Mobile edge-Networking Architectures and Control Policies for 5G Communication Systems

Dimitris Giatsios[†], George Iosifidis[*], and Leandros Tassiulas[*]
[*]Dept. of Electrical Engineering, and Institute for Network Science, Yale University, USA
[†]Dept. of Electrical and Computer Engineering, University of Thessaly, and CERTH, Greece

***Abstract*—Motivated by the recent proliferation of advanced handheld devices and the unprecedented growth of mobile data traffic, this paper proposes the concept of Mobile edge-Networks (MeNs), a solution that leverages the end-user devices to enhance the performance of emerging 5G systems. MeNs enable mobile users to collaborate with each other and address in a bottom-up fashion key problems in wireless systems, such as poor channel conditions. We design a dynamic cooperation policy that determines transmission parameters of the network in a utility-optimal fashion, ensuring that no user performs worse than she would without cooperation and that the benefits from the collaboration are shared among the users.**

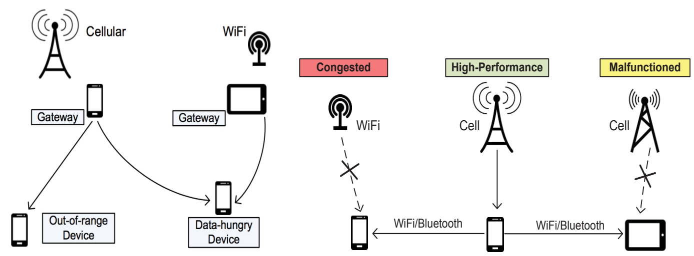

Fig. 1. (a): Multipath Internet access through cooperating devices; Relaying devices with poor channel conditions or being out of the cell range. (b): Dynamic bottom-up re-routing of traffic through heterogeneous networks.

I. Introduction

A. Motivation

Today we are witnessing an impressive transformation of the wireless networks landscape. The increasing needs of users for ubiquitous Internet connectivity create an ever growing volume of mobile data traffic [1], the number of handheld devices and mobile connections constantly increases [2], and novel applications with stringent performance requirements become very popular. These developments have led to broad consensus about the need for a new generation of wireless communication systems, the 5G cellular networks, that will meet the future capacity and performance demands of users [3], [4], [5]. Despite, however, the increasing focus and high prospects about 5G, an aspect that has received very little attention is the end-user equipment inclusion in the design of these systems.

At the same time, recent technological advancements have resulted in sophisticated user-owned hand-held equipment such as smartphones and tablets, with multiple radio interfaces, advanced antennas and chipsets supporting connections faster than 150Mbps. These devices are currently used only as simple transceivers and, following the rigid client-server scheme, are fully commanded by the cellular base stations. This conventional approach overlooks their potential to play a crucial role as active network components and add substantial flexibility and intelligence at the network edge. For example, these devices can serve as local micro-operators and provide multipath Internet connectivity to data-hungry mobile applications or address network coverage (or poor channel) problems acting as smart relays. Similarly, they can dynamically respond to network congestion or temporary malfunctions by shifting their traffic among different networks (Figure 1). These are only few examples manifesting how mobile devices can boost the utilization of critical resources (e.g., wireless spectrum and device energy). We introduce here the term *Mobile edge-Networks* (MeNs) to describe these systems where mobile users coordinate on-the-fly in order to heal network impairments and eventually improve their own performance.

Albeit attractive and promising, MeNs raise novel questions for which we currently lack answers. The most crucial, perhaps, is the need to design servicing policies that balance the efficiency and fairness in the allocation of network and device resources. Such policies determine which devices will act as gateways connecting the MeN with the infrastructure networks (cellular and non-3GPP), which of them will have a particular role within the MeN, e.g., relaying traffic to distant-located nodes, and how much service each of the participants will receive. Different devices have different energy consumption sensitivity, and different Internet connection capacity and costs; moreover, these parameters change with time, often in an unpredicted fashion. Therefore, designing a dynamic policy which can achieve the desirable outcome in an online fashion, without knowing the future state of the MeN and devices, or the traffic demands of the users, is an equally important and challenging goal. Besides, the latter are self-interested entities, and therefore they need proper incentivization so as to comply with any proposed MeN policy. Clearly, this further perplexes the policy design problem, as simple fairness or reciprocity rules are not adequate to ensure cooperation.

B. Related Works and Contribution

The idea of using mobile devices beyond their role as clients "slaved" to base stations is, clearly, not new. For example, a substantial amount of research has been conducted for mobile ad hoc networks [6], ad hoc tactical networks, and wireless sensor networks [7]. Nevertheless, these previous-generation approaches are fundamentally different than the proposed edge-networking systems since they are perceived as an alternative to infrastructure networks. This was actually imposed by the hitherto monolithic and closed-architecture design of cellular networks, not amenable to such approaches. Besides, the goals of these previous efforts were restrained by the limited capabilities of user equipment. This barrier has been now removed since modern mobile devices can serve as fully reconfigurable network components.

The first generation of wireless networks leveraging user equipment is summarized in [8]. These Wi-Fi access sharing models focused either on pairwise [9] or community-based [10] schemes, and do not consider mobile users. In [11] we presented an overview of the challenges that arise in collaborative mobile wireless networks. Reference [12] proposed an energy-prudent architecture for mobile hotspots, and [13] a revenue-maximizing servicing scheme. The problem of collaboration in mobile Internet sharing was recently studied in [14] for single-hop architectures, and in [15] with emphasis on energy conservation. In [16] we designed an incentive mechanism for richer architectures which however focused on static settings where users demands and network conditions are given. Related field trials were executed in [17] to obtain insights about the performance of these networks. One important conclusion was that such systems can be effectively built using SDN. This technology can transform mobile devices to active network components, and has already been tested in practice [18].

There have been some studies analyzing the capacity benefits of such hybrid architectures that include D2D links at the cell edge, e.g., see [19], [20], [21]. Also, there exist proposals for the power-aware dynamic control of mobile ad hoc networks, e.g., [22], [23], while more recently a dynamic Tit-for-Tat mechanism was also proposed to foster collaboration among the devices [24]. Although we build on these previous works, they differ substantially from the proposed MeN architectures that involve multihop, multipath connections and self-interested users who are connected in different and possibly heterogeneous infrastructure networks, with different energy consumption preferences and Internet access costs.

In this paper we propose an architecture for Mobile edge-Networks, which leverage user-owned hand-held devices and operate with the assistance of a network control service. We develop a dynamic control mechanism that maximizes a network-wide performance objective, while, at the same time, satisfies a key fairness criterion. Namely, it ensures that no user gets lower payoff than she would have when acting independently, i.e., without participating in the MeN. We use a broad definition for the performance, which encompasses, apart from the throughput-utility, the energy consumption and the monetary Internet access cost for each device. Specifically, we employ the Nash Bargaining Solution (NBS) as a performance objective, where the disagreement vector consists of the independent operation performance of each user. The devised multi-hop and multi-path policy yields the scheduling, routing, and flow control decisions for each time slot, and satisfies the most demanding users by employing the most resource-full devices.

To this end, the technical contributions of this work can be summarized as follows:

- The concept of Mobile edge-Networks for the emerging 5G systems is proposed. We explain why and how MeNs can play a crucial role in future networks, and discuss implementation methods.
- We design a dynamic control policy for these multi-hop/path networks, where the nodes have diverse and time-varying wireless links among them and with the infrastructure network. The policy copes with the unknown future demands, channel conditions, and Internet access costs of the MeN nodes, achieving the NBS solution.
- We conducted the performance analysis of the policy and proved that it is arbitrarily close to the optimal solution, i.e., the one obtained under full knowledge of system dynamics.
- A detailed numerical analysis verifies the stability and benefits of the proposed policy.

The rest of the paper is organized as follows. In Section II we present the system model, Section III introduces the respective NBS framework and the independent operation of the devices, and Section IV devises the MeN control policy. Section V provides the theoretical background behind the selection of the algorithms, section VI presents the numerical results and Section VI concludes the paper.

II. System Model

We consider a mobile edge-network (MeN) with downlink traffic, which operates in slotted time, with the slot duration normalized to 1. We represent this with an equivalent network of $N+1$ nodes. The nodes corresponding to the mobile devices of the users form the set $\mathcal{N}$ and are indexed $i = 1, ..., N$. There is also a super-node, explicitly indexed by 0, that represents the infrastructure network, i.e., the "Internet", where all traffic is generated. This node is monitored by the *network controller* as we will explain in the sequel.

Each mobile device features two network interfaces, a cellular interface for downloading data from the Internet and a WiFi interface for communicating with the other mobile devices. There is no restriction on the simultaneous use of the two interfaces of a device. The downloading capacity of the Internet link of node i during slot t is given by a non-negative stationary random process $C_{0i}(t)$, taking values in a finite set $\mathcal{C}_0 = \{0, \dots, C_0^{max}\}$. We assume there is no correlation among these N processes. The WiFi interfaces form a mobile edge-network among the N nodes. The transmission rates available for the links of this network during slot t, denoted by $\boldsymbol{C}(t) = (C_{ij}(t))$, are determined by a non-negative (matrix-valued) link transmission rate function $\hat{\boldsymbol{C}}(\boldsymbol{I}, S)$, so that

$$\boldsymbol{C}(t) = \hat{\boldsymbol{C}}(\boldsymbol{I}(t), S(t)),$$

where $S(t)$ represents the network topology state in t, and $\boldsymbol{I}(t) = (I_{ij}(t))$ is the link activation control action taken by the network during t. Each $C_{ij}(t)$ takes values in a finite set $\mathcal{C} = \{0, \dots, C_{max}\}$.

The topology state random process $S(t)$ represents all uncontrollable properties of the MeN that influence the set of feasible transmission rates. For instance, it might represent the current set of the mobile device locations and the current attenuation coefficients between each node pair. We assume that $S(t)$ is constant for the duration of a timeslot, and potentially changes on slot boundaries. We also assume its value is known to the network controller at the slot beginning.

The link control process $I_{ij}(t)$ takes the value 1 if link ij is activated during slot t and 0 otherwise. $\boldsymbol{I}(t) = (I_{ij}(t))$ is the matrix of link control processes for all links in slot t. For each time slot, it is restricted to a control space $\mathcal{I}_{S(t)}$, that covers the underlying interference constraints for the given topology state $S(t)$ by specifying all available link activation options.

At each time slot, $A_c(t)$ bits are generated with node $c \in \mathcal{N}$ as destination and enter infinite capacity transport layer reservoirs at node 0, with backlogs $L_c(t)$. Hereafter, we will refer to data destined for node c as commodity c data. We assume $A_c(t)$ is a stationary random process. At each time slot, an amount of $R_c(t)$ bits is admitted by the controller from its transport layer reservoir for c to its local network layer queue corresponding to this commodity, with backlog $U_0^{(c)}(t)$. We assume that $R_c(t) \leq R_{max}$ for every slot t and every commodity c, where R_{max} is lower-bounded by the maximum possible average amount of data a user can receive[1]. So we have, for all slots t,

$$R_c(t) \leq \min[L_c(t) + A_c(t), R_{max}] \,,$$
$$L_c(t+1) = L_c(t) + A_c(t) - R_c(t) \,. \quad (1)$$

A device can use its cellular capacity to download data of multiple commodities during each slot. We denote by $\mu_{0i}^{(c)}(t)$ the download rate offered for commodity c data at node i during slot t. Clearly, we have

$$\sum_c \mu_{0i}^{(c)}(t) \leq C_{0i}(t).$$

For simplifying notation, we will find it useful to denote $\sum_c \mu_{0i}^{(c)}(t)$ by $\mu_{0i}(t)$. We assume that $\mu_{0i}(t)$ takes values in the finite set $\mathcal{C}_0$.

The network layer queue at the controller for each destination c satisfies, for every slot t,

$$U_0^{(c)}(t+1) = \left[U_0^{(c)}(t) - \sum_i \mu_{0i}^{(c)}(t)\right]^+ + R_c(t), \quad (2)$$

where $[x]^+ = \max[x, 0]$.

Likewise, the available rates $C_{ij}(t)$ at each link of the MeN can be used to transfer data of multiple commodities. We denote by $\mu_{ij}^{(c)}(t)$ the rate offered to commodity c data over link ij in slot t. Clearly we have for all slots t

$$\sum_c \mu_{ij}^{(c)}(t) \leq C_{ij}(t).$$

Again, for simplifying notation, we will find it useful to denote $\sum_c \mu_{ij}^{(c)}(t)$ by $\mu_{ij}(t)$, and we assume $\mu_{ij}(t)$ takes values in the finite set $\mathcal{C}$.

Each device features network layer queues with backlogs $U_i^{(c)}(t)$ for each commodity c, and we have $U_i^{(i)}(t) = 0$ for every t, as data that reaches its destination exits the network layer. We assume transmission of idle fill bits whenever there is not enough commodity c data to cover the offered rate, thus we have

$$U_i^{(c)}(t+1) = \left[U_i^{(c)}(t) - \sum_j \mu_{ij}^{(c)}(t)\right]^+ + \sum_k \mu_{ki}^{(c)}(t) + \mu_{0i}^{(c)}(t) \quad (3)$$

We assume that a mobile device consumes energy only when transmitting data to a neighbor device and when downloading through its cellular interface. On the other hand, we neglect energy penalties deriving from receiving data from a neighbor device. This assumption is only made for simplifying the model, and reception energy costs can readily be incorporated in our proposed algorithm. Besides, such an approximation can be justified by real data, as transmission energy in a WiFi link is on average 10 times higher than the reception energy, while the average energy for reception in a cellular link is 5-10 times higher than WiFi reception, depending on the cellular technology [25].

For non-zero bitrates, the energy consumed per downloaded and per transmitted bit is given by decreasing functions $e_{b,d}(\mu_{0i}(t))$ and $e_{b,t}(\mu_{ij}(t))$ of the respective bitrates. In particular, we use $e_{b,d}(\mu_{0i}(t)) = \delta_d + \theta_d/\mu_{0i}(t)$ and $e_{b,t}(\mu_{ij}(t)) = \delta_t + \theta_t/\mu_{ij}(t)$, where δ_d, θ_d, δ_t, θ_t are positive constants. This model is in accordance with the measurement based study [25]. For bitrates equal to 0, we define $e_{b,d}(0) = 0$ and $e_{b,t}(0) = 0$. The aggregate energy consumption for user i at slot t, which we denote by $V_i(t)$ is thus:

$$V_i(t) = \mu_{0i}(t) e_{b,d}(\mu_{0i}(t)) + \sum_j \mu_{ij}(t) e_{b,t}(\mu_{ij}(t)). \quad (4)$$

Note that, as $\mu_{ij}(t)$ and $\mu_{0i}(t)$ admit values from finite sets, $V_i(t)$ also takes values in a finite set $\mathcal{V}$.

Each user pays for data it downloads from the Internet according to a function $H_i(t) \geq 0$. We consider here a time varying user-dependent price $p_i(t) \geq 0$ per bit, which is a stationary process taking values in a finite set. We thus have

$$H_i(t) = p_i(t)\mu_{0i}(t). \quad (5)$$

For instance, due to mobility, at some slots a user might have access to a public WiFi hotspot where she can download data for free, while at other slots she might only have access to a cellular infrastructure of a mobile network operator charging a fixed cost per byte.

User satisfaction is assumed to be a linear increasing function of the admitted data of her commodity, of the form $k_i R_i(t)$, where k_i is a user-dependent constant[2]. We assume that user dissatisfaction is given by the sum of the user energy cost multiplied by a user-dependent constant l_i and her monetary cost[3]. The payoff of the user is thus defined as

$$J_i(t) = k_i R_i(t) - l_i V_i(t) - H_i(t) \quad (6)$$

At each time slot, the network controller selects a link control action $\boldsymbol{I}(t)$, the routing variables $\boldsymbol{\mu}(t) = (\mu_{0i}^{(c)}(t); \mu_{ij}^{(c)}(t))$, and the flow control decisions $\boldsymbol{R}(t) = (R_i(t))$. Our goal is

[1] A theoretical lower bound for R_{max} is $C_0^{max} + (N-1)C_{max}$, in the case where a user can simultaneously receive data from multiple users. When $C_0^{max} \leq C_{max}$, as is typically the case, then this becomes NC_0^{max}, while if we further assume that it is technically feasible to receive relayed data from at most one other user at a time, this reduces to $2C_0^{max}$.

[2] For example, in LTE-A systems the QoS mechanism assigns different priority to each mobile user based on the application service (video, email, etc.), the subscription information, and the traffic management policy. This QoS is then translated to a specific rate that is delivered to each user. For more information we refer the reader to [26].

[3] Constants k_i and l_i also serve for expressing the terms constituting the payoff with the same unit (conveniently this could be dollars).

to coordinate MeN decisions to achieve a fair and efficient performance, with respect to each user's needs, and without the requirement of any knowledge for the availability of device resources and channel conditions.

In the next sections, we will often be using limits of time averages. Therefore, to simplify notation, we will use $\overline{x}$ to refer to $\lim_{t\to\infty}\frac{1}{t}\sum_{\tau=1}^{t}E[x(t)]$. We will also be referring to mean rate stability of queues, so we formally define that here.

Definition 1. *A queue $Q(t)$ is mean rate stable if*

$$\lim_{t\to\infty}\frac{E[|Q(t)|]}{t}=0.$$

III. Nash Bargaining and Independent Operation

The users that own the mobile devices in the MeN are self-interested, and are expected to participate in this service only if this ensures higher long-term expected payoffs for them. Our goal here is to design policies that achieve the Nash bargaining solution, which has desirable properties regarding the users' payoffs [27]. In particular, it is Pareto optimal and it considers the *independent operation* of each user. The last point is especially important, as a fairness rule based on direct resource allocation only, e.g., a tit-for-tat, may fail to incentivize all users to join the service.

Let us first introduce formally the Nash bargaining solution. Consider the bargaining game $\mathcal{G}=\langle\mathcal{N},\mathcal{A},\{u_i\},\{u_i^d\}\rangle$, where $\mathcal{N}\triangleq\{1,2,\dots,N\}$ is the set of players, and $\mathcal{A}$ is the feasible strategy space when the players collaborate. The payoff of each player i, $u_i(\cdot)$, depends on the strategy profile of all players, $\boldsymbol{a}=(a_1,a_2,\dots,a_N)$, with $\boldsymbol{a}\in\mathcal{A}$. Also, u_i^d is the *disagreement point* of player i, i.e., her payoff when a cooperation agreement is not reached. The NBS is [28]:

Definition 2 (Nash Bargaining Solution–NBS)**.** *A strategy profile $\boldsymbol{a}^*=(a_1^*,a_2^*,\dots,a_N^*)$ is an NBS, if it solves:*

$$\begin{aligned}&\max_{\boldsymbol{a}\in\mathcal{A}}\ \Pi_{i\in\mathcal{N}}(u_i(\boldsymbol{a})-u_i^d)\\&\textit{s.t.}\quad u_i(\boldsymbol{a})\geq u_i^d,\ \forall\, i\in\mathcal{N}\end{aligned}\tag{7}$$

In the sequel, we use the equivalent logarithmic formulation [27]. For the specific problem, the independent performance achievable by an individual user i is determined by the processes $A_i(t)$, $C_{0i}(t)$ and $p_i(t)$, which are the same as in the MeN network operation, and is assumed to be the output of an independent online optimization algorithm. Its calculation can be performed during a training period before each user joins the MeN, or in parallel with MeN operation. Here we consider the former case. Below we describe the network dynamics in independent operation mode and propose an algorithm for the solution of the respective optimization.

Data generated by the arrival process enter an infinite capacity transport layer reservoir with backlog $L_{i,s}(t)$. At each time slot, an amount of $R_{i,s}(t)$ bits are admitted from the transport layer reservoir to a network layer queue with backlog $U_{0,s}^{(i)}(t)$. We assume that $R_{i,s}(t)\leq C_0^{max}$ for all slots t. Let us denote the download rate employed by user i at each time slot by $\mu_{0i,s}(t)$. This rate takes values in the finite set $\mathcal{C}_0$ and is constrained by the link capacity, so that $\mu_{0i,s}(t)\leq C_{0i}(t),\ \forall t$.

The transport layer reservoir and network queue backlog evolve respectively as:

$$L_{i,s}(t+1)=L_{i,s}(t)-R_{i,s}(t)+A_i(t),\tag{8}$$

$$U_{0,s}^{(i)}(t+1)=[U_{0,s}^{(i)}(t)-\mu_{0i,s}(t)]^{+}+R_{i,s}(t).\tag{9}$$

In accordance with the MeN model, the per slot energy cost, monetary cost and payoff of user i in the independent operation are given respectively by

$$V_{i,s}(t)=e_{b,d}\big(\mu_{0i,s}(t)\big)\mu_{0i,s}(t),\tag{10}$$

$$H_{i,s}(t)=p_i(t)\mu_{0i,s}(t),\tag{11}$$

$$J_{i,s}(t)=k_iR_{i,s}(t)-l_iV_{i,s}(t)-H_{i,s}(t).\tag{12}$$

The independent optimization problem for user i, which we will refer to as ***I-OPT***, is a problem involving the long term time average payoff of the user and is defined as follows:

$$\begin{aligned}&\max\overline{J_{i,s}}\\&s.t.\\&U_{0,s}^{(i)}(t)\ \textit{mean rate stable}, &(13)\\&0\leq R_{i,s}(t)\leq\min[C_0^{max},A_i(t)+L_{i,s}(t)]\,,\forall t &(14)\\&\mu_{0i,s}(t)\leq C_{0i}(t),\forall t &(15)\\&\mu_{0i,s}(t)\in\mathcal{C}_0,\forall t &(16)\end{aligned}$$

where the maximization is with respect to $R_{i,s}(t)$ and $\mu_{0i,s}(t)$.

This problem can be solved by a stochastic optimization algorithm [29], specifically the one described in **Algorithm 1**. Inspecting the algorithm, we observe that it only chooses to download data whenever the sum of the per bit costs is below $U_{0,s}^{(i)}(t)/V$. In this way, the user can gain opportunistic benefits by only downloading when conditions are sufficiently favorable. On the downside, increasing V drives $U_{0,s}^{(i)}(t)$ to stabilize at higher levels, which translates in larger delay in data delivery for user i. In section V we prove that this algorithm stabilizes $U_{0,s}(t)$ and can approach the optimal objective function value of ***I-OPT*** arbitrarily close as V increases. We assume we stop calculations at the point where $U_{0,s}$ has stabilized. We store the corresponding time average payoff to plug it in the MeN algorithm, and denote it by $J_{i,s}^{opt}(V)$ in order to express its dependence on the V parameter.

IV. MeN Control Policies

In this section we formulate the optimization problem for the MeN considering the independent time average payoffs of the users for a given V parameter, $J_{i,s}^{opt}(V)$, as given constants, and propose a dynamic online algorithm for solving this optimization. We will be using the same parameter V for the MeN optimization problem as in the independent case. Regarding the selection of V, it can be linked to system decisions involving the desired tradeoff between optimality and delay.

The consideration of the NBS requires the introduction of a time average constraint referred to as the *individual rationality* constraint. In particular, we require

$$\overline{J_i}\geq J_{i,s}^{opt}(V)\forall i.$$

Algorithm 1: Independent Online Optimization Algorithm

Executed every slot t:

1 Observe $p_i(t)$, $C_{0i}(t)$, $A_i(t)$, $U_{0,s}^{(i)}(t)$

2 **if** $k_i V - U_{0,s}^{(i)}(t) > 0$ **then**
  $R_{i,s}(t) = \min[L_{i,s}(t) + A_i(t), C_0^{max}]$
else
  $R_{i,s}(t) = 0$
end

3 **if** $U_{0,s}^{(i)}(t) - Vp_i(t) - Vl_i\big(\delta_d + \theta_d/C_{0i}(t)\big) > 0$ **then**
  $\mu_{0i,s}(t) = C_{0i}(t)$
else
  $\mu_{0i,s}(t) = 0$
end

4 Update backlogs $L_{i,s}(t)$,$U_{0,s}^{(i)}(t)$ according to (8), (9).

We also require all network queues to be mean rate stable. The remaining constraints are slot-by-slot constraints. In addition, we note that if we follow the exact NBS objective expression

$$\sum_i log\left(\overline{J_i} - J_{i,s}^{opt}(V)\right)$$

and the payoff of at least one user in MeN operation is the same as its standalone payoff, then the value of the objective function becomes minus infinity. To avoid this undesired behavior of the $\log(\cdot)$ function, we adopt an approximate objective function for the NBS. In particular, we use

$$\phi\Big(\overline{J_1}, \ldots, \overline{J_N}\Big) = \sum_i log\Big[1 + D\big(\overline{J_i} - J_{i,s}^{opt}(V)\big)\Big],$$

where D is a large positive constant.

We now formulate the MeN optimization problem, which we will refer to as *MeN-OPT*. The maximization is with respect to the policies $\boldsymbol{I}(t)$, $\boldsymbol{R}(t)$ and $\boldsymbol{\mu}(t)$. We repeat all constraints here, to facilitate reading.

$$\max \sum_i log\Big[1 + D\big(\overline{J_i} - J_{i,s}^{opt}(V)\big)\Big]$$

$s.t.$

$$\overline{J_i} \geq J_{i,s}^{opt}(V)\, \forall i \quad (17)$$

$$\textit{Network Queues } U_0^{(c)}, U_i^{(c)} \textit{ mean rate stable}, \forall i, c \quad (18)$$

$$\boldsymbol{I}(t) \in \mathcal{I}_{S(t)}, \forall t \quad (19)$$

$$0 \leq R_{(c)}(t) \leq \min[A_c(t) + L_c(t), R_{max}], \forall c, t \quad (20)$$

$$\mu_{0i}^{(c)}(t) \geq 0, \forall i, c, t \quad (21)$$

$$\mu_{ij}^{(c)}(t) \geq 0, \forall i, j, c, t \quad (22)$$

$$\sum_c \mu_{0i}^{(c)}(t) \leq C_{0i}(t), \forall i, t \quad (23)$$

$$\sum_c \mu_{0i}^{(c)}(t) \in \mathcal{C}_0, \forall i, t \quad (24)$$

$$\sum_c \mu_{ij}^{(c)}(t) \leq \hat{C}_{ij}(\boldsymbol{I}(t), S(t)), \forall i, j, t \quad (25)$$

$$\sum_c \mu_{ij}^{(c)}(t) \in \mathcal{C}, \forall i, j, t \quad (26)$$

The above problem has an optimal value, which we denote by ϕ_{opt}. Its existence has been proved in [16].

In order to account for the non-linearity of the objective function, we introduce N auxiliary variables, one per user, denoted by $\gamma_i(t)$, which satisfy the following:

$$\overline{\gamma_i} \leq \overline{J_i}, \forall i \quad (27)$$

$$J_{i,s}^{opt}(V) \leq \gamma_i(t) \leq k_i R_{max}, \forall i, t \quad (28)$$

After introducing the auxiliary variables, we get the following equivalent optimization problem, which we denote by *MeN-T-OPT* ('T' stands for 'transformed'):

$$\max \left[\sum_i \overline{log\Big(1 + D(\gamma_i(t) - J_{i,s}^{opt}(V))\Big)}\right] \quad (29)$$

$$s.t.\ (18) - (28).$$

Note that we skip restating the individual rationality constraint (17) explicitly in this transformed problem, because it can be derived from the auxiliary variable related constraints (27) and (28). For satisfying the time average inequality constraints (27), we use N virtual queues denoted by $Z_i(t), i \in \mathcal{N}$, initially empty, which evolve as follows:

$$Z_i(t+1) = \max[Z_i(t) + \gamma_i(t) - J_i(t), 0] \quad (30)$$

The optimal payoffs obtained from solving *MeN-OPT* and *MeN-T-OPT* are the same. To see this, let ϕ^* and ϕ' represent the optimal objective function values for the two problems, respectively. Let $\boldsymbol{\alpha^*}(t)$ be an optimal policy for *MeN-OPT*, where $\boldsymbol{\alpha(t)}$ is the vector process $\boldsymbol{\alpha}(t) = (I_{ij}(t), R_c(t), \mu_{0i}^{(c)}(t), \mu_{ij}^{(c)}(t))$, yielding optimal time average payoffs $\overline{J_i^*}, \forall i \in \mathcal{N}$. Assume that for the solution of *MeN-T-OPT* we select $\boldsymbol{\alpha^*}(t)$, and auxiliary variables $\gamma_i(t) = \overline{J_i^*}, \forall i \in \mathcal{N}, \forall t$. Then all constraints of *MeN-T-OPT* are satisfied, and we get an objective function value equal to ϕ^*, which is not necessarily optimal, so we have $\phi' \geq \phi^*$. Now, let $\boldsymbol{\alpha'}(t)$ and $\gamma_i'(t), i \in \mathcal{N}$ be an optimal policy for *MeN-T-OPT*, yielding time average payoffs $\overline{J_i'}, \forall i \in \mathcal{N}$. Clearly, $\boldsymbol{\alpha'}(t)$ is a feasible possibly suboptimal solution for *MeN-OPT*, as it satisfies its constraints, and yields a value $\phi(\overline{J_1'}, \ldots, \overline{J_N'})$. We have

$$\phi^* \geq \phi(\overline{J_1'}, \ldots, \overline{J_N'}) \geq \phi(\overline{\gamma_1'}, \ldots, \overline{\gamma_N'}) \geq \overline{\phi(\gamma_1', \ldots, \gamma_N')} \geq \phi'$$

where the second inequality follows from (27) and the third from Jensen's inequality as ϕ is concave. We have shown that $\phi^* \geq \phi'$ and $\phi' \geq \phi^*$, so it is $\phi^* = \phi' = \phi_{opt}$. So, any solution to *MeN-T-OPT* also solves *MeN-OPT*.

To solve *MeN-T-OPT* we use a stochastic optimization algorithm, specifically the one described in **Algorithm 2**. From steps 3, 4 and 5 of this algorithm we observe that whenever the backlog $Z_i(t)$ of a user's virtual queue grows large, then data destined for this user is given priority at admission stage (step 3), while actions causing additional cost to that user are discouraged (steps 4, 5). Note also that only step 5 introduces coupling among the decisions associated with different users, so in terms of implementation, this discrete optimization is the most computationally intensive task. Finally, note that step 2 is the only step actually involving the objective function, and it calculates a value for $\gamma_i(t)$ that, by increasing D, can be made arbitrarily close to the one we would select with the exact NBS objective function.

Algorithm 2: Online MeN Optimization Algorithm

Executed every slot t:

1 Observe $S(t)$. For each user i, observe $p_i(t)$, $C_{0i}(t)$, $A_i(t)$, $L_i(t)$, $U_0^{(i)}(t)$ and $Z_i(t)$. For each i, c pair, observe $U_i^{(c)}(t)$.

2 For each user i, select $\gamma_i(t)$ as follows:

$$\gamma_i(t) = \left[\frac{V}{Z_i(t)} + J_{i,s}^{opt}(V) - \frac{1}{D} \right]_{J_{i,s}^{opt}(V)}^{k_i R_{max}}$$

where $[x]_a^b = \max(\min(x, b), a)$

3 For each user i, select $R_i(t)$ as follows:

$$R_i(t) = \begin{cases} \min[A_i(t) + L_i(t), R_{max}] & \text{, if } k_i Z_i(t) > U_0^{(i)}(t) \\ 0 & \text{, otherwise} \end{cases}$$

4 For each user i, $c_i^*(t) = \text{argmax}_c[U_0^{(c)}(t) - U_i^{(c)}(t)]$,

$$W_i^*(t) = U_0^{(c_i^*(t))}(t) - U_i^{(c_i^*(t))}(t) - Z_i(t)\big(p_i(t) + l_i e_{b,d}\big(\big(C_{0i}(t)\big)\big)$$

Select $\mu_{0i}^{(c)}(t)$ as follows:

$$\mu_{0i}^{(c)}(t) = \begin{cases} C_{0i}(t) & \text{, if } c = c_i^*(t),\ W_i^*(t) \geq 0 \\ 0 & \text{, otherwise} \end{cases}$$

5 For each link ij, $c_{ij}^*(t) = \text{argmax}_c[U_i^{(c)}(t) - U_j^{(c)}(t)]$, $W_{ij}^*(t) = \big[U_i^{(c_{ij}^*(t))}(t) - U_j^{(c_{ij}^*(t))}(t) - l_i Z_i(t) e_{b,t}(C_{ij}(t))\big]^+$. Select $\boldsymbol{I}(t)$ to solve:

$$\max_{C_{ij}(t)} \left[\sum_{ij} \left[C_{ij}(t) W_{ij}^*(t) \right] \right]$$
$$s.t.\ \boldsymbol{I}(t) \in \mathcal{I}_{S(t)},\ \boldsymbol{C}(t) = \hat{\boldsymbol{C}}(\boldsymbol{I}(t), S(t))$$

Then, select $\mu_{ij}^{(c)}(t)$ as follows:

$$\mu_{ij}^{(c)}(t) = \begin{cases} C_{ij}(t) & \text{, if } c = c_{ij}^*(t), I_{ij}(t) = 1, W_{ij}^*(t) > 0 \\ 0 & \text{, otherwise} \end{cases}$$

6 Finally, update all backlogs. $L_i(t)$, $U_0^{(c)}(t)$, $U_i^{(c)}(t)$, $Z_i(t)$ evolve as in (1), (2), (3), (30) respectively.

In terms of practical implementation of this algorithm, as we have already explained, we assume the existence of a MeN controller in the cloud which orchestrates network operation. Such an architecture has already been proposed in [17]. In a 5G implementation, such a controller could be running at the Radio Access Network in order to reduce the time required for exchange of control messages. In particular, we note that data admission (step 3) takes place at the controller side, and for step 4 the user must be informed about the backlogs $U_0^{(c)}(t)$ for all commodities c in the MeN. For step 5, however, although it includes a centralized optimization problem, there has been some work on suboptimal fully distributed algorithms which are able to guarantee performance within a fraction of optimality, see for instance [22]. We therefore propose a hybrid control scheme comprising both controller-driven and user-driven decisions.

V. Performance Analysis

In this section we provide results showing that Algorithm 1 and Algorithm 2 can approach the optimal objective function values of *I-OPT* and *MeN-OPT* arbitrarily close by increasing the V parameter, while preserving stability of all queues. Due to lack of space, most of the proofs constitute in showing that the assumptions of relevant theorems from generic stochastic optimization theory [29] apply in our model.

In *I-OPT* there is only one network queue to stabilize, $U_{0,s}^{(i)}(t)$. The Lyapunov function is defined to be equal to $\frac{1}{2}[U_{0,s}^{(i)}(t)]^2$. The corresponding Lyapunov drift is

$$\Delta(U_{0,s}^{(i)}(t)) = \frac{1}{2} E\left[(U_{0,s}^{(i)}(t+1))^2 - (U_{0,s}^{(i)}(t))^2 | (U_{0,s}^{(i)}(t)) \right]$$

Lemma 1. *Under any control algorithm for the selection of* $R_{i,s}(t)$ *and* $\mu_{0i,s}(t)$*, the following inequality is satisfied for each* t*:*

$$\begin{aligned} &\Delta(U_{0,s}^{(i)}(t)) - VE[J_{i,s}(t)|U_{0,s}^{(i)}(t)] \quad (31) \\ &\leq (C_0^{max})^2 - VE[J_{i,s}(t)|U_{0,s}^{(i)}(t)] \\ &+ U_{0,s}^{(i)}(t)\big(R_{i,s}(t) - \mu_{i,s}(t)\big) \end{aligned}$$

Proof. Squaring (9), using the inequalities $\max[x, 0]^2 \leq x^2$, $R_{i,s}(t) \leq C_0^{max}$, $\mu_{0i,s}(t) \leq C_0^{max}$, taking the expectation with respect to $U_{0,s}^{(i)}(t)$, dividing by 2, and subtracting the term $VE[J_{i,s}(t)|U_{0,s}^{(i)}(t)]$ yields the result. □

From the above lemma we can see the rationale behind Algorithm 1, which minimizes the right hand side of (31). This is important because it leads to the following result.

Lemma 2. *If* $R_{i,s}(t)$ *and* $\mu_{0i,s}(t)$ *are selected according to Algorithm 1, the processes* $A_i(t)$*,* $p_i(t)$ *and* $C_{0i}(t)$ *are i.i.d. over slots, and the initial backlog value* $U_{0,s}^{(i)}(0)$ *finite, then* $U_{0,s}^{(i)}(t)$ *is mean rate stable. In addition, we have*

$$\overline{J_{i,s}} \geq J_{i,s}^{opt} - \frac{(C_0^{max})^2}{V},$$

where $J_{i,s}^{opt}$ *is the optimal objective function value for I-OPT.*

Proof. To prove our claim we will show that all the assumptions from Theorem 4.8 of [29] are satisfied. We have, for all t, $R_{i,s}^2(t) \leq (C_0^{max})^2$ and $\mu_{0i,s}^2(t) \leq (C_0^{max})^2$. The problem *I-OPT* is feasible, as choosing $R_{i,s}(t) = 0$ and $\mu_{0i,s}(t) = 0$ for every slot trivially stabilizes $U_{0,s}^{(i)}$. Algorithm 1 is a 0-additive approximation, as it minimizes the right hand side of (31). □

For the MeN optimization problem, let $\boldsymbol{\Theta}(t) = [\boldsymbol{Z}(t); \boldsymbol{U}(t)]$ represent the combined matrix of all virtual queues and actual queues. The Lyapunov function for this optimization is then defined as follows:

$$L(\boldsymbol{\Theta}(t)) = \frac{1}{2} \sum_i \left[Z_i^2(t) + (U_0^{(i)})^2(t) + \sum_c (U_i^{(c)})^2(t) \right]$$

The Lyapunov drift for this combined queue matrix is defined as

$$\Delta(\boldsymbol{\Theta}(t)) = E\{L(\boldsymbol{\Theta}(t+1)) - L(\boldsymbol{\Theta}(t)) | \boldsymbol{\Theta}(t)\}$$

Lemma 3. *Under any control algorithm for selecting actions, the following inequality is satisfied for all t:*

$$\Delta(\mathbf{\Theta}(t)) - VE\Big[\sum_i \log\Big(1 + D(\gamma_i(t) - J_{i,s}^{opt}(V))\Big)|\mathbf{\Theta}(t)\Big] \tag{32}$$
$$\leq B - VE\Big[\sum_i \log\Big(1 + D(\gamma_i(t) - J_{i,s}^{opt}(V))\Big)|\mathbf{\Theta}(t)\Big]$$
$$+ \sum_i Z_i(t)\Big[\gamma_i(t) - k_i R_i(t)$$
$$+ \sum_j l_i e_{b,t}\big(\sum_c \mu_{ij}^{(c)}(t)\big)\sum_c \mu_{ij}^{(c)}(t)$$
$$+ l_i e_{b,d}\big(\sum_c \mu_{0i}^{(c)}(t)\big)\sum_c \mu_{0i}^{(c)}(t) + p_i(t)\sum_c \mu_{0i}^{(c)}(t)\Big]$$
$$+ \sum_c U_0^{(c)}(t)\Big[R_c(t) - \sum_i \mu_{0i}^{(c)}(t)\Big]$$
$$+ \sum_i\sum_c U_i^{(c)}(t)\Big[\sum_k \mu_{ki}^{(c)}(t) + \mu_{0i}^{(c)}(t) - \sum_j \mu_{ij}^{(c)}(t)\Big]$$

where B is a positive constant that depends on the bounds of the involved attributes and auxiliary variables.

Proof. Squaring (2), (3) and (30), and using the inequalities $\max[x,0]^2 \leq x^2$, $R_c(t) \leq R_{max}$, $\mu_{0i}(t) \leq C_0^{max}$, $\mu_{ij}(t) \leq C_{max}$, gives

$$(U_0^{(c)}(t+1))^2 \leq (U_0^{(c)}(t))^2$$
$$+ (NC_0^{max})^2 + R_{max}^2 + 2U_0^{(c)}(t)\big(R_c(t) - \sum_i \mu_{0i}^{(c)}(t)\big)$$

$$(U_i^{(c)}(t+1))^2 \leq (U_i^{(c)}(t))^2$$
$$+ [C_0^{max} + (N-1)C_{max}]^2 + [(N-1)C_{max}]^2$$
$$+ 2U_i^{(c)}(t)(\sum_k \mu_{ki}^{(c)}(t) + \mu_{0i}^{(c)}(t) - \sum_j \mu_{ij}^{(c)}(t))$$

$$Z_i^2(t+1) \leq Z_i^2(t)$$
$$+ \big[k_i R_{max} + C_0^{max} p_{max} + l_i(\delta_d C_0^{max} + \theta_d)$$
$$+ (N-1)l_i(\delta_t C_{max} + \theta_t)\big]^2$$
$$+ 2Z_i(t)[\gamma_i(t) - k_i R_i(t) + \sum_j l_i e_{b,t}\big(\sum_c \mu_{ij}^{(c)}(t)\big)\sum_c \mu_{ij}^{(c)}(t)$$
$$+ l_i e_{b,d}(\sum_c \mu_{0i}^{(c)}(t))\sum_c \mu_{0i}^{(c)}(t) + p_i(t)\sum_c \mu_{0i}^{(c)}(t)]$$

Summing the above inequalities for all i, c, dividing by two, and subtracting $VE\big[\sum_i \log\big(1 + D(\gamma_i(t) - J_{i,s}^{opt}(V))\big)|\mathbf{\Theta}(t)\big]$ yields the result. ☐

Lemma 4. *If $\gamma_i(t)$, $R_i(t)$, $\boldsymbol{I}(t)$, $\mu_{0i}^{(c)}(t)$ and $\mu_{ij}^{(c)}(t)$ are selected according to Algorithm 2, the processes $p_i(t)$, $A(t)$, $C_{0i}(t)$ and $C_{ij}(t)$ are i.i.d. over slots, and the initial backlog values of all actual and virtual queues are finite, then all actual and virtual queues are mean rate stable. In addition, we have*

$$\sum_i \log\Big(1 + D\big(\overline{J_i} - J_{i,s}^{opt}(V)\big)\Big) \geq \phi_{opt} - \frac{B}{V} \tag{33}$$

where ϕ_{opt} is the optimal value of MeN-OPT, and B has been defined in Lemma 1.

Proof. To prove our claim we will show that all the assumptions of Theorem 5.1 from [29] are satisfied. The objective function $\sum_i \log\Big(1 + D\big(\overline{J_i} - J_{i,s}^{opt}(V)\big)\Big)$ is continuous, strictly increasing and concave. The function $\sum_i \log(1 + D(\gamma_i(t) - J_{i,s}^{opt}(V)))$ is bounded above, since all $\gamma_i(t)$ are bounded by $k_i R_{max}$. The per-slot payoffs $J_i(t)$ are bounded above by $k_i R_{max}$ and also below because $V_i(t)$ and $H_i(t)$ take values in finite sets. All inputs and outputs of the actual queues are also bounded, as they are linear combinations of bounded variables $R_i(t)$, $\mu_{0i}^{(c)}(t)$ and $\mu_{ij}^{(c)}(t)$. The initial backlogs of all actual and virtual queues are finite, therefore the initial value of the Lyapunov function, $L(\mathbf{\Theta}(0))$, is finite. The problem *MeN-OPT*, augmented with the rectangle constraint $J_{i,s}^{opt}(V) \leq \overline{J_i} \leq k_i R_{max}$, is feasible, because we know that in the worst case the users can get payoff equal to their standalone payoffs $J_{i,s}$. All environment random variables are i.i.d. over time, as assumed in the lemma. Algorithm 2 is a 0-additive approximation, as it minimizes the right hand side of the drift-plus-penalty inequality every slot. ☐

Although the results in Lemma 2 and Lemma 4 assume i.i.d environment variables, it is well known that the Lyapunov optimization framework applies to non-i.i.d. stationary random processes, through the use of T-slot analysis, so there is no contradiction with our assumptions for stationary (possibly non i.i.d.) processes in Section II. We refer the reader to [30] for the related analysis and proofs.

VI. Numerical Results

We performed MATLAB simulations to assess the performance of the proposed algorithm. The simulations involved 5 users and the simulation time was always selected to be large enough to allow all queues to stabilize. The scale relationship of the values δ_t, δ_d, θ_t and θ_d has been chosen so as to reflect the scale of these parameters for LTE cellular links and WiFi links, as reported in [25]. The per unit data price were constant and equal to 0.1. We have chosen $V = 30$ and $D = 200$.

We have used a simple matchings model as our interference model, where the constraint is that a node cannot be participating in more than one active links during a timeslot (either as a transmitter or a receiver). That is, we have used the constraint $\sum_j I_{ij}(t) + \sum_k I_{ki}(t) \leq 1, \forall i \in \mathcal{N}$. The capacities of the D2D links, as well as the arrivals, have been modeled as i.i.d. processes with discrete uniform distributions, with expected values equal to 15 and 2 respectively. For the Internet access capacities, which have also been modeled as i.i.d. processes with discrete uniform distributions, we have simulated two scenarios. In the first scenario, all users are statistically identical, and share an expected value of 5. In the second scenario, there is diversity among the users, and the expected values of their Internet access capacities are given by 2.5, 4.5, 1.5, 2 and 0 (respectively for $i = 1, \ldots, 5$). Note that in this scenario we always assign zero capacity to user 5.

In Figure 2 we see the payoffs of the users in the first scenario, compared to their respective standalone payoffs. Each user gets approximately 8% more payoff. In Figure 3 we see the payoffs of the users in the second scenario, compared to their respective standalone payoffs. It is remarkable that user 5, who has a zero Internet access capacity himself, has

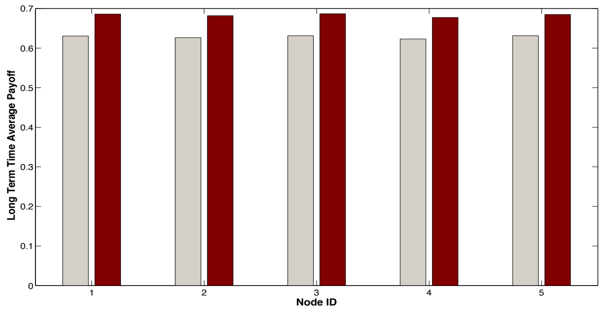

Fig. 2. Comparison of user payoffs in standalone and in MeN operation in the scenario with statistically identical users (Light color:Standalone, Dark Color: MeN).

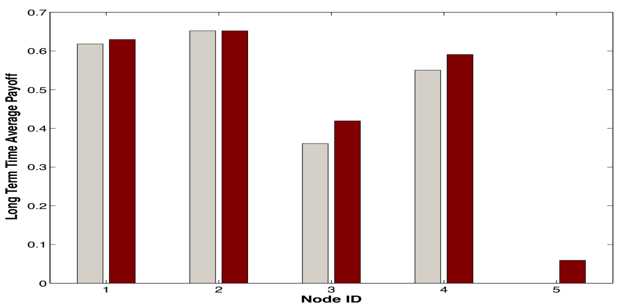

Fig. 3. Comparison of user payoffs in standalone and in MeN operation in the scenario with diverse Internet access capacity statistics across users (Light color:Standalone, Dark Color: MeN).

a non-negligible positive payoff as a reward for the relaying services he provides. We also observe that users with spare Internet capacity (whose arrivals do not saturate their Internet access links in independent operation) get less benefit than users in need of the extra capacity.

VII. Conclusion

We have introduced the concept of Mobile edge-Networks (MeNs), where users collaborate with the goal to collectively boost their performance. The concept of MeNs is fully aligned with the principles of decentralized control, virtualization of resources, and exploitation of end-user equipment, that have been already adopted for the emerging 5G systems. In particular, we modeled self-interested users through a payoff function capturing their energy and monetary costs, as well as their throughputs, and showed that a stochastic optimization algorithm, whose orchestration can be assisted by a cloud-based controller, can drive the network to achieve the Nash Bargaining Solution for the time average payoffs. This solution satisfies the individual rationality constraint, hence it incentivizes users to participate.

References

[1] Cisco, "Cisco visual networking index: Global mobile data traffic forecast update, 2014-2019," in *Proceedings of the 10th international conference on Mobile systems, applications, and services*, May 2015.
[2] Ericsson, "Ericsson mobility report," in *Press Release*, June 2015.
[3] NGMN, "5g," White Paper, February 2015.
[4] Ericsson, "5g systems," in *White Paper*, January 2015.
[5] J. G. Andrews, S. Buzzi, C. Wan, S. V. Hanly, A. Lozano, A. Soong, and J. Zhang, "What will 5g be?" *IEEE JSAC*, vol. 32, no. 6, 2014.
[6] T. Spyropoulos, K. Psounis, and C. Raghavendra, "Spray and wait: an efficient routing scheme for intermittently connected mobile networks," in *WTDN Workshop*. ACM, 2005, pp. 252 – 259.
[7] J.-H. Chang and L. Tassiulas, "Maximum lifetime routing in wireless sensor networks," *Transactions on Networking*, vol. 12, no. 4, pp. 609–619, 2004.
[8] R. Sofia and P. Mendes, "User-provided networks: Consumer as provider," *Communications Magazine*, vol. 46, no. 12, pp. 86–91, 2008.
[9] J. Musacchio and J. C. Walrand, "User-provided networks: Consumer as provider," *Transactions on Networking*, vol. 14, no. 2, pp. 289–301, 2006.
[10] M. H. Afrasiabi and R. Guerin, "Pricing strategies for user-provided connectivity services," in *Infocom*. IEEE, 2012.
[11] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "Incentive mechanisms for user-provided networks," *Communications Magazine*, vol. 52, no. 9, pp. 20–27, 2014.
[12] A. Sharma, V. Navda, R. Ramjee, V. N. Padmanabhan, and E. M. Belding, "Cool-tether: Energy efficient on-the-fly wifi hot-spots using mobile phones," in *CoNEXT*. ACM, 2009.
[13] N. Do, C. Hsu, and N. Venkaramanian, "Crowdmac: A crowdsourcing system for mobile access," in *Middleware*. ACM, 2012.
[14] T. Yu, Z. Zhou, D. Zhang, X. Wang, Y. Liu, and S. Lu, "Indapson: An incentive data plan sharing system based on self-organizing network," in *Infocom*. IEEE, 2014.
[15] E. Jung, Y. Wang, I. Prilepov, F. Maker, X. Liu, and V. Akella, "User-profile-driven collaborative bandwidth sharing on mobile phones," in *MCS*. ACM, 2010.
[16] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "Enabling crowd-sourced mobile internet access," in *Infocom*. IEEE, 2014.
[17] D. Syrivelis, G. Iosifidis, D. Delimpasis, K. Chounos, T. Korakis, and L. Tassiulas, "Bits & coins: Supporting collaborative consumption of mobile internet," in *Infocom*. IEEE, 2015.
[18] K. K. Yap, T. Y. Huang, M. Kobayashi, Y. Yiakoumis, N. McKeown, S. Katti, and G. M. Parulkar, "Making use of all the networks around us: A case study in android," *Computer Communication Review*, vol. 42, no. 4, pp. 455–460, 2012.
[19] L. K. Law, K. Pelechrinis, S. V. Krishnamurthy, and M. Faloutsos, "Downlink capacity of hybrid cellular ad hoc networks," *Transactions on Networking*, vol. 18, no. 1, pp. 243–256, 2010.
[20] L. Pan, X. Huang, and Y. Fang, "Capacity scaling of multihop cellular networks," in *Infocom*. IEEE, 2011.
[21] D.Wu, Y. Cai, L. Zhou, R. Q. Hu, and Y. Qian, "Energy-aware dynamic cooperative strategy selection for relay-assisted cellular networks," *Transactions on Vehicular Technology*, vol. 63, 2014.
[22] M. J. Neely, "Energy optimal control for time varying wireless networks," *Transactions on Information Theory*, vol. 52, no. 7, 2006.
[23] M. Gkatzianas, L. Georgiadis, and L. Tassiulas, "Control of wireless networks with rechargeable batteries," *Transactions on Wireless Communications*, vol. 9, no. 2, 2010.
[24] M. J. Neely, "Optimal peer-to-peer scheduling for mobile wireless networks with redundantly distributed data," *Transactions on Mobile Computing*, vol. 13, no. 9, pp. 2086–2099, 2014.
[25] J. Huang, F. Qian, A. Gerber, Z. M. Mao, S. Sen, and O. Spatscheck, "A close examination of performance and power characteristics of 4g lte networks," in *Proceedings of the 10th international conference on Mobile systems, applications, and services*. ACM, 2012, pp. 225–238.
[26] "End-to-end quality of service (qos) concepts and architectures," 3GPP Specification 23.207, December 2015.
[27] H. Yaiche, R. R. Mazumdar, and C. Rosenberg, "A game theoretic framework for bandwidth allocation and pricing in broadband networks," *Transactions on Networking*, vol. 8, no. 5, 2000.
[28] J. F. Nash, "The bargaining problem," *Econometrica*, vol. 18, 1950.
[29] M. J. Neely, "Stochastic network optimization with application to communication and queueing systems," *Synthesis Lectures on Communication Networks*, vol. 3, no. 1, pp. 1–211, 2010.
[30] L. Huang and M. J. Neely, "Max-weight achieves the exact $[o(1/v), o(v)]$ utility-delay tradeoff under markov dynamics," *arXiv preprint arXiv:1008.0200*, 2010.