Towards Flexible Network Deployment in 5G:
Nomadic Node Enhancement to Heterogeneous Networks

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***Abstract*—Mobile networks are experiencing the avalanche of data traffic, which is coupled with the billions of wirelessly connected data-intensive devices using diverse multimedia services and applications. Prospective studies suggest that traffic volume would increase a thousand-fold over the next decade. Furthermore, the users expect the utmost in quality with seamless connectivity to the broadband access. On this basis, moving networks emerge as a promising enhancement for fifth generation (5G) systems to enable flexible network deployment that goes beyond the scope of conventional fixed access nodes. Within the framework of moving networks, nomadic nodes (NNs) can enable demand-driven service provisioning to increase the network capacity or to extend the cell coverage area, and to reduce network energy consumption. NNs can be mounted on vehicles within a car-sharing fleet. In this paper, we look at the envisioned dynamic and flexible network deployment through NNs, and demonstrate analyses on the operation of nomadic networks.**

I. INTRODUCTION

One of the targets of the fifth generation (5G) mobile and wireless communications systems is handling the inhomogeneous distribution of increasing traffic demand over time and space in an agile manner [1]. That is, the network needs to react quickly and dynamically to fulfill the increased service requirements during a time period in a target region. One approach for providing coverage and/or capacity is to deploy fixed small cells, such as picocells, femtocells, and relay nodes overlaid by macrocells. In today's mobile networks, small cells may be deployed by operators at certain locations with power supply facilities, and the locations can be determined, for example, via network planning. However, the full operation of such a dense fixed small cell deployment is *not* needed anytime and anywhere due to the aforementioned notion of the inhomogeneous distribution of traffic over time and space, and also in order to achieve network energy savings.

In this context, moving networks emerge as a promising notion for 5G systems and aim at improving the integration of mobile terminals (MTs) and nodes into the network while enabling flexible network deployment and new services [2]. Within the framework of moving networks, nomadic nodes (NNs) can enable demand-driven service provisioning to increase the network capacity or to extend the cell coverage area [3], and to reduce network energy consumption [4]. NNs can be mounted on cars within a car-sharing fleet or on privately owned cars. This also reveals one of the fundamental features of NNs in contrary to fixed access nodes. Namely, an NN is associated with some uncertainty with regards to its availability, i.e., an NN may or may not be available in the target service region. Nevertheless, despite such uncertainty, a large number of NNs can be expected particularly in urban areas. In addition, to attain the aforementioned benefits of NNs, a flexible backhaul needs to be employed, where the capacity of the backhaul link plays a crucial role in the end-to-end user performance. Herein, we place the focus on the flexible network deployment via NNs as a complementary enhancement to heterogeneous networks. Accordingly, the 5G infrastructure is foreseen not solely to be based on the fixed access nodes but will integrate access nodes on the move like the NNs.

The remainder of this paper is organized as follows. Section II briefly presents the notion of flexible network deployment. In Section III, enabling technologies such as on-the-fly network planning and energy-aware network optimization are highlighted along with performance results and evaluations. Finally, Section VI concludes the paper.

II. FLEXIBLE NETWORK DEPLOYMENT VIA NOMADIC NODES

A. Definition of Nomadic Nodes

One promising 5G system component that tries to respond to the boosting traffic volume of the future information society is the concept of a nomadic network [5]. A nomadic network consists of randomly distributed non operator-deployed nodes (e.g., parked vehicles with on-board relay infrastructure and advanced backhaul antennas) offering the possibility for relaying between MTs and base stations (BSs). While the location of operator-deployed relay nodes is optimized by means of network planning, the location of the NNs in a nomadic network is out of control of a network operator, and, therefore, is considered to be random. Moreover, their availability and position may change in time (hence, the term

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Part of this work has been performed in the framework of the FP7 project ICT-317669 METIS, which is partly funded by the European Union. The authors would like to acknowledge the contributions of their colleagues in METIS, although the views expressed are those of the authors.

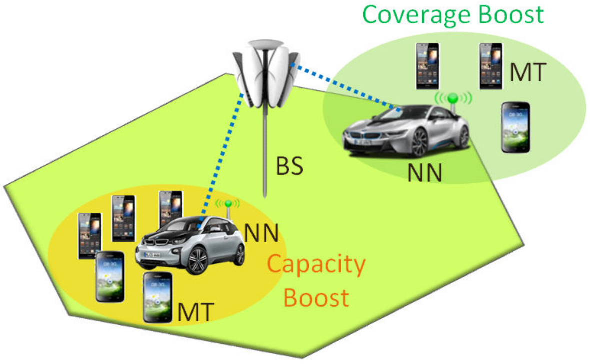

Fig. 1. NNs can provide capacity or coverage boost depending on the availability in the target service regions.

"nomadic") due to battery state and node movement. The NNs operate in a self-organized fashion and are in general activated and deactivated based on capacity, coverage, load balancing, or energy efficiency demands. Thus, the concept of a nomadic network describes an effective extension of the cellular infrastructure that allows for a dynamic network deployment.

B. *Uncertainty for the Availability of Nomadic Nodes*

The uncertainty for the availability of NNs is taken into account by the parking lot model described in [3], [6], which is based on continuous time Markov chain with time variant transition rate [7]. The model can be well defined by the parameters $\{\boldsymbol{O}(t),\ C,\ \Lambda(t),\ \nu(t)\}$. The state of occupation at time t is $\boldsymbol{O}(t) \in \{0,1\}^C$, i.e., it takes the value of one to indicate that there is a parked vehicle at that parking place and zero for a free parking place. The parking lot has a maximum capacity $C = M_{\max}$, corresponding to the maximal number of NN candidates in the parking lot. The arrival rate of the system is denoted as $\Lambda(t) \in \mathbb{R}_+$, and the departure rate of each parked vehicle is denoted as $\nu(t) \in \mathbb{R}_+$. The system is time variant, since $\Lambda(t)$ and $\nu(t)$ change over time due to varying human activities at different day times. The model suits well with the realistic vehicular movements by choosing proper $\Lambda(t)$ and $\nu(t)$ at different times.

C. *Advantages and Challenges*

The most attractive advantage of nomadic networks is the provision of relaying functionality for performance enhancement without relay site-leasing. A large number of potential NNs, both privately owned vehicles and company owned car fleets (e.g., car rental, car sharing, and taxi), are available for performing network optimization. Depending on the availability of NNs in the target service region, NN operation can provide both coverage and capacity enhancements, as shown in Fig. 1. Furthermore, there are larger spaces for the antenna and transceiver designs for vehicle-mounted NNs compared to conventional small-cell access nodes, allowing potential backhaul link enhancements and advanced relaying implementation.

On the other hand, the nomadic network, due to its randomness, raises as well challenges both in technical and non-technical aspects. The main technical challenge is the management of such a large number of dynamic network nodes, including radio resource management (RRM) solutions to combat interference for performance enhancements, security matters, and importantly the battery life time of the NNs. Furthermore, the business cooperation between mobile network operators, car manufactures and other private stakeholders should achieve a constructive compromise to enlarge the benefits for all stakeholders in the business.

III. ENABLING TECHNOLOGIES

In this section, we outline two enabling technologies for the successful and efficient NN operation in future wireless and mobile networks. The analyses are associated with example evaluations, which reveal promising performance improvements.

A. *On-the-fly Network Planning*

The flexible backhaul can be realized by inband relaying. Conventionally, the site planning tools are utilized as part of network deployment, i.e., *before actual operation*, to improve the performance of fixed inband relays [8], [9], [10], [11]. Therein, it is shown that by selecting a fixed relay site from a set of different possible locations, the backhaul link quality can be clearly improved. Within the framework of *on-the-fly network planning*, we apply dynamic NN selection *during operation* for performance enhancement of the network by means of relaxing the backhaul link limitations. To this end, dynamic NN selection schemes are introduced. In particular, the serving NN is selected from a set of candidates based on the backhaul link signal-to-interference-plus-noise ratio (SINR). The corresponding performance is evaluated in composite fading/shadowing environments with co-channel interference. Composite fading/shadowing is frequently experienced in scenarios with low or no mobility [12]. Further, given the full-frequency reuse in future cellular networks, co-channel interference is also taken into account. We show the SINR gains on the backhaul link and the amount of fading (AoF) reduction by the coarse NN selection (considering only shadowing; slow-scale selection) compared with the optimal NN selection (considering both shadowing and multi-path fading; fast-scale selection) as well as the baseline (macrocell-only deployment; no NNs).

1) Channel and System Models: Shadowing is modeled by a lognormal distribution with standard deviation σ and mean μ; σ defines the severity of shadowing. As the parameters of lognormal distribution are often given in decibels, the mappings $\sigma = \lambda\sigma_{\text{dB}}$ and $\mu = \lambda\mu_{\text{dB}}$ with $\lambda = \ln(10)/10$ can be utilized for the conversion. Besides, the small-scale multipath fading is often characterized by Nakagami distribution with the fading parameter $(0.5 \leq m_{\text{CL}} \leq \infty)$ on a communication link (abbreviated by CL in this notation), Rician or Rayleigh distribution. In case of Nakagami distribution, as m_{CL} increases, the multipath fading effect diminishes. Furthermore, Nakagami distribution yields Rayleigh distribution for $m_{\text{CL}} = 1$ [13].

The channel models pertain to a two-hop half-duplex decode-and-forward inband relaying operation through NNs

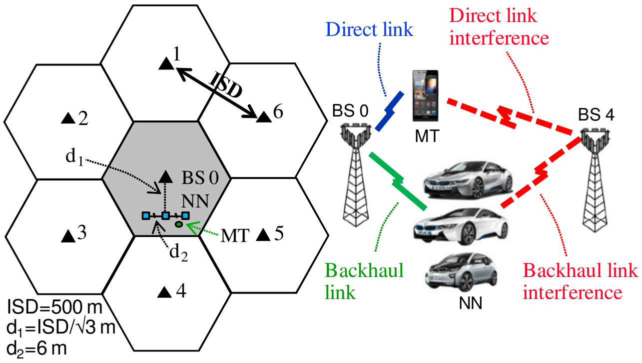

Fig. 2. The network layout and NN location trellis. The distance between two neighboring BSs is the inter-site distance (ISD).

where end-to-end performance is degraded also by interference on the backhaul link. An exemplified schematic with 3 candidate NNs is depicted in Fig. 2. In the baseline scenario (i.e., NNs are not active), an MT is communicating with a BS on the direct link. The illustration on the right exemplifies the interference caused by BS 4 on the backhaul link as well as the direct link. We model the backhaul and direct links by Nakagami-lognormal distribution, which is a common model in the literature [12], [13]. As the Nakagami-lognormal composite distribution does not have a closed-form expression, we utilize mixture gamma (MG) distribution [14] to approximate it with a closed-form expression. It is assumed that interfering signals on the backhaul and direct links are subject to Rayleigh-lognormal (aka Suzuki) composite fading/shadowing. In the following, the instantaneous signal-to-noise ratio (SNR) and the average SNR are denoted by γ and $\bar{\gamma}$, respectively.

a) MG Distribution: The cumulative distribution function (CDF) of the SNR is modeled by MG distribution consisting of N gamma components as [9], [14]

$$F_\gamma(x) = \sum_{i=1}^{N} \alpha_i \zeta_i^{-\beta_i} \gamma(\beta_i, \zeta_i x), \tag{1}$$

where α_i, β_i, and ζ_i are the parameters of the i^{th} gamma component. Further, $\alpha_i = \theta_i / C$, and $C = \sum_{i=1}^{N} \theta_i \Gamma(\beta_i) \zeta_i^{-\beta_i}$ with $\Gamma(\cdot)$ being the gamma function denotes a normalization factor. Thus, θ_i is also a parameter of the i^{th} gamma component. In addition, $\gamma(a,b) \triangleq \int_0^b t^{a-1} e^{-t} dt$ is the lower incomplete gamma function. The number of components N determines the accuracy of the approximation [9], [14].

The AoF, which reflects the severity of fading, can be calculated from the first and the second moments of the SNR as [12]

$$AoF = \frac{\mathrm{var}(\gamma)}{[\mathrm{E}(\gamma)]^2} = \frac{\mathrm{E}(\gamma^2) - [\mathrm{E}(\gamma)]^2}{[\mathrm{E}(\gamma)]^2} = \frac{\mathrm{E}(\gamma^2)}{[\mathrm{E}(\gamma)]^2} - 1, \tag{2}$$

where $\mathrm{var}(\cdot)$ denotes variance.

b) SNR Distribution on the Backhaul and Direct Links: The instantaneous SNR on the backhaul link is modeled by a gamma-lognormal distribution (occurs in Nakagami-lognormal channel [12], [14]). The parameters of i^{th} gamma component

TABLE I
SYSTEM PARAMETERS

Parameter	**Value**
Carrier Frequency	2 GHz
Thermal Noise	-174 dBm/Hz
BS Parameters	
Transmit Power	46 dBm
Antenna Gain	14 dBi
Antenna Configuration and Pattern	Tx-1, Omni-directional
NN Parameters	
Antenna Gain	5 dBi
Antenna Configuration and Pattern	Rx-1, Omni-directional
Noise Figure	5 dB
MT Parameters	
Antenna Gain	0 dBi
Antenna Configuration and Pattern	Rx-1, Omni-directional
Noise Figure	9 dB
Backhaul Link & Direct Link Path-Loss	
Path-Loss Exponent	3.63
Propagation Constant	125.2 dB

are expressed as [14]

$$\begin{aligned} \theta_i &= \left(\frac{m_{\mathrm{BL}}}{\bar{\gamma}}\right)^{m_{\mathrm{BL}}} \frac{w_i e^{-m_{\mathrm{BL}}(\sqrt{2}\sigma t_i + \mu)}}{\sqrt{\pi}\,\Gamma(m_{\mathrm{BL}})}, \\ \beta_i &= m_{\mathrm{BL}}, \quad \zeta_i = \frac{m_{\mathrm{BL}}}{\bar{\gamma}} e^{-(\sqrt{2}\sigma t_i + \mu)}, \end{aligned} \tag{3}$$

where m_{BL} is the fading parameter of Nakagami distribution on the backhaul link (abbreviated by BL in this notation), and t_i and w_i are, respectively, abscissas and weight factors of N^{th} order Hermite integration.

Since the NNs have the same height of 1.5 m as the MTs, the direct link between the MT and the BS is assumed to follow the same SNR distribution as the backhaul link.

2) NN Selection Schemes: Dynamic NN selection takes into account the channel properties at different candidate NNs and considers their link qualities toward the serving BS in order to enhance the backhaul link quality. At a given time instant, there are M available candidates in cell k out of which we select the best NN in terms of downlink SINR. In the target service region, an NN is assumed to be served by a predefined BS solely. Then, the SINR at the selected NN $\hat{m}_{\mathrm{c}}$ is of the following form in case of coarse NN selection

$$\Upsilon^{\mathrm{c}}_{\hat{m}_{\mathrm{c}},k} = \max\{\Upsilon^{\mathrm{c}}_{m,k} : m = 1, 2, ..., M\}, \tag{4}$$

where $\Upsilon^{\mathrm{c}}_{m,k}$ is the SINR for the m^{th} candidate NN in the k^{th} cell considering shadowing only. In case of optimal NN selection, the SINR at the selected NN $\hat{m}$ is

$$\Upsilon_{\hat{m},k} = \max\{\Upsilon_{m,k} : m = 1, 2, ..., M\}, \tag{5}$$

where $\Upsilon_{m,k}$ is the SINR for the m^{th} candidate NN in the k^{th} cell considering both shadowing and multi-path fading. Accordingly, for coarse NN selection, the SINR at the selected NN $\Upsilon^{\mathrm{c}}_{\hat{m}_{\mathrm{c}},k}$ can be different than that of the actual SINR $\Upsilon_{\hat{m}_{\mathrm{c}},k}$, which reflects the actual channel conditions impaired by both shadowing and multi-path fading, i.e., coarse NN selection is carried out based on $\Upsilon^{\mathrm{c}}_{m,k}$; however, $\Upsilon_{m,k}$ is the actual SINR during the operation. The selected NN may also be different, i.e., $\hat{m}_{\mathrm{c}}$ may not be the same as $\hat{m}$.

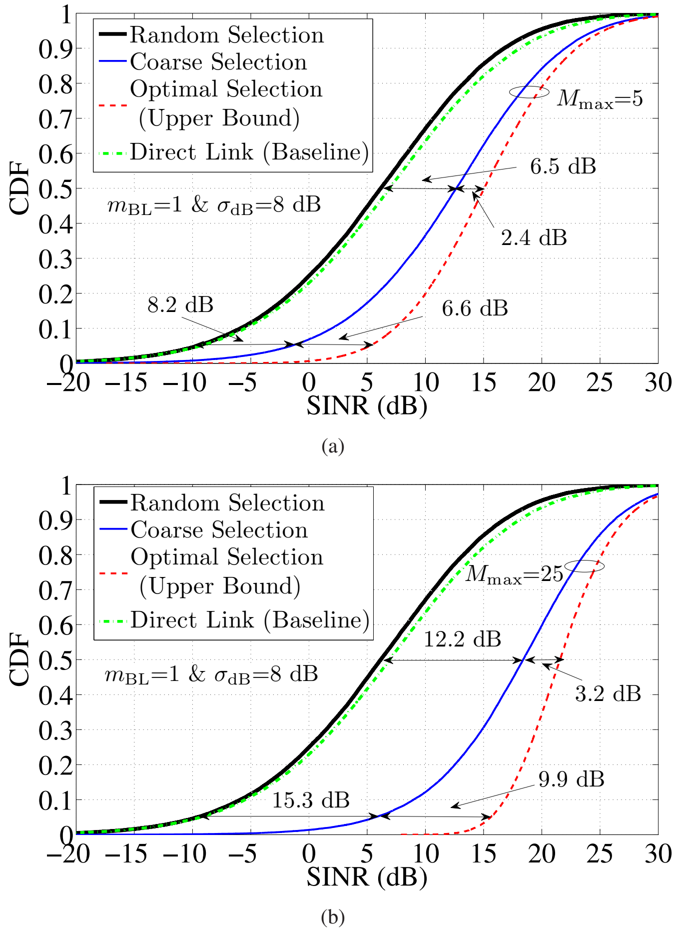

Fig. 3. CDFs of SINR on the backhaul link when $M_{\max} = 5$ (a) and when $M_{\max} = 25$ (b).

3) Example Results: Herein, we evaluate the effect of NN selection schemes on the backhaul link quality. The simulations are conducted using MATLAB as the computational environment. The Nakagami fading parameter is set to one (Rayleigh fading) to simulate more severe fading characteristics, and shadowing standard deviation is set to 8 dB, i.e., $(m_{\text{BL}}; \sigma_{\text{dB}})$ = (1; 8). We set the parking lot model parameters in Section II-B as (Λ, ν) = (15, 300) min such that a regular day time is simulated [3]. The rest of the system parameters are tabulated in Table I.

The impact of NN selection on the backhaul link SINR is illustrated by CDF plots in Fig. 3. When a large number of parking lot slots are available ($M_{\max} = 25$; Fig. 3.b), it is noticed that coarse NN selection provides high SINR gains of about 15 dB and 12 dB at lower and median CDF percentiles, respectively. Even for a smaller number of parking places ($M_{\max} = 5$; Fig. 3.a), clear gains can be observed. Further, the direct link performance is similar to that of random NN selection, which reveals the importance of the proposed dynamic NN selection schemes.

More insights into the impact of NN selection schemes are shown in Fig. 4, where the AoF values on the backhaul link are depicted as a function of the shadowing standard deviation. The case of random NN selection is taken as a reference. It is seen that AoF on the backhaul link decreases clearly when coarse NN selection is performed and σ_{dB} is large, i.e., heavy shadowing. Thus, Fig. 4 illustrates the effectiveness of coarse NN selection in mitigating the deleterious impact of shadowing on the backhaul link. The lower bound for AoF is reached when optimal NN selection is utilized. It is worth noting that optimal NN selection requires frequent channel measurements, which increases signaling overhead.

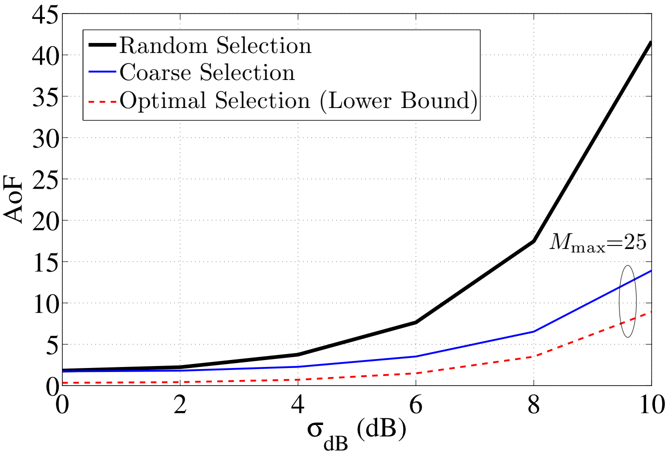

Fig. 4. AoF on the backhaul link as a function of the shadowing standard deviation.

B. Energy-aware Network Optimization

Power consumption and carbon emissions are becoming an eminent problem for Information and Communication Technology (ICT) systems, especially due to the radio access network of the cellular systems [15], [16]. In particular, the souring electricity cost and the high energy consumption of BSs significantly increase the operational expenditure (OPEX) of the operators ($3000/$30000 per year for on/off-grid BSs [17]). Adding the fact that a large number of BS sites are required for covering the expanding metropolitan region, a substantial amount of power consumption and energy cost is required for delivering services through cellular systems. Furthermore, parked vehicles do not have power supply, causing energy saving to be one of the main requirements in the optimization of the nomadic network. Therefore, the energy saving problem is a key issue for a successful commercialization of nomadic networks.

1) Problem Formulation: Assuming a simple static energy consumption c_i for a active cell i (either a BS and an NN), we can formulate the energy saving optimization problem as:

$$\begin{aligned} \min_{\mathbf{X}} \quad & \sum\nolimits_{i=1}^{m+k} c_i ||\rho_i||_0 && \text{(6a)} \\ \text{subject to} \quad & \mathbf{X}^T \cdot \mathbf{1}^{m+k} \geq \mathbf{1}^{n+k}, && \text{(6b)} \\ & \mathbf{X} \in \{0,1\}^{(m+k)\times(n+k)} && \text{(6c)} \\ & \boldsymbol{\rho} = \mathbf{F}(\boldsymbol{\rho}, \mathbf{X}) \leq \mathbf{1}^{n+k}. && \text{(6d)} \end{aligned}$$

Herein, m, k and n refer to the number of BSs, NNs and MTs, respectively, whereas $\mathbf{X} = \left(\begin{smallmatrix} \mathbf{X}^d & \mathbf{X}^r \\ \mathbf{X}^a & \mathbf{0}^{k\times k} \end{smallmatrix}\right)$ is the assignment matrix including the connections all the direct ($\mathbf{X}^d \in \{0,1\}^{(m)\times(n)}$),

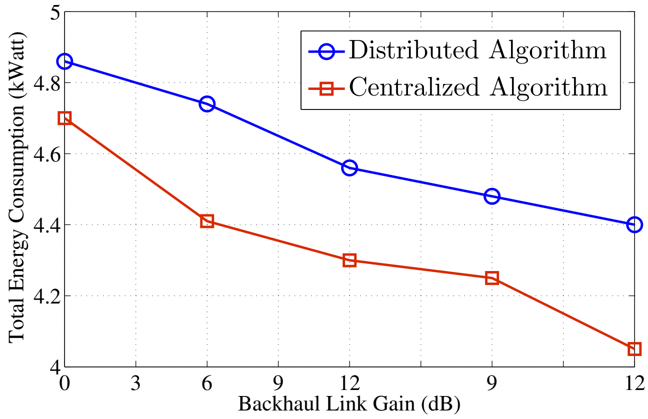

Fig. 5. Total network energy consumption with varying backhaul link quality.

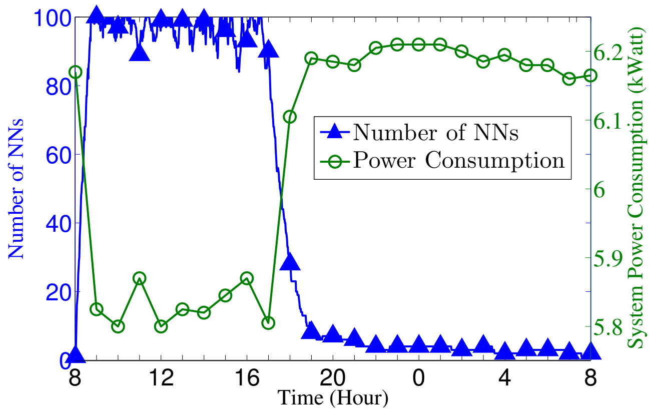

Fig. 6. Total network energy consumption with daily varying availability.

relay ($\mathbf{X}^r \in \{0,1\}^{(m)\times(k)}$) and access ($\mathbf{X}^a \in \{0,1\}^{(k)\times(n)}$) links. Therefore, the expression in (6b) indicates that each MT and NN must be attached to one of the cells in the network. Furthermore, the load, denoted by $\boldsymbol{\rho} \in \mathcal{R}^{m+k}$, is the ratio of the required resources for satisfying the minimum QoS of the connected MTs to the total available bandwidth. It states in (6d) the fact that the load must be smaller than 1 such that there are sufficient resources to serve the connected MTs. Herein, $\mathbf{F}$ is a function that maps network load, assignments, spectral efficiency and user rate into the load. Readers are referred to [18], [19] for further details on $\mathbf{F}$. Finally, the l_0-norm in the objective (6a) expresses the cardinality of the vector. In this case, $||\rho_i||_0 = 0$ if and only if ρ_i is zero, i.e., no traffic passes cell i and, therefore, we can switch it off.

2) Algorithms and Example Results: The problem is difficult to solve since 1) it is discontinuous due to the l_0-norm and 2) the load function $\mathbf{F}$ is non-convex with respect to the assignment $\mathbf{X}$. Therefore, we have developed both centralized approaches in [18], [19] and distributed algorithms in [20] that make use of the available radio measurements to solve the problem efficiently.

The common idea of both centralized and distributed solutions is the concave approximation of the discrete l_0-norm. For the centralized approaches, the majorization minimization (MM)-algorithm [21] is performed to iteratively minimize the concave approximation, whereas the non-convex constraints are (one-step or iteratively) relaxed into linear constraints. For the distributed approach, we propose a novel cell selection criterion that takes into account the network load situation and the link connection quality. According to the algorithm, an MT or an NN tends to connect to a cell with higher load and better connection quality. Furthermore, the load constraint is ensured by performing admission control at the BSs and NNs to avoid overloading.

In Fig. 5, we evaluate the total energy consumption of both centralized (SRR in [18]) and distributed algorithm with varying backhaul link quality. We adapt the same network layout as shown in Fig. 2, i.e., 7 BSs with ISD of 500 m. We choose 200 NNs in the network and 50 MTs that are randomly distributed with an average user data rate of 100 kbps. The energy consumption of an active BS is assumed to be 1 kWatt, whereas an NN consumes 10 Watt when it is actively transmitting. The backhaul link gain may result in from the on-the-fly network planning described in Section III-A or from advanced antenna design. The results show that a significant energy reduction can be expected especially with large backhaul gains (up to 20% more compared with no backhaul gain). Furthermore, the distributed algorithm and the centralized approach achieve similar energy saving gains.

In Fig. 6, the performance of the distributed algorithm is shown. In this scenario, we also consider the dynamic birth-death process described in Section II-B. We assume a backhaul gain of 6 dB and 100 NNs in the network, while 100 MTs are randomly distributed with an average user data rate of 100 kbps. As an NN tends to leave the network, the connected MTs need to be handed over to the underlying macro cells or other NNs. This mechanism ensures that the proposed distributed algorithm also applies to nomadic networks, where NNs may turn suddenly unavailable. Furthermore, a strong inverse correlation is observed between the number of available NNs and the total energy consumption. This is due to the fact that a larger amount of NNs results in a higher probability of having suitable NNs to redirect data traffic and to shut-down more BSs. At daytime, especially, 20% energy savings are possible when many parked cars can serve as potential NNs.

IV. CONCLUSION

In this paper, we have introduced the notion of flexible network deployment based on the concept of NNs. In this context, we have demonstrated two enabling technologies along with analyses and performance improvements for autonomous and efficient NN operation. The NN operation implies a dynamic network through which the varying service requirements over time and space can be addressed flexibly. Therefore, nomadic network is envisioned as a promising component for 5G systems.

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