This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2017.2754273, IEEE Transactions on Vehicular Technology

Resource Allocation for Green Cloud Radio Access Networks with Hybrid Energy Supplies

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***Abstract*—In this paper, we study sustainable resource allocation for cloud radio access networks (CRANs) powered by hybrid energy supplies (HES). Specifically, the central unit (CU) in the CRANs distributes data to a set of radio units (RUs) powered by both on-grid energy and energy harvested from green sources, and allocates channels to the selected RUs for downlink transmissions. We formulate an optimization problem to maximize the net gain of the system which is the difference between the user utility gain and on-grid energy costs, taking into consideration the stochastic nature of energy harvesting process, time-varying on-grid energy price, and dynamic wireless channel conditions. A resource allocation framework is developed to decompose the formulated problem into three subproblems, i.e., the hybrid energy management, data requesting, and channel and power allocation. Based on the solutions of the subproblems, we propose a net gain-optimal resource allocation (GRA) algorithm to maximize the net gain while stabilizing the data buffers and ensuring the sustainability of batteries. Performance analysis demonstrates that the GRA algorithm can achieve close-to-optimal net gain with bounded data buffer and battery capacity. Extensive simulations validate the analysis and demonstrate that GRA algorithm outperforms other algorithms in terms of the net gain and delay performance.**

***Index Terms*—Cloud radio access network, energy harvesting, hybrid energy supplies, resource allocation, stochastic optimization**

I. Introduction

The global mobile data traffic in the coming 5G era is predicted to increase by eightfold in the next five years [2]. To cater such intense demand, traditional cellular networks urge densified deployments of base stations (BSs) to improve the spatial spectral efficiency. However, the large number of BSs requires high expenditure on both infrastructure construction and operation maintenance. Alternatively, the cloud-assisted radio access network (CRAN) has been envisioned as a cost-efficient solution for future cellular network architecture [3]. A typical CRAN divides the function of a BS into two parts, i.e., a cloud-based central unit (CU) which accumulates the baseband signal processing and control functions, and the radio unit (RU) which provides radio access for mobile users. Taking advantage of cloud computing technology, the mobile operator only needs to enhance the CU and deploy low-cost RUs to boost the network capacity. Furthermore, the overall knowledge available at the CU enables the CRAN to timely assign radio resources to RUs according to the changes in user demand and mobility.

Despite these advantages, the densely deployed RUs consume considerable amount of energy and lead to a surge of carbon footprints [4]. To address this issue, it is highly desirable to incorporate the energy harvesting (EH) capability into RUs, which enables RUs to scavenge energy from the ambient energy sources, e.g., solar and wind [5]–[8]. It is reported in [9] that 20% greenhouse gas emission can be reduced by powering cellular networks with harvested energy. Unfortunately, the availability of harvested energy is prone to environmental factors such as solar radiation and wind speed, and thus can be variable and intermittent over time and locations [10]. As a result, only operating on harvested energy may degrade the quality of service (QoS) provisioned by the CRAN. To enhance the stability, RUs can be powered by both green energy and power grid, i.e., hybrid energy supply.

Although more energy efficient, the hybrid energy supplies powered CRANs (referred to as HES-CRANs hereafter) still face several new challenges. First, the dynamics in EH process and on-grid energy price make the energy management challenging. The EH process is generally time-varying and exhibits strongly stochastic behavior [1], [11]. In addition to the EH process, the price of on-grid energy also changes in reality, which introduces a new dimension of resource management in HES-CRANs. Specifically, RUs can purchase more on-grid energy during low-price period and store in battery for future use, to reduce the total expenditure on on-grid energy. Furthermore, the scalability of the designed resource allocation algorithm is also a critical issue, especially under the dense scenario with a large number of RUs. Research works in the literature mainly focus on energy efficient operation in CRANs without considering the stochasticity in EH process and on-grid energy price [12]–[16]. In addition, the proposed solutions in the literature is designed for a network with a limited number of BSs [17]–[22], which may not be applicable for a CRAN with a large number of RUs. To fill the research gap, we make an effort to efficiently allocate resource in HES-CRANs while considering the dynamics in EH process and on-grid energy price, and the scalability of the solution to desified HES-CRANs.

To address the above challenges, this paper develops a

Part of this paper was presented at the IEEE Globecom 2016 [1]. D. Zhang, Z. Chen, and S. Duan are with the School of Software, J. Ren and Y. Zhang are with the School of Information Science and Engineering, in Central South University, Changsha, China, 410083. J. Ren is the corresponding author. (e-mail: {zdy876, czg, dsjyfd012, renju, zyx}@csu.edu.cn)

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resource allocation framework that jointly considers renewable and on-grid energy management, transmission power control, and channel allocation in an HES-CRAN, where a CU and numerous RUs are linked through the fronthaul links. Specifically, an optimization problem is formulated to maximize the net gain, i.e., the difference between the utility gain of users and cost of on-grid energy purchase, of an HES-CRAN. The developed framework captures the randomness in the EH process, on-grid energy price, and wireless channel fading. Based on the framework, we propose an online algorithm to strike the balance between user gain and the cost on on-grid energy purchase, while maintaining the data queue stability and energy sustainability at RUs. Notably, the computational complexity of the proposed algorithm does not rely on the number of RUs, and thus guarantees its scalability in HES-CRANs with densely deployed RUs. The main contributions are summarized as follows:

1) We formulate a stochastic optimization problem to jointly consider the energy management, channel allocation and power control in the HES-CRAN, aiming at the net gain of users under the constraints of data queue stability and energy sustainability.
2) We develop a resource allocation framework to decompose the stochastic optimization problem to three subproblems, i.e., the hybrid energy management, the data requesting, and the channel and power allocation. The solutions of these subproblems constitute the net gain-optimal algorithm which makes control decisions without *a priori* knowledge of the stochastic processes.
3) We derive the required data buffer length and battery capacity for the operation of the proposed algorithm, which provides important guidelines for the deployment of an HES-CRAN. Furthermore, we theoretically prove the bounds of the gap between the net gain achieved by our algorithm and the optimal solution, which shows that our algorithm can achieve close-to-optimal solution.

The reminder of this paper is organized as follows: Section II presents related works in the existing literature. Section III introduces the system model and the problem formulation. Section IV proposes the resource allocation framework and the online resource allocation algorithm. Section V provides the performance analysis, followed by simulations in Section VI. Section VII concludes this paper.

II. Related Work

Numerous works in the literature focus on the energy efficient resource allocation in CRANs [12]–[16]. Dai and Yu in [12] studied the energy efficiency of data compression in CRANs, in which the CU performs precoding of the user messages, before sending user data to RUs. The authors formulate an optimization problem to minimize the energy consumption under data rate constraints. In [13], Peng et al. investigated the user association and power control in a heterogeneous CRAN with multiple RUs deployed in a macro cell. The optimal transmission power and user association were obtained to maximize an energy efficiency metric, by solving a mixed integer programming problem. In [16], Zuo et al. proposed multiple algorithms for energy efficient user association in a CRAN system empowered with Massive MIMO considering both power consumption at fronthaul links and the circuit attached to antennas. The aforementioned works assumed the simple model with sufficient energy supply and full data buffer without considering the time-varying nature of wireless channels. Some of the recent studies have taken the time-varying channel states into consideration [14] [15]. In [14], Li et al. aimed to minimize the consumed energy to support random traffic arrivals, while considering the time-varying fading channels. Furthermore, the authors of [15] have scheduled the resource allocation and admission control of a CRAN over a long time horizon to maximize the time average energy efficiency, which could maintain network stability while optimize the energy usage. The above-mentioned works only consider the on-grid energy supply, which may not be applicable in HES-CRANs.

To conserve the on-grid energy consumption, the hybrid energy-powered cellular networks have drawn increasing attentions recently [17]–[22]. In [21], Sheng et al. investigated the energy sharing and load shifting among the base stations (BSs) with EH capability. The authors formulate a NP-hard optimization problem to minimize the on-grid energy consumption. Chamola et al. in [22] developed a greedy algorithm to optimize the power control subject to network latency. Refs. [17], [19], [20] applied the Lyapunov optimization approach to account for the intermittent arrival of harvested energy. Mao et al. in [17] investigated user association and power control between two BSs to minimize the time-average on-grid energy consumption. Considering the lack of non-causal information of the EH process, the authors proposed a resource allocation algorithm which only requires instantaneous information of the channel fading and EH process. With the same objective of [17], [19] investigated the power and channel allocations for one BS. In [20], Yang et al. investigated the tradeoff between the network throughput and on-grid energy consumption in a relay network, while considering the stochastic characteristics of renewable energy and mobile traffic. These works were mainly designed for conventional cellular networks, which cannot be applied to CRAN systems due to the different network architecture. Furthermore, the complexity of the proposed algorithms can increase significantly with number of BSs, which cannot be applied in practical networks in dense scenarios.

III. System Model

In this section, we present the system model of an HES-CRAN powered by hybrid energy sources and formulate a net gain maximization problem.

A. Network Model

We consider an HES-CRAN which is composed of a CU and N radio units (RUs), as shown in Fig. 1. The RUs are responsible to serve downlink data transmission to M users. The sets of RUs and users are denoted by $\mathcal{N} = \{1, \cdots, n, \cdots, N\}$ and $\mathcal{M} = \{1, \cdots, m, \cdots, M\}$, respectively. Each RU is equipped with an EH module including solar panel or wind

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TABLE I
KEY NOTATIONS

Notation	**Definition**
$n, N, \mathcal{N}$	The index, the number, and the set of RUs
$k, K, \mathcal{K}$	The index, the number, and the set of channels
$m, M, \mathcal{M}$	The index, the number, and the set of users
$t, T, \mathcal{T}$	The index, the number, and the set of time slots
$i_{n,m}^k(t)$	Channel allocation indicator, takes one if channel k is assigned to link RU n and user m in time slot t
$p_{n,m}^k(t)$	Transmission power of RU n to user m over channel k in time slot t
$d_{n,m}(t)$	Data requested by RU n for user m from the CU in time slot t
P_T	The upper bound of transmission power over a channel
F_n	The fronthaul link capacity of RU n
A_m	Available data of user m in time slot t the CU
Π_n	The battery capacity of RU n
$\phi_{n,m}^k(t)$	The capacity of channel k between RU n and user m at slot t
$\eta_{n,m}^k(t)$	The channel condition between RU n and user m on channel k in time slot t
$g_n(t)$	Energy bought by RU n from the power grid in time slot t
$\psi_n(t)$	Ambient energy that can be harvested by RU n in time slot t
$\alpha(t)$	Energy price in time slot t
$e_n(t)$	Energy harvested by RU n in time slot t
$Q_{n,m}(t)$	The data backlog of RU n for user m in time slot t
$E_n(t)$	Energy queue length of RU n in time slot t
η_{max}	The upper bound on channel conditions
ϕ_{max}	The upper bound of channel capacity
ψ_{max}	The upper bound on $\psi_n(t)$
P_{max}	The upper bound of energy consumption of one RU in each time slot

turbine. Since the renewable energy is sporadic and intermittent by nature, only relying on renewable energy may hinder the HES-CRAN to provide satisfactory services for users. Therefore, the RUs can also purchase energy from the power grid. Each RU has a rechargeable battery and a data buffer. The downlink data transmission is considered. The CU firstly transmits data to the RUs through the wired fronthaul links, and then the RUs transmit data to users wirelessly. Utilizing the information of RUs' energy availability and network topology, the CU can properly distribute data to various RUs for efficient data transmissions.

The following notations are used throughout this paper. $\mathbb{E}[X]$ stands for the expectation of a random variable X, and $\mathbb{E}[X|A]$ stands for the conditional expectation of X on event A. The function $[x]^+$ denotes a non-negative value, i.e., $\max(x, 0)$. Furthermore, we have $[x]_a^b = \min(\max(x, a), b)$.

The HES-CRAN operates over unit time slots denoted as $t \in \mathcal{T} = \{1, 2, \cdots T\}$ [23]. The operating spectrum bandwidth is equally divided into K orthogonal channels denoted as $\mathcal{K} = \{1 \cdots, k, \cdots, K\}$ [24]. The CU periodically allocates

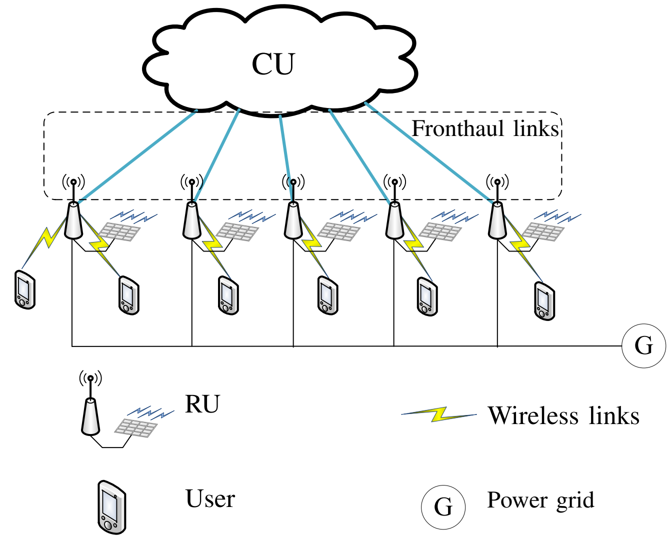

Fig. 1. HES-CRAN with energy harvesting and on-grid power supply.

channels to RUs for data transmissions. For channel allocation, we define a 3-dimensional matrix $\mathbf{i}(t)$ with elements $i_{n,m}^k(t), \forall n \in \mathcal{N}, k \in \mathcal{K}, m \in \mathcal{M}$. $i_{n,m}^k(t)$ equals one if RU n is scheduled to serve user m using channel k in time slot t, and 0 otherwise. Each channel can be allocated to at most one user to avoid excessive co-channel interference among users,

$$\sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{M}} i_{n,m}^k(t) \leq 1, \forall k \in \mathcal{K}. \tag{1}$$

In addition, each user can be served by at most one RU with one channel in each time slot,

$$\sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} i_{n,m}^k(t) \leq 1, \forall m \in \mathcal{M}. \tag{2}$$

B. Hybrid Energy Supply and Energy Queue Dynamics

RUs can harvest energy from the ambient energy sources or purchase energy from the power grid. Denote by $e_n(t)$ the harvested energy by RU n in time slot t. The following EH constraint holds in each time slot:

$$e_n(t) \leq \psi_n(t), \tag{3}$$

where $\psi_n(t)$ denotes the ambient energy that can be harvested by RU n in time slot t. To capture the impact of environmental changes on the EH process, the value of $\psi_n(t)$ potentially changes across time slots [25], which is upper bounded by ψ_{max}, i.e., $\psi_n(t) \leq \psi_{max}, \forall n \in \mathcal{N}$. Denote $\boldsymbol{\psi}(t) = (\psi_1(t), \cdots, \psi_N(t))$ as the vector of available renewable energy at all RUs.

Denote $g_n(t)$ the amount of energy purchased by RU n in time slot t, which is bounded by g_{max}, i.e., the upper bound of purchased on-grid energy:

$$0 \leq g_n(t) \leq g_{max}. \tag{4}$$

Let $\alpha(t)$ denote the purchase price of unit on-grid energy in time slot t, which is constant during one time slot. Due to the unbalance between energy provision and energy consumption in power grid, $\alpha(t)$ randomly changes across the time slots, as in [26].

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Let $p^k_{n,m}(t)$ denote the transmission power[1] of RU n to user m over channel k, and matrix $\mathbf{p}(t)$ with element $p^k_{n,m}(t)$ denote the transmission power of all RUs. The upper bound of transmission power on each channel is denoted by P_T:

$$0 \leq p^k_{n,m}(t) \leq P_T, \forall n \in \mathcal{N}, m \in \mathcal{M}. \quad (5)$$

Each RU can serve at most K users in each time slot. Therefore, the maximum energy consumption of an RU per time slot can be derived to $P_{max} = KP_T$.

Denote $E_n(t)$ as the available energy of RU n in time slot t. With the energy from renewable energy sources and power grid as the input, and the energy consumed by data transmission as the output, the dynamics of $E_n(t)$ across time slots can be expressed by:

$$E_n(t+1) = E_n(t) - \sum_{k \in \mathcal{K}} i^k_{n,m}(t) p^k_{n,m}(t) + g_n(t) + e_n(t). \quad (6)$$

The consumed energy cannot exceed the available energy, i.e.,

$$E_n(t) \geq \sum_{k \in \mathcal{K}} i^k_{n,m}(t) p^k_{n,m}(t). \quad (7)$$

Furthermore, the sum of available energy and input energy is upper bounded by the battery capacity of RUs, i.e.,

$$E_n(t) + g_n(t) + e_n(t) \leq \Pi_n, \forall n \in \mathcal{N}, \quad (8)$$

where Π_n is the battery capacity of RU n.

C. User Data Request and Data Queue Dynamics

The RUs request user data from the CU through the fronthaul links. The total amount of data requested by RU n in time slot t is bounded by the capacity of the fronthaul link between RU n and the CU. Denote $d_{n,m}(t)$ the amount of data requested by RU n for user m in time slot t, and $\mathbf{d}(t)$ the matrix of requested data with $d_{n,m}(t)$ as elements. Let F_n denote the fronthaul link capacity. The fronthaul capacity constraint can be expressed by:

$$\sum_{m \in \mathcal{M}} d_{n,m}(t) \leq F_n, \forall n \in \mathcal{N}. \quad (9)$$

The available data of user m at the CU is denoted by A_m. In any time slot, the data requested for user m cannot exceed A_m, i.e.,

$$\sum_{n \in \mathcal{N}} d_{n,m}(t) \leq A_m, \forall m \in \mathcal{M}. \quad (10)$$

RU stores the requested data in the data buffer. Let $Q_{n,m}(t)$ denote the data queue length, i.e., the data of user m saved at RU n in time slot t. The RU transmits the data to users through the allocated channel. Recalling that $p^k_{n,m}(t)$ denotes the transmission power of RU n to user m over channel k, the corresponding channel capacity $\phi^k_{n,m}(t)$ can be expressed by :

$$\phi^k_{n,m}(t) = W \log_2 \left(1 + \frac{h^k_{n,m}(t) p^k_{n,m}(t)}{l^3_{n,m} W N_0}\right) \quad (11)$$

[1]Since the time is slotted with unit size, we omit the multiplication by 1 slot when converting between power and energy in one slot [25].

where $h^k_{n,m}(t)$, $l_{n,m}$, and N_0 are the channel gain, the distance between RU n and user m, and the spectral noise power, respectively. For simplicity, let $\eta^k_{n,m}(t) = \frac{h^k_{n,m}(t)}{l^3_{n,m} W N_0}$ denote the channel condition between RU n and user m over channel k. Due to the impact of shadowing and multipath fading, $\eta^k_{n,m}(t)$ may change over the slots [25]. There exists an upper bound on the channel gain, and the corresponding upper bound on the channel capacity, denoted by η_{max} and ϕ_{max}, respectively.

Each RU is equipped with a data queue to save the requested data for each user. The queue length $Q_{n,m}(t)$ evolves across time slots as follows:

$$Q_{n,m}(t+1) = \left[Q_{n,m}(t) - \sum_{k \in \mathcal{K}} i^k_{n,m}(t) \phi^k_{n,m}(t)\right]^+ + d_{n,m}(t), \quad (12)$$

where the input is the requested data and the output is the transmitted data.

To maintain the network stability, the time-average requested amount of data per slot can not exceed the time-average transmitted amount of data per slot, i.e.,

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} d_{n,m}(t) < \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{k \in \mathcal{K}} i^k_{n,m}(t) \phi^k_{n,m}(t). \quad (13)$$

D. Net Gain and Problem Formulation

The gain of the HES-CRAN depends on the sum of users' gain and the cost on energy purchase, which is referred to as net gain hereafter. The net gain in time slot t can be expressed by:

$$\mathcal{U}(t) = \sum_{m \in \mathcal{M}} U\left(\sum_{n \in \mathcal{N}} d_{n,m}(t)\right) - \beta \sum_{n \in \mathcal{N}} \alpha(t) g_n(t), \quad (14)$$

where β denotes the normalization factor associated with the cost on energy purchase. $U(\cdot)$ represents a gain function with finite first-order derivative denoted by ϱ_U, which is non-decreasing, concave, and twice-differentiable w.r.t. $\sum_{n \in \mathcal{N}} d_{n,m}(t)$. The concavity of the gain function comes from the observation that the increasing rate of net gain decreases as the amount of transmitted data increases [14]. Furthermore, the concavity of the utility function guarantees the fairness between users, because serving the user with less amount of transmitted data can gain higher utility. Notably, given that the network stability constraint (13) is satisfied, all the requested data can be transmitted to the user eventually.

Based on the aforementioned system models, we formulate an optimization problem with the objective to maximize the time-average net gain, i.e.,

$$\bar{\mathcal{U}} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T} \mathbb{E}[\mathcal{U}(t)]. \quad (15)$$

where the expectation is taken over variable system parameters including the EH process $\psi_n(t)$, channel condition $\eta^k_{n,m}(t)$, on-grid energy price $\alpha(t)$, and the potentially random channel allocation, data requesting, and power control. To simplify the presentation, let $\mathbf{g}(t)$ and $\boldsymbol{e}(t)$ denote the vector of purchased

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energy and harvested energy of all RUs in each time slot, respectively. Let $\mathbf{\Psi}(t) = \{\mathbf{d}(t), \mathbf{i}(t), \mathbf{p}(t), \mathbf{g}(t), \boldsymbol{e}(t)\}$ to represent all variables to be optimized in each time slot. The user utility maximization problem can be formulated as:

$$(\mathbf{UUM}) \ \max_{\mathbf{\Psi}(t)} \bar{\mathcal{U}}$$
$$\text{s.t.} \quad (1) \text{ to } (13).$$

As we can see from the formulation of **UUM**, the decisions on variables couple on time to impact the net gain of the HES-CRAN. To solve the problem in an offline manner introduces infinite number of variables to optimize. Therefore, in the following section, we transform **UUM** to several deterministic subproblems in each time slot to design an online algorithm.

IV. Resource Allocation Framework

Based on the system model proposed in Section III, we observe that the difficulty to solve **UUM** mainly comes from two folds. The first one is the lack of future information regarding the on-grid energy price, channel gain, and EH process. Since the maximization of time-average net gain relies on the control decisions over the whole operation time, the lack of the future information hinders the HES-CRAN to attain the maximum net gain. Secondly, the energy consumption and channel capacity are jointly determined by the channel allocation, i.e., the integer variable $\mathbf{i}(t)$, and the power control, i.e., the continuous variable $\mathbf{p}(t)$. Therefore, the optimization of **UUM** falls in the category of mixed integer programming, which is in general difficult to solve. Considering these difficulties, we pursue a close-to-optimal solution for **UUM**. To this end, a resource allocation framework is designed, which transforms the stochastic problem into deterministic subproblems subject to the data queue stability and energy availability, using Lyapunov optimization approach.

A. Problem Transformation

We first use $\mathbf{\Omega}(t) = (\mathbf{Q}(t), \boldsymbol{E}(t))$ to denote the network state which captures the data queue length and energy queue length. Then, a Lyapunov function is defined to measure the backlogs of data queues and the difference between the energy queue length and the battery capacity, which is a quadratic function w.r.t. the queue lengths:

$$L(t) = \frac{1}{2}\left(\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}(Q_{n,m}(t))^2 + \sum_{n\in\mathcal{N}}(E_n(t) - \Pi_n)^2\right) \tag{17}$$

A small value of $L(t)$ implies that the backlogs of data queue are small and the batteries are almost fully charged. Furthermore, by carefully determining the value of battery capacity Π_n which will be specified later, we can guarantee that the RUs always have enough energy for downlink data service, such that the energy availability constraint (7) is met.

Based on the Lyapunov function, we introduce a Lyapunov drift to quantify the increase of Lyapunov function in each time slot, i.e.,

$$\Delta(t) = \mathbb{E}[L(t+1) - L(t)|\mathbf{\Omega}(t)]. \tag{18}$$

Suppose that the data queues of all RUs are initially empty, we can guarantee the stability of data queues by minimizing the Lyapunov drift in each time slot [27]. Recalling that the objective of **UUM** is to maximize the net gain defined in Eqn. (15), we insert a weighted version of the net gain into the Lyapunov drift, which yields the drift-minus-gain:

$$\Gamma(t) = \mathbb{E}[\Delta(t) - V\mathcal{U}(t)|\mathbf{\Omega}(t)], \tag{19}$$

where the weight V is used to strike the balance between queue stability and net gain maximization. A larger V implies that we emphasize more on the gain maximization, and vise versa. By minimizing the right hand side of Eqn. (19), the one jointly minimizes $\Delta(t)$ to guarantee network stability, and maximizes $V\mathcal{U}(t)$ to achieve a higher net gain.

To simplify the minimization of the drift-minus-gain, we develop the upper bound of Eqn. (19) under any feasible control action in Theorem 1, which is a linear function w.r.t. the variables in $\mathbf{\Psi}(t)$ and the queue lengths, rather than the quadratic function in Eqn. (19).

Theorem 1. *Under any feasible algorithms, the following inequality holds:*

$$\Gamma(t) \leq B + \mathbb{E}[\Theta_V(t)|\mathbf{\Omega}(t)] \tag{20}$$

where

$$\begin{aligned} B =& \frac{N}{2}\left[(\psi_{max} + g_{max})^2 + (P_{max})^2\right] \\ &+ \frac{NM}{2}\left[(A_m)^2 + (\phi_{max})^2\right]. \end{aligned} \tag{21}$$

All the variables reside in $\Theta_V(t)$ given by Eqn. (22).

The proof of Theorem 1 can be found in Appendix A. As we can see from Eqn. (21), the value of B can be obtained using the parameters given in the system model. Therefore, we only need to minimize $\Theta_V(t)$ by optimizing the requested data $\mathbf{d}(t)$, the harvested energy $\boldsymbol{e}(t)$, the purchased energy $\boldsymbol{g}(t)$, the channel allocation $\mathbf{i}(t)$, and the transmission power $\mathbf{p}(t)$. Notably, except the coupling between $\mathbf{i}(t)$ and $\mathbf{p}(t)$, other variables are linearly combined in $\Theta_V(t)$ and therefore can be separately optimized. In the following, we propose the solutions to minimize $\Theta_V(t)$ in each time slot.

B. Subproblem Solution

The linear structure the RHS of Eqn. (22) enables us to decompose the minimization of $\Theta_V(t)$ into three subproblems. The first one is the hybrid energy management subproblem which optimizes the harvested energy $\boldsymbol{e}(t)$ and the purchased energy $\boldsymbol{g}(t)$. Then, the requested data $\mathbf{d}(t)$ can be determined by addressing the data requesting subproblem. Last but not least, the transmission power $\mathbf{p}(t)$ and channel allocation $\mathbf{i}(t)$ are jointly optimized by addressing the power and channel allocation subproblem. The solutions of the three subproblems constitute the resource allocation framework.

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$$\begin{aligned}\Theta_V(t) = &\sum_{n\in\mathcal{N}} \left[(e_n(t)+g_n(t))(E_n(t)-\Pi_n)+g_n(t)V\beta\alpha(t)\right] \\ &+\sum_{m\in\mathcal{M}}\left[\sum_{n\in\mathcal{N}} Q_{n,m}(t)d_{n,m}(t) - V\sum_{m\in\mathcal{M}}\mathcal{U}\left(\sum_{n\in\mathcal{N}} d_{n,m}(t)\right)\right] \\ &+\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} i_{n,m}^k(t)\left[(\Pi_n-E_n(t))p_{n,m}^k(t)-Q_{n,m}(t)\phi_{n,m}^k(t)\right]\end{aligned} \tag{22}$$

1) Hybrid Energy Management: Considering the first term in Eqn. (22), we formulate the hybrid energy management subproblem to determine the harvested energy $\boldsymbol{e}(t)$ and purchased energy $\boldsymbol{g}(t)$:

$$\begin{aligned}(\textbf{HEM})\quad \min_{\boldsymbol{e}(t),\boldsymbol{g}(t)} \quad &\sum_{n\in\mathcal{N}}[e_n(t)(E_n(t)-\Pi_n) \\ &+g_n(t)(V\beta\alpha(t)+E_n(t)-\Pi_n)] \\ \text{s.t.}\quad &(3),(4),(8).\end{aligned}$$

Since $\boldsymbol{e}(t)$ and $\boldsymbol{g}(t)$ are linearly combined in the objective function, we can optimize them separately. Because the available energy cannot exceed the battery capacity, i.e., $E_n(t)-\Pi_n<0$, it can be found that the objective function of **HEM** monotonically decreases with the value of harvested energy $e_n(t), \forall n\in\mathcal{N}$. Therefore, $e_n(t)$ should be as large as possible to minimize the objective function of **HEM**. Considering constraints (3) and (8), we can find the optimal harvested energy to be:

$$e_n^*(t)=\min[\psi_n(t),\Pi_n-E_n(t)], \forall n\in\mathcal{N}. \tag{23}$$

Eqn. (23) implies that solving **HEM** requires the RUs to harvest energy as much as possible for battery recharging, since the harvested energy is free-of-charge comparing with the on-grid energy.

Considering the optimization of the purchased energy $\boldsymbol{g}(t)$, we see that if $V\beta\alpha(t)+E_n(t)-\Pi_n<0$, then the objective function of **HEM** monotonically decreases with the value of $g_n(t), \forall n\in\mathcal{N}$. Otherwise, the objective function increases with the value of $g_n(t)$. Therefore, the optimal value of purchased energy can be summarized to

$$g_n^*(t)=\begin{cases}0, \text{if } E_n(t)-\Pi_n+\beta V\alpha(t)\geq 0\\ \min[g_{max},\Pi_n-e_n^*(t)-E_n(t)], \text{otherwise.}\end{cases} \tag{24}$$

Notably, solving $e_n^*(t)$ and $g_n^*(t)$ only requires the local information at each RU. Therefore, **HEM** can be solved by each RU distributedly.

2) Data Requesting: To minimize the second term in Eqn. (22) under constraints (9) and (10), we formulate the following data requesting subproblem to determine the requested data $\mathbf{d}(t)$:

$$\begin{aligned}(\textbf{DR})\quad \min_{\mathbf{d}(t)} \quad &\sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}} Q_{n,m}(t)d_{n,m}(t) \\ &-V\sum_{m\in\mathcal{M}}\mathcal{U}\left(\sum_{n\in\mathcal{N}} d_{n,m}(t)\right) \\ \text{s.t.}\quad &(9),(10).\end{aligned}$$

The gain function $\mathcal{U}(\sum_{n\in\mathcal{N}} d_{n,m}(t))$ is a concave function and the constraints (9) and (10) are both linear w.r.t. the requested data $\mathbf{d}(t)$. Therefore, **DR** is a convex problem which can be efficiently solved using a standard convex optimization tool such as the disciplined convex programming (cvx) [28].

3) Power and Channel Allocation: To minimize the third term in Eqn. (22), we formulate the power and channel allocation subproblem to jointly optimize the transmission power $\mathbf{p}(t)$ and the channel allocation $\mathbf{i}(t)$:

$$\begin{aligned}(\textbf{PCA})\quad \min_{\mathbf{p}(t),\mathbf{i}(t)} &\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} i_{n,m}^k(t)\left[(\Pi_n-E_n(t))p_{n,m}^k(t)\right. \\ &\left.-Q_{n,m}(t)\phi_{n,m}^k(t)\right] \\ \text{s.t.}\quad &(1),(2),(5).\end{aligned}$$

The objective function of **PCA** consists of the product of $p_{n,m}^k(t)$ and $i_{n,m}^k(t)$, and the product of $i_{n,m}^k(t)$ and the logarithm function of $p_{n,m}^k(t)$, i.e., the channel capacity $\phi_{n,m}^k(t)$. The coupling of the integer variable $\mathbf{i}(t)$ and continuous variable $\mathbf{p}(t)$ makes **PCA** a difficult mixed integer programming problem. To address **PCA**, we transform this problem into a bipartite matching problem over two steps.

First, we prove that $\mathbf{p}(t)$ can be optimized without considering the value of $\mathbf{i}(t)$ in Lemma 1. By inserting the optimal value of $\mathbf{p}(t)$ into the objective function of **PCA**, we can transform the problem into a 3-dimensional matching problem with $\mathbf{i}(t)$ as the variable, i.e., the channel allocation subproblem (**CA**). Second, Lemma 2 shows that if the optimal solution of **CA** assigns RU n to serve user m using channel k, RU n must be the one with the minimum matching weight, comparing with other RUs. Therefore, we can further reduce **CA** to a bipartite matching problem that can be solved by the Hungarian algorithm [29].

In the following, we first determine the optimal transmission power $p_{n,m}^k(t)$ in Lemma 1.

Lemma 1. *Let $\mathbf{i}^*(t)$ and $\mathbf{p}^*(t)$ be the optimal solution for **PCA**. If $i_{n,m}^{k,*}(t)=1$, i.e., RU n serves user m over channel k in time slot t in the optimal solution, then the optimal transmission power is:*

$$p_{n,m}^{k,*}(t)=\left[\frac{WQ_{n,m}(t)}{\ln 2\cdot(\Pi_n-E_n(t))}-\frac{1}{\eta_{n,m}^k(t)}\right]_0^{P_T}. \tag{25}$$

The proof of Lemma 1 can be found in Appendix B. Substituting $p_{n,m}^{k,*}(t)$ into **PCA** yields the channel allocation

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subproblem to determine $\mathbf{i}(t)$:

$$(\mathbf{CA})\ \min_{\mathbf{i}(t)} \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} O^k_{n,m}(t)$$
$$\text{s.t.}\quad (1),(2),$$

where $O^k_{n,m}(t) = (\Pi_n - E_n(t))p^{k,*}_{n,m}(t) - Q_{n,m}(t)\phi^{k,*}_{n,m}(t)$ denotes the weight of the allocation of RUs and channels to users, and $\phi^{k,*}_{n,m}(t)$ denotes the channel capacity under optimal transmission power. **CA** can be considered as a 3-dimensional matching which is a well-known NP-hard problem. In Lemma 2, we prove that **CA** is equivalent to a bipartite matching.

Lemma 2. *Supposing $\mathbf{i}^*(t)$ to be the optimal solution for **CA**, if RU n^* is the optimal RU to transmit data to user m over channel k, i.e., $i^{k,*}_{n,m} = 1$, then we have:*

$$n^* = \arg\min_{n\in\mathcal{N}} O^k_{n,m}(t), \forall m \in \mathcal{M}, k \in \mathcal{K}. \tag{26}$$

The proof of Lemma 2 is provided in Appendix C. Based on Lemma 2, we can replace $O^k_{n,m}$ in the objective function of **CA** to the weight of allocating channels to users served by the optimal RUs

$$\tilde{O}^k_m(t) = \min_{n\in\mathcal{N}} O^k_{n,m}(t), \forall m \in \mathcal{M}, k \in \mathcal{K}. \tag{27}$$

After finding the optimal RU, we modify the **CA** to a refined channel allocation (**r-CA**) problem which allocates channels to users. To this end, we reduce the 3-dimensional matrix $\mathbf{i}(t)$ to a 2-dimensional matrix $\tilde{\mathbf{i}}(t)$ with element $\tilde{i}^k_m(t)$ to indicate the allocation of channels to users. $\tilde{i}^k_m(t)$ equals one if channel i is allocated to user m in time slot t and 0 otherwise. We formulate **r-CA** under constraints (1) and (2) as follows:

$$(\mathbf{r\text{-}CA})\min_{\mathbf{i}(t)} \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} \tilde{O}^k_m(t)$$
$$\text{s.t.}\quad (1),(2).$$

As we can see from the structure of **r-CA**, it is a bipartite one-to-one matching problem that can be optimally solved by the Hungarian algorithm [29].

C. Net Gain-optimal Resource Allocation Algorithm

In this section, we propose a net gain-optimal resource allocation algorithm (GRA) based on the resource allocation framework provided in Section IV-B. The GRA algorithm solves the **HES**, **DR**, and **PCA** subproblems sequentially, then updates the data queues and energy queues lengths for resource allocation in the next time slot.

The computational complexity of the GRA algorithm is discussed as follows. Since the closed-form solution of **HEM** are provided in Eqns. (23) and (24), and **DR** is a convex problem, the complexities of solving these two subproblems are negligible. As a result, the computational complexity of the GRA algorithm mainly depends on the mixed-integer programming **PCA**. The complexity of the Hungarian algorithm for **r-CA** is $\mathcal{O}(MK^2 + M\log M)$ [29]. Combining with solving the optimal transmission power $p^{k,*}_{n,m}$ and the optimal RU n^*, the complexity of **PCA** is

$$\begin{aligned}&\mathcal{O}(NMK + MK + MK^2 + M\log M)\\ &= \mathcal{O}(NMK + MK^2 + M\log M),\end{aligned} \tag{28}$$

where $\mathcal{O}(NMK)$ and $\mathcal{O}(MK)$ are the complexity to obtain $p^{k,*}_{n,m}$ and n^*, respectively. Solving of $p^{k,*}_{n,m}$ in Eqn. (25) only requires the local information at each RU. Therefore, the RUs can compute $p^{k,*}_{n,m}$ in a parallel manner, and then fuse the solutions to the CU. It enables us to further reduce the complexity of **PCA** to $\mathcal{O}(MK^2 + M\log M)$ that is irrelevant to the number of RUs N. Therefore, the proposed algorithm is efficient for the a desified HES-CRSN with a large number of RUs. Notably, the solution of GRA algorithm requires the central unit with global network information, including channel conditions, harvested energy of RUs, etc. It is suitable for HES-CRANs with central units to make efficient decisions while adapting to the system dynamics.

Algorithm 1: Net Gain-optimal Resource Allocation Algorithm

Data: $\boldsymbol{Q}(t), \boldsymbol{E}(t)$, $\psi_n(t), \forall n \in \mathcal{N}$,
$\phi^k_{n,m}(t), \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}$.
Result: $\boldsymbol{e}^*(t)$, $\boldsymbol{g}^*(t)$, $\mathbf{d}^*(t)$, $\mathbf{i}^*(t)$, $\mathbf{Q}(t+1)$, $\boldsymbol{E}(t+1)$.
`/* Hybrid Energy Management (HEM) */`
foreach $n \in \mathcal{N}$ **do**
  $e^*_n(t) = \min(\Omega_n - E_n(t), \zeta_n(t))$;
  Compute $g^*_n(t)$ based on Eqn.(24);
`/* Data Requesting (DR) */`
Solve **DR** problem and set $\mathbf{d}^*(t)$;
`/* Power and Channel Allocation (PCA) */`
foreach $n \in \mathcal{N}$, $m \in \mathcal{M}$, $k \in \mathcal{K}$ **do**
  Set $p^{k,*}_{n,m}(t)$ by solving Eqn. (25);
Set $\tilde{\mathbf{i}}^*(t)$ by solving the **r-CA** problem;
foreach $k \in \mathcal{K}$ **do**
  if $\tilde{i}^{k,*}_m(t) == 1, \forall m \in \mathcal{M}$ **then**
    $n^* = \arg\min_{n\in\mathcal{N}} O^k_{n,m}(t)$;
    $i^{k,*}_{n^*,m} = 1$;
`/* Queues Updating */`
foreach $n \in \mathcal{N}$ *and* $m \in \mathcal{M}$ **do**
  Compute $Q_{n,m}(t+1)$ based on (12);
foreach $n \in \mathcal{N}$ **do**
  Compute $E_n(t+1)$ based on (6);

V. Performance Analysis

In this section, we further analyze the network stability and the optimality of the proposed algorithm. First, we derive the upper bound on the data queue in Proposition 1, and thereby guarantees the network stability. Then, the required battery capacity to support the sustainable network operation is provided in Proposition 2, such that the RUs can only transmit data to users if they have sufficient energy. At last, we analyze the performance gap between the net gain achieved by the GRA algorithm and that achieved by the optimal solution.

A. Upper Bounds on Data queues

Proposition 1 shows the upper bound on the data queues. Since all data queues are finite in the HES-CRAN, the network

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stability constraint (13) can be satisfied.

Proposition 1. *Suppose that $V > 0$ and all the data queues are initialized as $Q_{n,m}(t) = 0, \forall n \in \mathcal{N}, m \in \mathcal{M}$, the following inequality holds over the operation time:*

$$0 \leq Q_{n,m}(t) \leq Q_{max}, 0 \leq t \leq T, \tag{29}$$

where $Q_{max} = V\varrho_U + A_m$ denotes the upper bounds of data queues.

The proof of Proposition 1 is provided in Appendix D. Proposition 1 demonstrates the necessary data buffer of RUs to be MQ_{max}, such that the RUs can accommodate the data queues for M users. Notably, the value of Q_{max} linearly increases with parameter V. Recalling that a larger V can bring higher net gain, Eqn. (29) implies that higher gain can be achieved at the cost of a larger data buffer.

B. Battery Capacity

Considering the sustainable operation of the HES-CRAN, we need to guarantee that the energy consumption of each RU should be upper bounded by its energy queue length, i.e., the energy availability constraint (7). Note that RUs tend to have more available energy to serve users with a larger battery capacity [25]. With a sufficiently large battery capacity, the RU can only serve users if its available energy is larger than the maximum energy consumption of an RU in one time slot, i.e., $E_n(t) \geq P_{max}$. Therefore, the energy availability constraint (7) can be satisfied. In Proposition 2, we analyze the required battery capacity to achieve this goal.

Proposition 2. *Suppose that the battery capacity of RU n satisfies:*

$$\Pi_n = WQ_{max}\eta_{max}/\ln 2 + P_{max}, \tag{30}$$

if the available energy of RU n is less than the maximum energy consumption, i.e., $E_n(t) < P_{max}$, then the optimal transmission power from RU n to users must be zero, i.e., $p_{n,m}^{k,*} = 0, m \in \mathcal{M}$. Therefore, RU n can have $p_{n,m}^{k,*} > 0, \forall m \in \mathcal{M}$ if and only if $E_n(t) \geq P_{max}$, which makes the energy availability constraint (7) redundant.

The proof of Proposition 2 can be found in Appendix E. Substituting the upper bounds on data queues, i.e., Eqn. (29), into Eqn. (30), we can see that the battery capacity linearly increases with the value of V. It implies that achieving higher gain also requires RUs to equip with a larger battery capacity, in addition to a larger data buffer.

C. Performance Guarantee of the GRA Algorithm

In Theorem 2, we show the gap between the net gain achieved by the GRA algorithm and that by the optimal solution.

Theorem 2. *Denote $\bar{\mathcal{U}}$ and $\mathcal{U}^*$ to be the net gain achieved by the GRA algorithm and that by the optimal solution, respectively. Suppose that the EH process $\boldsymbol{\phi}(t)$, the channel condition $\mathbf{h}(t)$ and the on-grid energy price $\boldsymbol{\alpha}(t)$ are identical and independent distributed (i.i.d.) across the time slots. Then we have the following inequality:*

$$\bar{\mathcal{U}} \geq \mathcal{U}^* - B/V, \tag{31}$$

where B is given by Eqn. (21).

The proof of Theorem 2 is provided in Appendix F. As we can see from Eqn. (21), the value of B is irrelevant to that of V. Therefore, Eqn. (31) shows that the achieved net gain asymptotically approaches the optimal gain with increasing V. Furthermore, the increasing rate of the net gain decreases as V increases. It implies that the HES-CRAN can fully utilize the harvested and purchased energy for net gain maximization with a sufficiently large V. In this case, the HES-CRAN needs extra supply of harvested energy or less expensive on-grid energy to achieve a higher net gain.

Although Theorem 2 assumes that $\boldsymbol{\phi}(t)$, $\mathbf{h}(t)$, and $\boldsymbol{\alpha}(t)$ evolve in an i.i.d. manner over time slots, the conclusions in the theorem also hold in more general cases where the above-mentioned processes evolve according to some finite-state irreducible and aperiodic Markov process [25]. The performance guarantee can be obtained by the so-called delayed Lyapunov drift method, as shown in Theorem 2 of [30].

VI. Simulation Results

In this section, we conduct simulations to evaluate the performance of GRA algorithm in an HES-CRAN. The simulated HES-CRAN consists of a CU and $N = 10$ RUs that are randomly distributed in a circle area with a radius of 100 m [14]. The RUs provide downlink data transmission service to $M = 25$ users. The HES-CRAN operates over a 100 MHz spectrum that is equally divided into 32 channels. The spectral noise power on each channel is $N_0 = 10^{-10}$ W/Hz [20] and the peak transmission power is $P_T = 40$ W [18]. The channel gain $h_{n,m}^k(t)$ is uniformly distributed over [5, 14] and varies across time slots in an i.i.d. manner [18]. The channel capacity is upper bounded by $\phi_{max} = 20$ Mbps. The fronthaul link capacity is $F_n = 32$ Mbps$, \forall n \in \mathcal{N}$ [31], and the available data is $A_m = 20$ Mbps$, \forall m \in \mathcal{M}$. Similar to [20], we adopt the gain function to be a logarithm function of the amount of downlink data, i.e., $U(\sum_{n\in\mathcal{N}} d_{n,m}(t)) = \log(1+\sum_{n\in\mathcal{N}} d_{n,m}(t))$, to ensure the fairness between users. The length of each time slot is 1 min, and the total operating time is $T = 5000$ min.

Regarding the parameters related to the harvested energy and the purchased energy, the following settings are used. The normalization factor associated with purchased on-grid energy is set to $\beta = \frac{1}{32}$ [20]. The price of on-grid energy randomly changes across time slots according to a folded normal distribution $\mathcal{N}(3, 3)$ [32]. The upper bound of on-grid energy is $g_{max} = 100$ J. Furthermore, the harvested energy $\psi_n, \forall n \in \mathcal{N}$ uniformly distributes between [0, 90] J [21].

Fig. 2 shows the net gain with the increasing V. Since a larger V means that the GRA algorithm emphasizes more on net gain maximization, the net gain monotonically increases with the value of V. However, the increasing rate decreases with a higher V. Recalling that a higher V requires a RU to be equipped with a larger data buffer and energy buffer,

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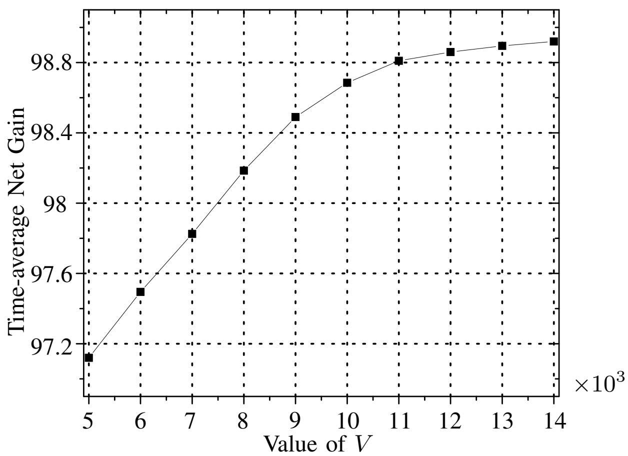

Fig. 2. Time-average net gain versus V.

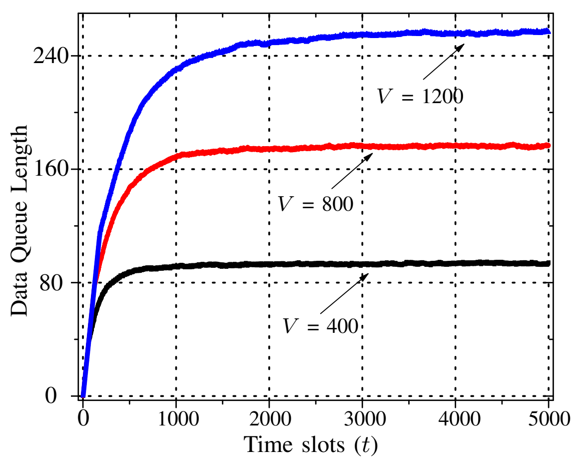

Fig. 3. Data queue dynamics with different values of V.

the decreasing of the increasing rate implies that the benefits brought by larger data and energy buffers diminish as V increases. In this case, the HES-CRAN needs more harvested energy or low-cost on-grid energy to boost the net gain. Notably, this is consistent with the Eqn. (31) in Theorem 2, which shows that the net gain achieved by the GRA algorithm is a concave function of V.

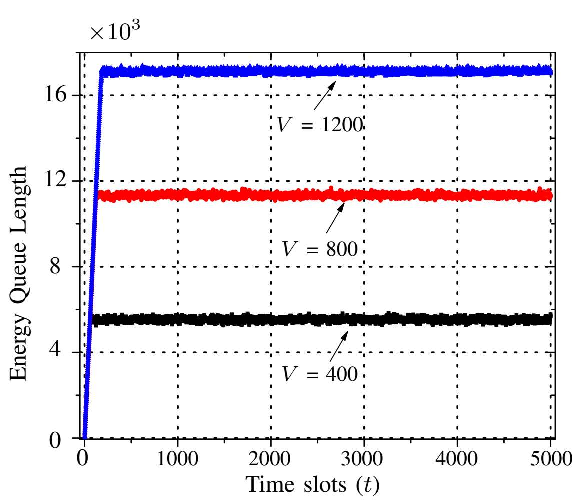

Fig. 4. Energy queue dynamics with different values of V.

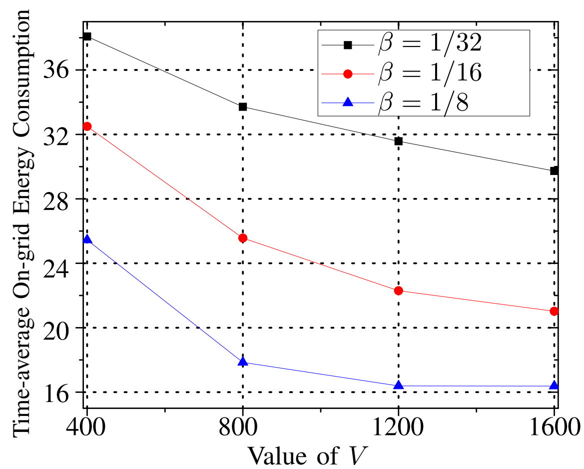

Fig. 5. Time-average on-grid energy consumption versus value of V.

Fig. 3 shows the data queue dynamics across the operation time under different values of V. Since the RUs tend to request user data from the CU to maximize the net gain and do not have enough energy for data transmissions in the startup phase, the data queue length increases at the beginning of the operation, as we can see from the figure. After the startup phase, the data queue converges and fluctuates around a time-average value, which implies the balance between data requesting and transmission. Furthermore, the time-average value increases linearly with the value of V, which is consistent with Proposition 1.

Similar to the dynamics of data queue, the energy queue increases at the startup phase and then fluctuates around a time-average value, as shown in Fig. 4. It indicates that the RUs tend to charge their batteries, rather than transmit data at the startup phase. When the battery is charged to a certain level, the RUs start data transmission to balance the energy charging and discharging, and thus the fluctuation appears around the time-average value. Notably, the time-average value also increases linearly with the value of V, which indicates the necessity to equip a larger battery capacity to an HES-CRAN with a higher V.

Fig. 5 shows the time-average on-grid energy consumption versus different values of V. Since the cost on on-grid energy becomes dominant in the **UUM** problem as V increases, the on-grid energy consumption decreases. However, the decreasing rate decreases when V becomes larger. This is because the RUs can transmit more data to achieve a higher user gain by purchasing on-grid energy. Furthermore, since a smaller normalization factor β represents a higher efficiency of achieving user gain by consuming on-grid energy, the on-grid energy consumption increases with decreasing β.

A. Performance Comparison

To better investigate the performance of the GRA algorithm, we compare the GRA algorithm with a baseline algorithm, which makes greedy decisions to maximize the net gain [33]. In each time slot, the greedy algorithm schedules the data requesting to maximize the net gain given in Eqn. (14),

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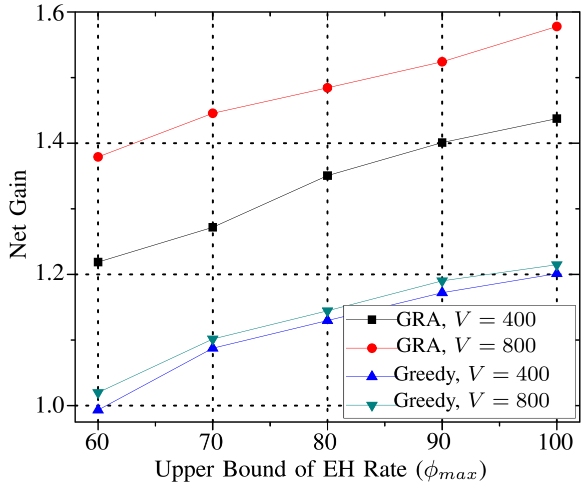

Fig. 6. Comparison of net gain between the greedy algorithm and the GRA algorithm.

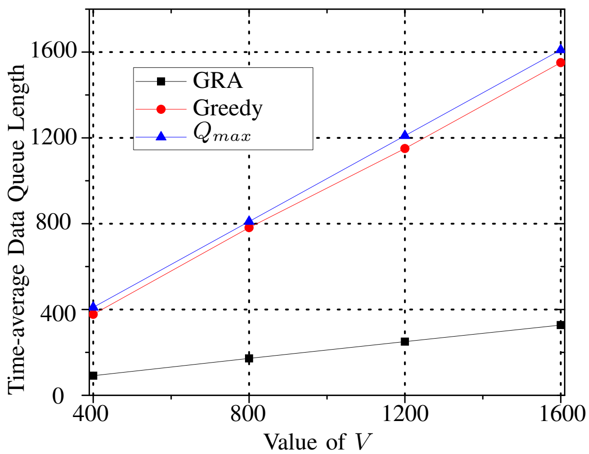

Fig. 7. Comparison of time-average data queue length between the greedy algorithm and the GRA algorithm.

subject to the fronthaul capacity, the user data availability, and the data buffer length. Considering the channel and power allocation, the greedy algorithm first arranges the data queues in a descending order with respect to their lengthes. Secondly, it assigns the channel with the best condition to the longest data queue for data transmission using the availably maximum power (bounded by P_T) in the RU. At last, the data queue is removed from the arrangement. The channel and power allocation continues until all the channels are assigned.

We first compares the net gain achieved by the GRA algorithm and the greedy algorithm versus the maximum EH rate ranging from 60 W to 100 W in Fig. 6. Although the greedy algorithm may request more data to maximize the objective function in Eqn. (14), it does not take the balance between the queue lengthes and the gain maximization into consideration. Therefore, it has relatively lower net gain as compared with the GRA algorithm. Besides, in comparison with the GRA algorithm, the greedy algorithm only achieve slightly higher net gain as V increases from 400 to 800, which implies that the greedy algorithm cannot fully exploit the benefits brought by a larger data buffer and higher battery capacity.

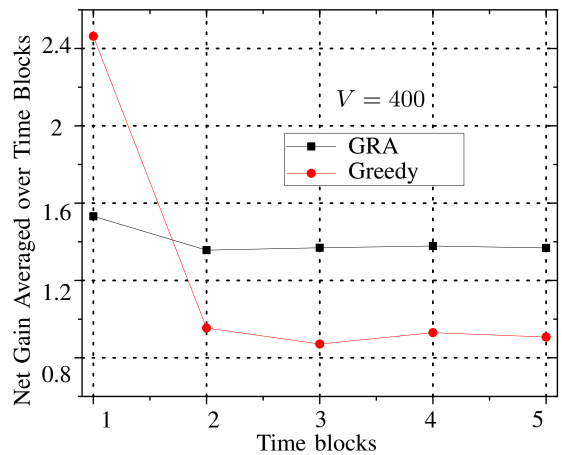

Fig. 8. Algorithm performance comparison of the net gain in different time block.

Fig. 7 compares the time-average data queue length of the two algorithms, taking the data buffer size Q_{max} as a benchmark. The results show that the time-average data queue length of the greedy algorithm is close to the data buffer size, which is much larger than that of the GRA algorithm. Since the time-average queue length is proportional to the queueing delay according to Little's law, the results in Fig. 7 indicate that the GRA algorithm outperforms the greedy algorithm in terms of the delay performance.

In the following, we divide the network operation time into 5 time blocks, each of which is 1000 min long. In Fig. 8, we compare the GRA algorithm and the greedy algorithm in terms of the net gain averaged over each time block, which implies the variation of the net gain achieved by the two algorithms over the operation time. The net gain of the greedy algorithm is shown to be high in the first time block, then decreases drastically to a stable value in the following time blocks. The reason is that the greedy algorithm motivates the RUs to request as much as data to maximize the objective function in Eqn. (14) at the beginning of the operation. However, the channel allocation and power control in the greedy algorithm cannot efficiently schedule the data transmission of RUs to vacate the capacity of data buffers. In comparison, although the GRA algorithm achieves a relatively lower net gain in the first time block, the achieved net gain of the GRA algorithm in the stable state exceeds that of the greedy algorithm.

VII. Conclusion

In this paper, we have formulated a net gain optimization problem to allocate the resources of an HES-CRAN, considering the stochastic nature of EH process, on-grid energy price, and wireless channel conditions. By applying the Lyapunov optimization approach, we have designed a resource allocation framework which decomposes the stochastic problem into three subproblems, i.e., the hybrid energy management, the data requesting, and the channel and power allocation. The solutions of the subproblems constitute an online and scalable net gain-optimal resource allocation (GRA) algorithm. Furthermore, we have derived the required data buffer and battery capacity, and the optimality gap between the GRA algorithm

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and the optimal solution, which provide useful insights into the design and deployment of practical HES-CRANs. Extensive simulations have been conducted to validate the superior performance of the GRA algorithm.

For the future work, the interference management and delay-sensitive service provisioning in HES-CRANs will be investigated where channels can be allocated to multiple users for downlink transmissions. The co-design of the computation and communication in HES-CRANs is another interesting problem, which considers the energy consumed by both the computation at the CU and the data transmissions at the RUs.

Appendix A
Proof of Theorem 1

Based on $([Q-b]^{+}+a)^2 \leq a^2+b^2+2Q(a-b)$, we can obtain Eqns. (32) and (33) by sparing the both sides of Eqns. (12) and (6), respectively. Rearranging the terms of the obtained results yields Eqn. (20).

$$\begin{aligned}
&(Q_{n,m}(t+1))^2-(Q_{n,m}(t))^2\\
\leq&\left(\sum_{k\in\mathcal{K}} i^k_{n,m}(t)\phi^k_{n,m}(t)\right)^2+d_{n,m}(t)^2\\
&+2Q_{n,m}\left(d_{n,m}(t)-\sum_{k\in\mathcal{K}} i^k_{n,m}(t)\phi^k_{n,m}(t)\right)\\
\leq&(d_{max})^2+(\phi_{max})^2+2Q_{n,m}\left(d_{n,m}(t)-\sum_{k\in\mathcal{K}} i^k_{n,m}(t)\phi^k_{n,m}(t)\right).
\end{aligned}\tag{32}$$

$$\begin{aligned}
&(E_n(t+1)-\Pi_n)^2-(E_n(t)-\Pi_n)^2\\
\leq&(e_n(t)+g_n(t))^2+\left(\sum_{k\in\mathcal{K}} i^k_{n,m}(t)p^k_{n,m}(t)\right)^2\\
&+2(E_n(t)-\Pi_n)\left(e_n(t)+g_n(t)-\sum_{k\in\mathcal{K}} i^k_{n,m}(t)p^k_{n,m}(t)\right)\\
\leq&(\psi_{max}+g_{max})^2+(P_{max})^2\\
&+2(E_n(t)-\Pi_n)\left(e_n(t)+g_n(t)-\sum_{k\in\mathcal{K}} i^k_{n,m}(t)p^k_{n,m}(t)\right).
\end{aligned}\tag{33}$$

Appendix B
Proof of Lemma 1

We first show that Eqn. (25) is the optimal transmission if RU n serves user m over channel k. It can be proved that Eqn. (25) is the optimal solution for the power allocation subproblem:

$$\textbf{(PA)}\ \min_{p^k_{n,m}(t)} (\Pi_n-E_n(t))p^k_{n,m}(t)-Q_{n,m}(t)\phi^k_{n,m}(t)$$
$$\text{s.t.}\quad (5).$$

As shown in Eqn. (11), the channel capacity $\phi^k_{n,m}(t)$ is concave w.r.t. $p^k_{n,m}(t)$, which makes **PA** a convex problem. By taking the first order derivative of the objective function and setting the derivative to zero, we can obtain Eqn. (25).

If the optimal channel allocation $i^k_{n,m}=1$ and Eqn. (25) does not hold, the achieved value of the objective function of **PCA** must be larger than the one achieved by Eqn. (25). Therefore, we can prove Lemma 1.

Appendix C
Proof of Lemma 2

Lemma 2 can be proved by contradiction. If $i^k_{n^*,m}=1$ is the optimal solution to **CA** and Eq. (26) does not hold, then there exists another RU $\tilde{n}$ and $O^k_{\tilde{n},m}(t)<O^k_{n^*,m}(t)$. If we change n^* to $\tilde{n}$, i.e., set $i^k_{\tilde{n},m}=1$, the objective function of **CA** problem can be further decreased. This contradicts that $i^k_{n^*,m}=1$ is the optimal solution to **CA** problem. Therefore, Lemma 2 is proved.

Appendix D
Proof of Proposition 1

The proof of the upper bound on data queues proceeds by inductions. Since the data queue length is initially empty $Q_{n,m}(0)=0$, it can be seen that Eqn. (29) holds in time slot 0. In the following, we prove that if Eqn. (29) holds in time slot t, then it holds in time slot $t+1$.

If $Q_{n,m}(t)\leq V\varrho_U$, then it is easy to see that $Q_{n,m}(t)\leq V\varrho_U+A_m$ according to the data availability constraint (10).

Suppose $Q_{n,m}(t)>V\varrho_U$, we prove Eqn. (29) by showing that the objective function of the **DR** problem monotonically increases with $d_{n,m}(t)$. Therefore, the $d^*_{n,m}(t)=0$ is the optimal solution for the **DR** problem. Taking derivative of the objective function in the **DR** problem w.r.t. $d_{n,m}(t)$ yields $Q_{n,m}(t)-V\mathcal{U}'(\sum_{n\in\mathcal{N}} d_{n,m}(t))$. Recalling that ϱ_U denotes the upper bound of the first derivative of the utility, it can be proved that the derivative of the objective function is larger than 0. Therefore, minimizing the objective function yields $d^*_{n,m}(t)=0$, which proves Eqn. (29).

Appendix E
Proof of Proposition 2

Based on Eqn. (25), the optimal transmission power takes a value of zero if the following inequality holds

$$\frac{WQ_{n,m}(t)}{\ln 2\cdot(\Pi_n-E_n(t))}-\frac{1}{\eta^k_{n,m}(t)}<0\tag{34}$$

Resorting Eqn. (34) yields

$$\Pi_n>WQ_{n,m}(t)\eta^k_{n,m}(t)/\ln 2+E_n(t).\tag{35}$$

To guarantee that the RU does not serve any user when $E_n(t)\leq P_{max}$, we can set the battery capacity to

$$\Pi_n=WQ_{max}\eta_{max}/\ln 2+P_{max},$$

such that Eqn. (35) must hold if the available energy does not exceed the maximum power consumption of an RU in each time slot. This concludes the proof of Proposition 2.

Appendix F
Proof of Theorem 2

This theorem can be proved by comparing the drift-minus-gain in Eqn. (19) obtained by the proposed algorithm and a stationary randomized algorithm denoted by π. $\mathbf{d}^\pi(t)$, $\mathbf{i}^\pi(t)$, $\mathbf{p}^\pi(t)$, $\boldsymbol{g}^\pi(t)$, $\boldsymbol{e}^\pi(t)$ represent the variables optimized by algorithm π. Supposing the channel gain, on-grid energy price, and EH process change in an i.i.d. manner across the time slots, such a algorithm π exists to satisfy the following inequalities according to Theorem 4.5 in [34] :

$$\mathbb{E}\left[\sum_{m\in\mathcal{M}} U\left(\sum_{n\in\mathcal{N}} d^{\pi}_{n,m}(t)\right) - \beta \sum_{n\in\mathcal{N}} \alpha(t) g^{\pi}_{n}(t)\right] \leq \mathcal{U}^{*} + \sigma,$$

$$\mathbb{E}\left[\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}\left(d^{\pi}_{n,m}(t) - \sum_{k\in\mathcal{K}} i^{k,\pi}_{n,m}(t)\phi^{k,\pi}_{n,m}(t)\right)\right] \leq \gamma_1\sigma,$$

$$\mathbb{E}\left[\sum_{n\in\mathcal{N}}\left(g^{\pi}_{n}(t) + e^{\pi}_{n}(t) - \sum_{k\in\mathcal{K}} i^{k,\pi}_{n,m}(t)p^{k,\pi}_{n,m}(t)\right)\right] \leq \gamma_2\sigma,$$

where σ is a arbitrarily small parameter, and γ_1 and γ_2 are positive scalars.

In each time slot, the proposed GRA algorithm minimizes the right hand side (RHS) of Eqn. (20). Therefore, the RHS of Eqn. (20) achieved by the GRA algorithm is less than any other algorithm, including algorithm π, which yields the following inequality

$$\begin{aligned}\Delta(t) - V\mathbb{E}\left[\mathcal{U}(t)\right] \leq & B + \mathbb{E}\left[\Theta^{GRA}_{V}(t)|\boldsymbol{\Omega}(t)\right]\\ \leq & B + \mathbb{E}[\Theta^{\pi}_{V}(t)]\\ \leq & B + (\gamma_1+\gamma_2+1)\sigma - V\mathcal{U}^{*},\end{aligned} \tag{36}$$

where Θ^{GRA}_{V} and Θ^{π}_{V} denote the value of Θ_V achieved by the GRA algorithm and algorithm π, respectively. By letting σ be zero, we have

$$\Delta(t) - V\mathbb{E}\left[\mathcal{U}(t)\right] \leq B - V\mathcal{U}^{*}. \tag{37}$$

We sum the both sides of Eqn. (37) over time slots $t \in (0, 1, \cdots, T-1)$ and divide them by T to obtain

$$\frac{L(T-1) - L(0)}{T} - \frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left[\mathcal{U}(t)\right] \leq B - V\mathcal{U}^{*} \tag{38}$$

Letting $T \to \infty$ and using the fact that both $L(T-1)$ and $L(0)$ are finite, we have $\bar{\mathcal{U}} \geq \mathcal{U}^{*} - B/V$ to conclude the proof.

ACKNOWLEDGEMENT

This research work is supported by National Natural Science Foundation of China (61702561, 61702562, 61379057), NSF ECCS-1554576, the Innovation-Driven Project of Central South University (No. 2016CXS013), International Science and Technology Cooperation Program of China (No. 2013DFB10070), China Hunan Provincial Science and Technology Program (No. 2012GK4106), and Research Project of the State Key Laboratory of Industrial Control Technology, Zhejiang University ,China (No.ICT170318).

REFERENCES

[1] D. Zhang, Z. Chen, L. X. Cai, H. Zhou, J. Ren, and X. Shen, "Resource allocation for green cloud radio access networks powered by renewable energy," in *IEEE Global Communications Conference (GLOBECOM)*, 2016, pp. 1–6.

[2] C. V. N. I. Cisco, "Global mobile data traffic forecast update, 2015–2020," *white paper*, 2016.

[3] A. Checko, H. L. Christiansen, Y. Yan, L. Scolari, G. Kardaras, M. S. Berger, and L. Dittmann, "Cloud ran for mobile networksa technology overview," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 405–426, 2015.

[4] J. Liu, H. Guo, Z. M. Fadlullah, and N. Kato, "Energy consumption minimization for FiWi Enhanced LTE-A HetNets with UE connection constraint," *IEEE Commun. Mag.*, vol. 54, no. 11, pp. 56–62, 2016.

[5] L. X. Cai, H. V. Poor, Y. Liu, T. H. Luan, X. Shen, and J. W. Mark, "Dimensioning network deployment and resource management in green mesh networks," *IEEE Wireless Commun.*, vol. 18, no. 5, pp. 58–65, 2011.

[6] D. Zhang, Z. Chen, J. Ren, N. Zhang, M. K. Awad, H. Zhou, and X. S. Shen, "Energy-harvesting-aided spectrum sensing and data transmission in heterogeneous cognitive radio sensor network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 831–843, 2017.

[7] J. Ren, Y. Zhang, R. Deng, N. Zhang, D. Zhang, and X. Shen, "Joint channel access and sampling rate control in energy harvesting cognitive radio sensor networks," *IEEE Trans. Emerg. Topics Comput.*, to appear, DOI :10.1109/TETC.2016.2555806.

[8] K. Suto, H. Nishiyama, and N. Kato, "Post-disaster user location maneuvering method for improving the qoe guaranteed service time in energy harvesting small cell networks," *IEEE Trans. Veh. Technol.*, to appear, DOI: 10.1109/TVT.2017.2702750.

[9] G. Piro, M. Miozzo, G. Forte, N. Baldo, L. A. Grieco, G. Boggia, and P. Dini, "Hetnets powered by renewable energy sources: Sustainable next-generation cellular networks," *IEEE Internet Comput.*, vol. 17, no. 1, pp. 32–39, 2013.

[10] D. Niyato, E. Hossain, and A. Fallahi, "Sleep and wakeup strategies in solar-powered wireless sensor/mesh networks: Performance analysis and optimization," *IEEE Trans. Mobile Comput.*, vol. 6, no. 2, pp. 221–236, 2007.

[11] L. X. Cai, Y. Liu, T. H. Luan, X. S. Shen, J. W. Mark, and H. V. Poor, "Sustainability analysis and resource management for wireless mesh networks with renewable energy supplies," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 2, pp. 345–355, 2014.

[12] B. Dai and W. Yu, "Energy efficiency of downlink transmission strategies for cloud radio access networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 1037–1050, 2016.

[13] M. Peng, K. Zhang, J. Jiang, J. Wang, and W. Wang, "Energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 11, pp. 5275–5287, 2015.

[14] J. Li, J. Wu, M. Peng, and P. Zhang, "Queue-aware energy-efficient joint remote radio head activation and beamforming in cloud radio access networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 6, pp. 3880 – 3894, 2016.

[15] J. Li, M. Peng, Y. Yu, and Z. Ding, "Energy-efficient joint congestion control and resource optimization in heterogeneous cloud radio access networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9873–9887, 2016.

[16] J. Zuo, J. Zhang, C. Yuen, W. Jiang, and W. Luo, "Energy efficient user association for cloud radio access networks," *IEEE Access*, vol. 4, pp. 2429–2438, 2016.

[17] Y. Mao, J. Zhang, and K. B. Letaief, "A lyapunov optimization approach for green cellular networks with hybrid energy supplies," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2463–2477, 2015.

[18] D. Zhai, M. Sheng, X. Wang, and Y. Li, "Leakage-aware dynamic resource allocation in hybrid energy powered cellular networks," *IEEE Trans. Commun.*, vol. 63, no. 11, pp. 4591–4603, 2015.

[19] J. Yang, Q. Yang, Z. Shen, and K. S. Kwak, "Suboptimal online resource allocation in hybrid energy supplied ofdma cellular networks," *IEEE Commun. Lett.*, vol. 20, no. 8, pp. 1639–1642, 2016.

[20] B. Yang, Y. Shen, Q. Han, C. Chen, X. Guan, and W. Zhang, "Energy-efficient resource allocation for time-varying OFDMA relay systems with hybrid energy supplies," *IEEE Syst. J.*, to appear, DOI: 10.1109/JSYST.2016.2551319.

[21] M. Sheng, D. Zhai, X. Wang, Y. Li, Y. Shi, and J. Li, "Intelligent energy and traffic coordination for green cellular networks with hybrid energy supplies," *IEEE Trans. Veh. Technol.*, to appear, DOI: 10.1109/TVT.2016.2554618.

[22] V. Chamola, B. Sikdar, and B. Krishnamachari, "Delay aware resource management for grid energy savings in green cellular base stations with hybrid power supplies," *IEEE Trans. Commun.*, to appear, DOI: 10.1109/TCOMM.2016.2629502.

[23] Q. Ye and W. Zhuang, "Token-based adaptive mac for a two-hop internet-of-things enabled manet," *IEEE Internet Things J.*, to appear, DOI: 10.1109/JIOT.2017.2679119.

[24] J. Ren, Y. Zhang, N. Zhang, D. Zhang, and X. Shen, "Dynamic channel access to improve energy efficiency in cognitive radio sensor networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, pp. 3143–3156, May 2016.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2017.2754273, IEEE Transactions on Vehicular Technology

[25] L. Huang and M. Neely, "Utility optimal scheduling in energy-harvesting networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1117–1130, 2013.

[26] Y. Guo, M. Pan, Y. Fang, and P. P. Khargonekar, "Decentralized coordination of energy utilization for residential households in the smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1341–1350, 2013.

[27] D. Zhang, Z. Chen, M. K. Awad, N. Zhang, H. Zhou, and X. S. Shen, "Utility-optimal resource management and allocation algorithm for energy harvesting cognitive radio sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3552–3565, 2016.

[28] S. Boyd and L. Vandenberghe, "Convex optimization," *Cambridge university press*, 2004.

[29] H. W. Kuhn, "The hungarian method for the assignment problem," *Naval research logistics quarterly*, vol. 2, pp. 83–97, 1955.

[30] R. Urgaonkar and M. Neely, "Opportunistic scheduling with reliability guarantees in cognitive radio networks," *IEEE Trans. Mobile Comput.*, vol. 8, no. 6, pp. 766–777, 2009.

[31] Y. Jeon, S. H. Park, C. Song, J. Moon, S. Maeng, and I. Lee, "Joint designs of fronthaul compression and precoding for full-duplex cloud radio access networks," *IEEE Wireless Commun. Lett.*, vol. 5, no. 6, pp. 632–635, 2016.

[32] X. Wang, Y. Zhang, T. Chen, and G. B. Giannakis, "Dynamic energy management for smart-grid-powered coordinated multipoint systems," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1348–1359, 2016.

[33] W. Fang, X. Yao, X. Zhao, J. Yin, and N. Xiong, "A stochastic control approach to maximize profit on service provisioning for mobile cloudlet platforms," *IEEE Trans. Syst., Man, Cybern., Syst.*, to appear, DOI: 10.1109/TSMC.2016.2606400.

[34] M. J. Neely, "Stochastic network optimization with application to communication and queueing systems," *Morgan & Claypool Publishers*, 2010.