluster radius is 50 m: a) $p = 0$ (i.e., pure Matern), CoV = 5.47; b) $p = 0.2$, CoV = 4.79; c) $p = 0.4$, CoV = 4.04; d) $p = 0.6$, CoV = 3.27; e) $p = 0.8$, CoV=2.16; f) $p = 1$, CoV = 1 (i.e., pure PPP).

networks specifically. There are two main aspects of experienced rate which are affected by user distribution: the load on BSs which is determined by the clustering properties of user distribution, and the spectral efficiency of UEs which is a function of signal-to-interference-plus-noise ratio (SINR) which is, in turn, a function of distance between UEs and BSs. In this section, we propose a novel wireless cellular network modeling approach that has the following properties:

- The spatial distribution of wireless traffic demand (active UEs) is not homogeneous (uniform) but adjustable and heterogeneous (nonuniform).
- The capacity of backhaul connections is not unlimited (infinite) but constrained (finite).

UE Distribution Model

While the homogeneous PPP assumption for the UE distribution is not realistic, highly clustered distributions with no standalone UEs are also unrealistic. The requirement is an adjustable model that is tunable (preferably with few parameters) to model a wide range of scenarios from highly homogeneous PPP to highly heterogeneous clustered scenarios.

To generate such an adjustable and heterogeneous spatial traffic demand, we should first note that the wireless devices (i.e., UEs) can be divided into two different categories:

- Wireless devices that are correlated (collocated) with social points of interest, including residential and office buildings, bus stations, shopping malls, and so forth
- Wireless devices that are not attracted around the points of interest,that is, wireless devices that are independent from the points of interest

We assume that the set of points of interest is the same as the set of BSs, that is, all points of interest are equipped with BSs. Sample scenarios are illustrated in Fig. 2.

The proposed user distribution model in this article is as follows: N_u active user devices are generated while N_u follows a Poisson distribution with mean $\lambda_u \times A$ ($N_u \sim \text{Poisson}(\lambda_u \times A)$), where A is the total network area. Every new user is labeled as BS-independent with a probability of p or BS-correlated with a probability of $1 - p$. The BS-independent devices are distributed uniformly by a homogeneous Poisson process, while the BS-correlated points are located uniformly in a ball centered at one of the points of interest. The points of interest might have different weights attracting devices with different probabilities. In this article, we assume that all of the points of interest have equal weight.

The real-world traffic distribution is very similar to the described model. Consider a snapshot of user locations in a cellular network (e.g., a campus snapshot). Users can be divided into two main categories. The first category includes nomadic users who are inside or around buildings or other points of interest. The second category is mobile users moving from one building to another, or from one point of interest to another. We do not claim that this model can fit to any scenario of user distribution, but this model covers a majority of users and can be adjusted to various scenarios with limited number of parameters.

In particular, the distribution of UEs is an overlay (a superposition) of two independent distributions. The first one is a PPP with density $p\lambda_u$ and the second one is a Matern point process [11] with total density of $(1 - p)\lambda_u$. In Matern point processes, first, a parent process of clusterheads are distributed uniformly in a region; then cluster members are distributed uniformly in circles around the clusterheads.

In a network scenario with $p = 0$, all devices are located around points of interest, and the resulting pattern is a clustered Matern point process. On the contrary, a point pattern generated with $p = 1$ is totally random (i.e., traditional uniform PPP). Any other value of p results in an overlay pattern with superposition of a PPP and a Matern point process (Fig. 2).

A very important problem in heterogeneous UE modeling is the measurement of the level of heterogeneity. It is crucial to have a benchmark metric that determines the heterogeneity of the distribution with one (or few) parameter(s) so that it is easy for everybody to gain an understanding of the level of clustering of UEs by having this metric value. In [7], we proposed simple metrics for the measurement and understanding of the heterogeneity of spatial point patterns. Specifically, we proposed the statistical characteristics of the random tessellations of point distributions as accurate and very appropriate metrics of spatial heterogeneity. We showed that the coefficient of variation (CoV), defined as the standard deviation σ divided by mean μ, (σ/μ), is a revealing statistical parameter that captures a majority of the statistical characteristics of a metric. We also showed that the geometrical inferences of conventional tessellations such as Voronoi and Delaunay tessellations are very promising candidates. Such metrics as Voronoi cell areas and Delaunay cell edge lengths are shown to be accurate enough and can be considered as analogs of the popular interarrival times metric in temporal traffic modeling.

A CoV value of 0 means that the UEs are organized in a very structured manner, and the Voronoi cells and Delaunay cells are all equal. A CoV value of 1 is associated with a completely random distribution where UEs are PPP distributed. CoV values between 0 and 1 refer to sub-Poissonian distributions in which the distribution is more homogeneous than Poisson. Finally, a CoV value of more than 1 means that the points are distributed heterogeneously (or non-uniformly) compared to PPP (super-Poissonian).

This gives the opportunity for unified and non-parameterized traffic modeling and measurement in the time and space domains. Indeed, a parameter such as p in our model in this article is an internal parameter of the traffic generation process, while CoV is a benchmark parameter that can be used to compare the heterogeneity of different patterns.

System Model

We model the downlink of a heterogeneous wireless cellular network with heterogeneous traffic distribution (HetHetNet) comprising K tiers of BSs (e.g., macro, pico, and femto) with omnidirectional antennas. BSs of tier K have transmission power of p_k, backhaul capacity of C_k and are spatially distributed as a PPP Φ_k of spatial density λ_k. The BSs of different tiers of the network are distributed independently.

The fading (power) between a BS and a UE is assumed to be i.i.d exponential (Rayleigh fading). The standard path loss function is given by a simple model reciprocal to the α-power of distance where $\alpha > 2$ is the path loss exponent. Hence, assuming that the antenna gains are included in the transmission power, the received power at a typical UE from a BS belonging to tier i is the product of transmit power at that tier by the power loss. Assuming that the UE connects to this BS, the resulting aggregate interference and the SINR expression can be calculated accordingly. We assume that each UE connects to the BS with the average signal power; hence, average SINR is the strongest. The spectral efficiency (SE) can be stated as $\eta_x = \log_2(1 + \gamma_x)$ using the Shannon formula. Assuming equal resource scheduling, the user rate can be calculated as $R_u = \min(1, C_{a_u}/L_{a_u}) \times \eta_{x_u} W N_{a_u}^{-1}$ where W is the total BS bandwidth, $a_u \in \cup_{k=1}^{K} \Phi_k$ is the BS associated with u, L_{a_u} is the aggregate load on a_u (i.e., the summation of UE loads in an unlimited backhaul scenario, which depends on the locations and channel quality of UEs), and N_{a_u} is the number of UEs associated with a_u. The backhaul capacity limits the user rates by a factor of C_{a_u}/L_{a_u} compared to the unlimited backhaul scenarios. UE temporal traffic model is assumed to be full buffer and best effort.

Basic UIL

In this section, we describe the UIL concept and explain the basic UIL schemes which already exist in the literature.

The basic UIL concept aims at controlling the user (layer 8) behavior in a wireless network in order to obtain a better SE by convincing the users to move from one location to a better one or avoid traffic congestion by postponing session traffic outside of busy hours. Depending on this impact dimension, the approach is called spatial or temporal UIL control [3]. In both cases the user is within, and part of, a closed-loop control system shown in Fig. 3. In this article, we are concerned with spatial UIL.

The user receives suggestions and incentives (or penalties) in order to convince him/her to diverge from the default behavior. A user within a closed control loop receives this control information (CI) in the form of suggestions on the graphical user interface, such as a map and directions toward a better location, a better time to start his/her session (outside of busy hours), or a simple color indicator (e.g., green, yellow, red). Before the user moves to the new location, all information such as the amount of SE

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increase, the amount of incentive, and the distance between the current and target locations are known.

Obviously, the effectiveness of UIL in improving UE experience as well as network throughput depends strongly on the degree of conformance of users regarding the guiding information, which, in turn, depends on the incentives suggested to the users. For instance, a 20 percent discount ignites less motivation in the users to move compared to a 40 percent discount. A wise selection of control parameters can lead to increased system throughput as well as network revenue since the increased throughput raises the opportunity for network operators to increase the number of subscribers in general.

The user decides to move or not to move based on the information. The user and its behavior is naturally not subject to a precise science. In order to get some usable properties of the input/output system response, two surveys were conducted [12, 13]. A fitting mathematical model derived from the empirical distributions follows an exponential shape for the function between incentive and the probability $p_d = \exp(-\beta d)$ of using the service where d is the distance between current user location and suggested location and β depends on individuals, incentives, and many other parameters. So, the model can be customized for each user and recorded in central databases. For this article, for the sake of simplicity, we assume that the p_d function has the same shape (β parameter) for all users. Figure 4 illustrates the probability of movement and the fitting functions based on the surveys conducted in [12, 13].

The main objective of the basic UIL is to suggest to the user the location which maximizes the utility of the user denoted as $U_u^x = \eta_x p_x$, where η_x is the spectral efficiency at location x and p_x is the probability of the user moving the distance $d_x = |x_u^0 - x|$ between the current location of the user x_u^0 and location x. The location that gives the best utility, x_u^*, is suggested to the user u and he accepts the suggestion with probability p_x and moves to x_u^* to experience spectral efficiency of ηx^*_u.

Two different schemes can be used for basic UIL: in the first scheme (Baseline-I), the user is not re-associated with a new BS; therefore, only the locations inside the coverage area of the current serving BS are searched. In the second scheme (Baseline-II), the best SE from all BSs in the network can be searched, and if a location with higher SE from another BS is selected and the user agrees to move, the user is re-associated with the new BS.

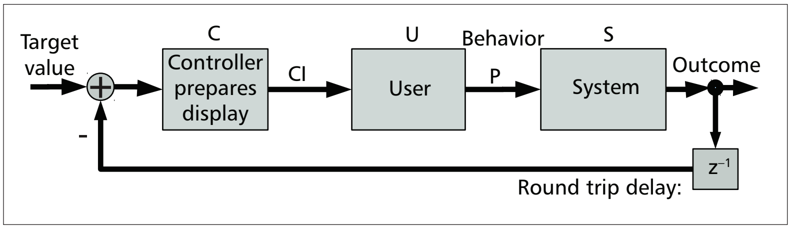

Figure 3. UIL aims to control user behavior in a network. A user is guided to transmit at a better time or move to a better location [3]. Based on the target behavior and the previous user behavior, the controller decides on the control information (CI) displayed on the screen of the user equipment for the user with the associated incentives (or penalties). The user decides 1) to follow the suggestion and deviate from his/her default behavior in order to receive the offered rewards, or 2) not to follow the suggestion and lose the offered rewards.

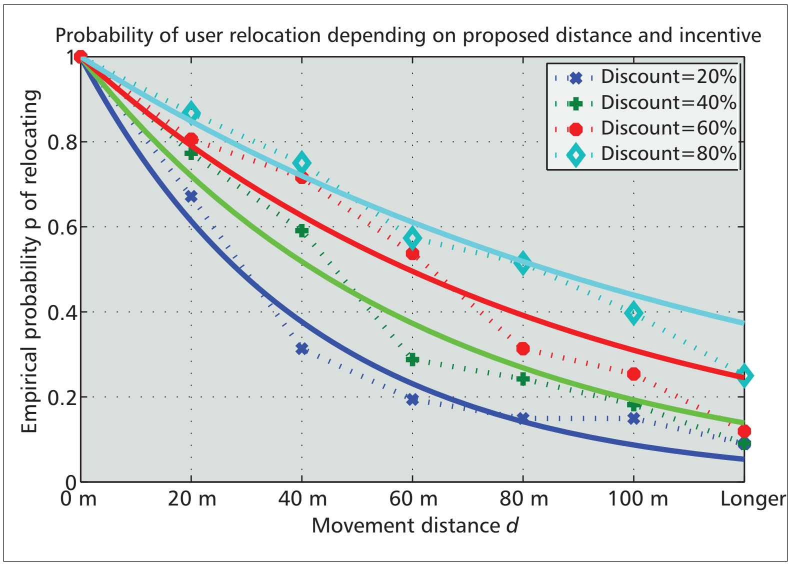

Figure 4. Based on the surveys conducted in [12, 13], a fitting mathematical model is derived from the empirical probability distributions of using the offered services. The derived model is expressed as an exponential function parameterized by the offered moving distance and the associated incentives (or penalties) [3].

Advanced UIL Schemes Based on BS Loads and Backhaul Capacities

The user rate R_u in a wireless cellular network depends not only on the SE but also on the load and the backhaul capacity of the BS associated with it. Specifically, a UE associated with a highly loaded BS, even with relatively high SINR, has to share the BS resources with other UEs. Moreover, a UE associated with a BS that has limited backhaul capacity cannot achieve high rate. While in the basic UIL only the spectral efficiency of the users is considered in the utility function, in this section, we introduce advanced schemes for UIL that take into account the user rates based on BS load information, backhaul capacity, and SE in the utility function.

In this article, we assume that the UEs arrive in the network sequentially. Thus, the new location is suggested to the newly arrived UEs one by one as time passes. As a result, an optimization framework for the entire network in one shot is not considered. Optimization solutions are suggested as interesting future extensions of this work.

It must be noted that consecutive suggestions to users to move might be annoying and unacceptable. Hence, in this article, we assume that every user is offered a new location only at the arrival at the network (at the beginning of a session). In an optimization paradigm for UIL, the time and frequency of performing UIL optimization is an important parameter. If the optimization is done frequently, the users might not accept it and choose not to move. On the other hand, if the optimization is done infrequently, many users might complete a full session in an interval without being considered for UIL optimization.

In the UIL scheme, the objective function must be defined in a way that maximizes the rate of a user by suggesting a wise movement to the user so that with minimum possible movement, the user can achieve a considerable higher rate. This might result in re-association with a new BS. First, we introduce an advanced UIL scheme (Adv-UIL-load) whereby the utility function includes the BS loads to make sure that the network load is balanced among BSs. Furthermore, an improved UIL scheme (Adv-UIL-load-backhaul) can be considered whereby the utility function is constructed based on the BS load data as well as the BS backhaul capacity.

In future HetHetNets, where the backhaul limitation is predicted to be a real issue, the proposed UIL schemes can have considerable impact. We present the simulation results.

Experimental Results

Based on the proposed HetHetNet modeling and UIL schemes, in this section, we present the simulation parameters and experimental results.

We used a MATLAB-based simulation environment. UEs with mean overall density of λ_u = 1000/km^2 were dropped in a 1 km × 1 km network area. A 3-tier HetNet is simulated consisting of macro-BSs with mean density of λ_1 = 5/km^2, pico-BSs with mean density of λ_2 = 25/km^2, and femto-BSs with mean density of λ_3 = 25/km^2. The macro-BSs, pico-BSs, and femto-BSs are assumed to be connected to the backhaul network with capacities of C_1 = 1 Gb/s, C_2 = 100 Mb/s, and C_3 = 10 Mb/s, respectively, all with omnidirectional antennas. We repeated the experiment for 1000 drops and gathered the results for each drop. The UEs are presumed to have a full-buffer traffic model in the time domain. As suggested by the Third Generation Partnership Project (3GPP) technical specification group for evolved universal terrestrial radio access (E-UTRA), the transmit power for macro-, pico-, and femto-BSs are set to be p_1 = 46 dBm, p_2 = 30 dBm, and p_3 = 23 dBm, respectively. Table 1 summarizes the simulation parameters used in this article.

The network mean user rates vs. the CoV of Voronoi cell areas is illustrated in Fig. 5. As shown in Fig. 5, with decreasing CoV (with increasing p, i.e., the ratio of BS-independent UEs), the network mean user rate decreases as expected. This is because the number of users near BSs with high-quality channel status is decreased. Moreover, the new proposed UIL schemes, Adv-UIL-load and Adv-UIL-load-backhaul, show superior performance compared to the basic schemes. This is due to the fact that in the advanced proposed schemes, if the backhaul connection of a BS does not have enough capacity to support new traffic, even if the access connection is in good quality, the UE is not guided to this BS. However, in the basic UIL schemes, the backhaul capacity is not taken into account.

The next metric investigated is the coverage probability. Figure 5 illustrates the coverage probabilities vs. the CoV of Voronoi cell areas. The minimum rate for coverage can be a simulation parameter. In this article, we set the minimum rate threshold to be 1 Mb/s.

It can be seen again that the coverage probability is increased by the UIL schemes, and the new proposed schemes improve the coverage probability compared to the basic UIL schemes. For highly uncorrelated traffic to the BSs, the

One might be concerned about how the user-in-the-loop exists in HetNets, probably in C-RAN, or how a virtual operator would bring it to the user. We refer interested readers to the growing interest in "smart data pricing" [14]. We also reference the patents existing on load balancing with UIL [15], which means that there is industry support. However, assuming that UIL will not be a reality in the near future, it is wise to integrate this functionality into 5G standards to be prepared for the future. In practice, this means that an application programming interface (API) has to be defined where Google's Android and Apple's iOS get the information from the cellular network (C-RAN). Then they can adapt their operating system to include UIL, together with maps and their data usage statistics.
The next important concern is that it is difficult to determine the locations of indoor users precisely due to the weak penetration of GPS signals. Many researchers are working on this for navigation purposes, and good methods are being developed. Therefore, UIL can build on this once it is solved well. Meanwhile, the signal strengths of many neighbor base stations, which are recorded anyway, can be used directly to estimate the user location and guide the user.

Box 1. Practical aspects of UIL.

In the Adv-UIL-load scheme, for a UE u, originally located at x_u^0, the utility function is defined as

$$U_u^x = \frac{W\eta_x p_x}{N_x},$$

where N_x is the number of UEs associated with the BS serving point x, W is the total available bandwidth, η_x is the spectral efficiency at point x, and p_x is the probability of the user u moving to point x. This scheme takes into account the BS load, by incorporating W/N_x into the utility formula, as well as the channel quality (i.e., the spectral efficiency). The location x_u^* providing the highest utility is suggested to the UE u to move to.

In the Adv-UIL-load-backhaul scheme, the utility function for a UE u, originally located at x_u^0, is defined as

$$U_u^x = \min(1, \frac{C_{a_x}}{L_{a_x}}) \times \frac{W\eta_x p_x}{N_x},$$

where a_x is the BS associated with point x, C_{a_x} is the backhaul capacity of a_x, and L_{a_x} is the aggregate load offered on a_x. In a network with finite backhaul capacity, for every point in the network, one of the following cases might happen:

1) The backhaul capacity is more than the wireless access link capacity. In this case, the backhaul capacity is not a bottleneck, and every user receives the exact rate that is offered by the wireless access connection (i.e., $W\eta_x p_x/N_x$).
2) The backhaul capacity is less than the wireless access capacity. In this case, the backhaul capacity limits the user rates, and every user receives just a certain portion of the available access rate. In other words, the wireless access rate for each point is decreased by a factor of C_{a_x}/L_{a_x}.

Box 2. Mathematical analysis of the proposed UIL schemes.

coverage probability is enhanced from less than 30 percent to about 60 percent (more than doubled). However, note that the realistic distribution of traffic is not represented by this uniform case ($p = 1$).

Conclusions and Remarks

We propose an adjustable spatial traffic model for HetHetNets with limited backhaul connection capacity. With the novel network model, we introduce improved UIL schemes whereby the BS loads and BS backhaul connections are taken into account. The simulation results confirm that the new UIL scheme improves such important network performance metrics as the mean user rate and the coverage probabilities in the future 5G networks.

This work can be extended in many directions. First, in this article, we investigate only the spatial heterogeneity of traffic. A combination of time domain and space domain traffic modeling can also be used to capture the effect of time domain traffic demand variations. Second, in this article, we use sequential UIL schemes where the user locations are updated one by one. Optimization frameworks for UIL can be considered to improve the network performance. Finally, in this article, we have used our simulation parameters that we believe are realistic. However, changing these parameters affects the results. It is important to study the sensitivity of the results to the backhaul limit values.

Parameter	Symbol	Value
Spatial density of UEs	λ_u	1000/km^2
Number of network tiers	K	3
Spatial density of macro-BSs	λ_1	5/km^2
Spatial density of pico-BSs	λ_2	25/km^2
Spatial density of femto-BSs	λ_3	25/km^2
Total network area	A	1km × 1km
Macro-BS Backhaul capacity	C^1	1 Gb/s
Pico-BS Backhaul capacity	C^2	100 Mb/s
Femto-BS Backhaul capacity	C^3	10 Mb/s
Macro-BS antenna height	—	25 m
Pico-BS antenna height	—	10 m
Femto-BS antenna height	—	10 m
Number of drops	—	1000
Bandwidth (downlink)	W	10 MHz
Noise power	σ_n^2	—174 dBm/Hz
Total macro-BS transmit power	P_1	46 dBm
Total pico-BS transmit power	P_2	30 dBm
Total femto-BS transmit power	P_3	23 dBm
Path-loss exponent	α	3.7
BS and UE antenna gain	—	0 dBi
Time domain traffic model	—	Full buffer
Antenna model	—	Omnidirectional
UE antenna height	—	1.5 m
Fading model	—	Rayleigh fading

Table 1. Simulation parameters.

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Biographies

Meisam Mirahsan [S'2013] (mirahsan@sce.carleton.ca) received his B.Sc. and M.A.Sc. degrees in information technology engineering and computer network engineering from Amirkabir University of Technology, Tehran, Iran, in 2007 and 2010, respectively. His research interests include wireless networks, traffic modeling, stochastic geometry, network virtualization, and resource allocation in radio access networks. He has been a Ph.D. candidate in electrical engineering in

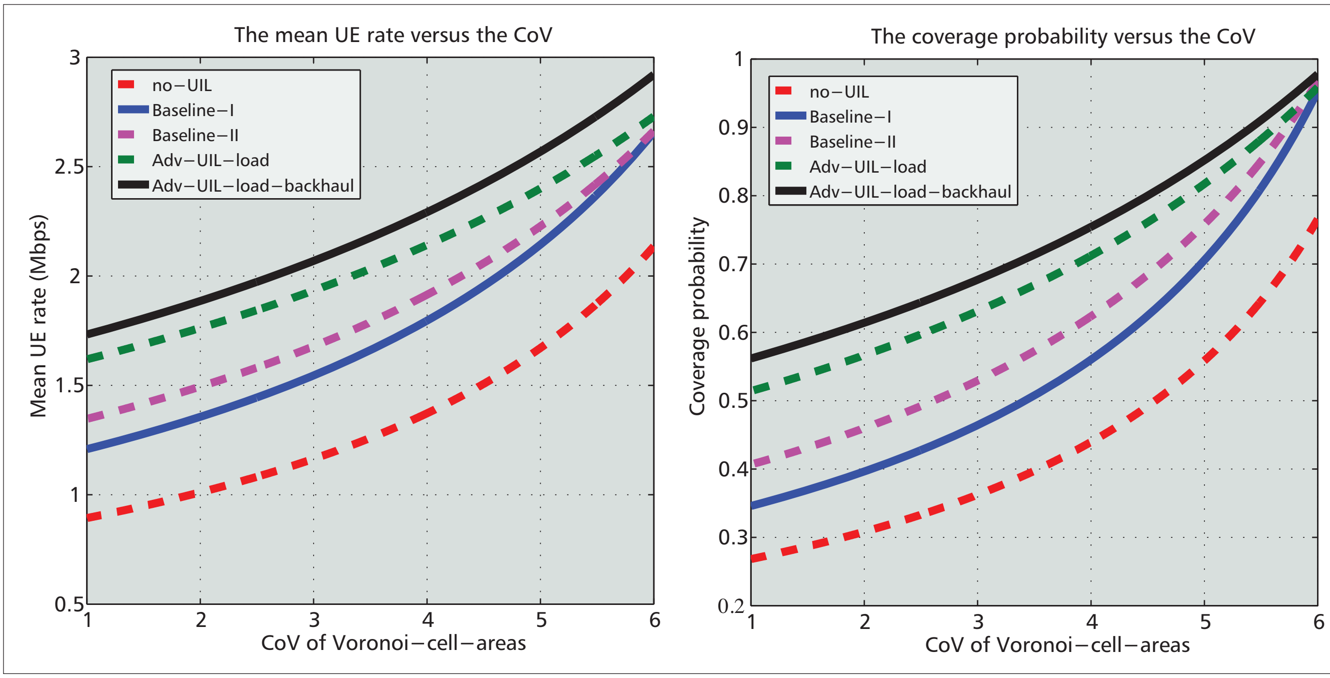

Figure 5. The mean user rate averaged over the entire network (left) and the coverage probability with minimum rate of 1 Mbps (right) are shown in this figure (y-axis). The x-axis shows the CoV values. Nonlinear least-squares fitting is used to show the curve trends.

the Systems and Computer Engineering Department of Carleton University, Ottawa, Ontario, Canada, under the supervision of Prof. Halim Yanikomeroglu since 2013. He worked in the leading network design company, Favapars, in Tehran 2009–2012 as the network design team manager on Iran's national backhaul IP/MPLS network design. During 2015 he is doing an internship as a wireless network engineer in Huawei Technologies, Ottawa R&D, Canada.

Rainer Schoenen [SM'2013] (rs@sce.carleton.ca) received his German Dipl.Ing. and Ph.D. degrees from RWTH Aachen University in electrical engineering in 1995 and 2000, respectively. His research interests include stochastic Petri nets and queuing systems, ATM, TCP/IP, switching, flow control, QoS, tariffs, userin-the-loop (UIL), wireless resource and packet scheduling, and the MAC layer of 4+5G systems. His Ph.D. thesis was *System Components for Broadband Universal Networks with QoS Guarantee* with the ISS group of Prof. Heinrich Meyr at RWTH Aachen University from 1995 to 2000. He started as self-employed in 2000. He was a senior researcher at the Communication Networks (ComNets) Research Group, RWTH Aachen, with Prof. Walke from 2005 to 2009, working on computer networks, queuing theory, Petri nets, LTE-Advanced, FDD relaying, scheduling, OSI layer 2 (MAC), and IMT-Advanced evaluation within WINNER+. From 2010 to 2014 he worked at the Department of Systems and Computer Engineering, Carleton University, as a project manager supporting Prof. Halim Yanikomeroglu. Since 2015 he is a professor at HAW Hamburg, Germany.

Halim Yanikomeroglu (halim@sce.carleton.ca) is a professor in the Department of Systems and Computer Engineering, Carleton University. His research interests cover many aspects of wireless technologies with a special emphasis on cellular networks. In recent years, his research has been funded by Huawei, Telus, Blackberry, Samsung, Communications Research Centre of Canada (CRC), and Nortel. This collaborative research has resulted in over 20 patents (granted and applied). He is a Distinguished Lecturer for the IEEE Communications and IEEE Vehicular Technology Societies on 5G+ technologies.

Gamini Senarath (gamini.senarath@huawei.com) received his B.Sc. degree in electrical and electronics engineering from Moratuwa University, Sri Lanka, in 1980, his Master's degree in electronics engineering from Eindhoven (Phillips) International Institute, the Netherlands, in 1986, and his Ph.D. degree in telecommunications engineering from the University of Melbourne, Australia, in 1996, respectively. During 1980–1990, he was with the public telecommunication provider of the Government of Sri Lanka as a radio transmission engineer and a regional telecommunication manager. During 1996 to 2009 he was with the Advanced Wireless Technology Labs, Nortel Networks, Ottawa, Canada, where he was involved in many next generation wireless system research projects and contributed to various 3G and 4G wireless standard development activities. The main focus was on propagation, cell planning, relaying, and MAC/RRM areas. Since 2009, he has been with 5G Research Lab, Huawei Technologies Canada. His current research work involves software defined networks, virtual network embedding, power, and the resource management of third party infrastructure provided by multiple operators for the 5G wireless systems. His work has resulted in more than 50 granted patents in wireless communication systems. He is also the project manager for Huawei's external collaboration project with Carleton University, Telus, and the Communications Research Centre of Canada (CRC).

Ngọc-Dũng Đao (ngoc.dao@huawei.com) is a senior research engineer of Huawei Technologies Canada. He received his Ph.D. degree from the University of Alberta, Canada, in 2006. He was with Siemens Communications Networks in Vietnam from 1995 to 2000, and Toshiba Research Europe in the United Kingdom from 2007 to 2010. His recent research interests include SDN and NFV for radio access networks, heterogeneous and dense networks, and reliable video communications for 5G mobile networks. He is an Editor of *IEEE Transactions on Vehicular Technology*, *IEEE Communications Surveys and Tutorials*, Associate Technical Editor of *IEEE Communications Magazine*, and Guest Editor of the 5G Special Issue of the *Eurasip Journal on Wireless Communications and Networking*.