IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 15, 2016, accepted November 9, 2016, date of publication December 8, 2016, date of current version February 25, 2017.

Digital Object Identifier 10.1109/ACCESS.2016.2635878

Joint Deployment and Mobility Management of Energy Harvesting Small Cells in Heterogeneous Networks

GUANHUA QIAO, (Student Member, IEEE), SUPENG LENG, (Member, IEEE), KE ZHANG, AND KUN YANG, (Senior Member, IEEE)
School of Communication and Information Engineering University of Electronic Science and Technology of China, Chengdu 611731, China

Corresponding author: S. Leng (spleng@uestc.edu.cn)

This work was supported in part by the National S&T Major Project of China under Grant 2014ZX03004-003, in part by the Fundamental Research Funds for the Central Universities, China, and in part by the EU FP7 Project CLIMBER under Grant PIRSES-GA-2012-318939.

ABSTRACT Small heterogeneous cells have been introduced to improve the system capacity and provide the ubiquitous service requirements. In order to make flexible deployment and management of massive small cells, the utilization of self-powered small cell base stations with energy harvesting (EH-SCBSs) is becoming a promising solution due to low-cost expenditure. However, the deployment of static EH-SCBSs entails several intractable challenges in terms of the randomness of renewable energy arrival and dynamics of traffic load with spatio-temporal fluctuation. To tackle these challenges, we develop a tractable framework of the location deployment and mobility management of EH-SCBSs with various traffic load distributions an environmental energy models. In this paper, the joint optimization problem for location deployment and mobile management is investigated for maximizing the total system utility of both users and network operators. Since the formulated problem is a NP-hard problem, we propose a low-complex algorithm that decouples the joint optimization into the location updating approach and the association matching approach. A suboptimal solution for the optimization problem can be guaranteed using the iteration of two stage approaches. Performance evaluation shows that the proposed schemes can efficiently solve the target problems while striking a better overall system utility, compared with other traditional deployment and management strategies.

INDEX TERMS Small heterogeneous networks, energy harvesting, small cell deployment, mobility management, matching theory.

I. INTRODUCTION

In the near future, in order to cope with exponential growth of the demands for mobile data and ubiquitous anywhere-anytime service, small heterogenous cells as one of important enablers are widely deployed by network operators towards the fifth generation (5G) mobile cellular networks. Unlike the traditional macro-base stations (MBSs) with large power consumption and high deployment expenditure, small cell base stations (SCBSs), including picocells, microcells, femtocells and metrocells, cover small areas and hence require low transmission powers. The significant low cost makes the deployment of ultra-dense networks (UDNs) as a feasible way to improve the network coverage and user experience [1], [2]. However, despite the low power consumption of a single SCBS, the daily energy cost of UDNs has been a large portion of network operators' expenditure as well lead to more CO_2 emission correspondingly [3]. On the other hand, the massive deployment and irregular location of SCBSs result in some of them being inaccessible to the power gird [4], [5].

Fortunately, with the rapid development of advancing energy harvesting (EH) technique, the expectation of network devices solely powered by renewable energy (e.g., solar, wind, and kinetic activities) is becoming promising and economic way to prolong the network lifetime and improve the overall energy efficiency of communication systems [6]–[8]. Accordingly, the communication policies need to be redesigned by considering the randomness of the energy harvesting process, from single nodes [9], point-to-point links [10], [11], multiple-users systems [12], [13], to heterogeneous networks recently [14], [15] However, there is no systematic works to efficiently utilize the energy harvesting technologies in small heterogeneous cells [16], including the deployment of the massive EH-SCBSs, the design of user association mechanism, the optimization of mobility management for EH-SCBSs, etc. Generally, most existing works in EH-HetNets simply assume the location of users following a deterministic distribution (e.g., uniform distribution or Poisson Point Process), the optimal locations of MBSs are determined by providing largest bias received power for users. However, the trajectory of mobile users in a realistic environment will experience significantly change across space-time variation. Thus, any specific traffic distribution cannot fully reflect the realistic characteristic of traffic load over the time scale [36], [37]. On the other hand, the static deployment of small cell is not flexible because the harvested energy largely depend on the environment status and placement location of EH-SCBSs. Moreover, it is still under exploration that how to adaptively adjust the location of EH-SCBSs without any knowledge of the harvestable energy and traffic load distribution. Beside this, the traditional evaluation metrics contribute little on balancing between energy consumption and traffic load.

To capture the key characteristics of small heterogeneous cells with EH, we propose an adaptive "drop and play" deployment and mobility management of small cells to replace the static solutions. In this work, we consider a multi-tier heterogeneous networks, which is composed of MBSs and EH-SCBSs with diverse transmission powers, energy harvesting rates and traffic load distributions. The MBSs are solely powered by power grid to guarantee the fairness association chance and stringent quality of service (QoS) requirement for each user, and all SCBSs are solely powered by renewable energy for achieving the energy consumption and traffic load tradeoff.

In this paper, we first study the dynamics of traffic load and energy availability in terms of space-time fluctuation under the realistic environment. Combing the characteristics of traffic load and energy harvesting process, the joint locations and mobile management of EH-SCBSs are formulated to optimize the total system utility. Due to the difficulty derived from closed analytical expression and high computational complexity, the joint optimization problem is divided in two stage including location updating stage and association and cooperation of small cells stage. The location updating approach automatically regulate their locations that only keep tack of the current available energy and traffic load left in the EH-SCBSs. Having the determined deployment locations, the optimal user association vector will be recalculated according to the two-side matching algorithm. The main contributions of this paper can be listed as follows:

- We develop a tractable framework for statistical analysis of various traffic load distributions and environmental energy models. Combing the characteristics of mobile "drop and play" small cells with energy harvesting, we present a guideline to design the location deployment and mobility management toward next generation mobile cellular networks.
- We formulate the joint location and mobility management of EH-SCBSs as an optimization, which maximizes the total system utility, considering not only users' data transmission requirement but also the energy consumption and traffic load tradeoff from the perspective of network operators.
- The joint optimization problem is a NP-hard problem with massive small cells and users, and the centralized solution may lead to high communication overhead and outdated dynamics of traffic and energy harvesting process. Therefore, we propose a tractable solution that the formulated problem is solved in two stages, which consist of the location updating stage and association and cooperation of small cells stage. A suboptimal solution for the optimization problem can be guaranteed using the iteration of two stage approaches.

The rest part of the paper is organized as follows. Section II investigates the state-of-art of small cell deployment and operations. Section III presents the preliminaries and feasibility analysis on various traffic load distributions and environmental energy models. The system model and problem definition are described in Section IV. Then, the association and cooperation of small cell is formulated as the Hospital/Rsidents matching model in Section V. In section VI, we propose an online location updating algorithm conducted with randomly external environment. Performance evaluation are discussed in Section VII. Finally, conclusion and future work are summarized in the Section VIII.

II. RELATED WORK

Although there is no systematic work on the deployment and mobility management in small heterogeneous cells with energy harvesting, researchers have extensively studied resource allocation and energy scheduling for HetNets with EH technology, deployment and operation of small cells without EH. Specifically, these excellent work can give basic guidelines for solving the aforementioned challenges. In this section, the related work can be classified as heterogeneous networks with EH and small cell deployment without EH.

A. HETEROGENEOUS NETWORKS WITH EH

The randomness and intermittence of the energy arrival has a considerable impact on the overall energy efficiency and system capacity, meanwhile faces several significant challenges in small heterogeneous cells. Most existing works in HetNets with EH focus on the energy and communication cooperation [17], [18], energy trading [19]–[21], user association and energy scheduling for various energy supply methods [22]–[27]. Xu *et al.* [17] and Liu *et al.* [18] propose a novel energy and communication cooperation scheme for minimizing energy cost in EH-HetNets powered by hybrid energy source (e.g., power grid and renewable energy source). Furthermore, the various energy trading frameworks are proposed for enhancing renewable energy utilization efficiently [19]–[21]. Reference [22] investigates the users association and energy scheduling strategies for HetNets powered by different energy supply methods including renewable energy [23], hybrid energy [24], enabled energy cooperation [25] and wireless power transfer (WPT) [26], [27] respectively. In the context of statistical modeling the multi-tiers heterogeneous networks with EH, Dhillon *et al.* [14], Yu *et al.* [15], Sakr and Hossain [28], Zhang *et al.* [29], and Thuc *et al.* [30] present a framework for different performance evaluations that are derived from the various system parameters by utilizing the stochastic geometry theory. It is noted that the locations of MBSs are determined by largest received power for users based on a deterministic distribution (uniform distribution or Poisson Point Process). The authors propose a new communication architecture in HetNets that towards secure energy harvesting [31] and integrates several characteristics between mobile social networking and energy harvesting techniques into D2D communications networks for local data dissemination [32]. A comprehensive overview in [16] provides some key problems for EH-SCBSs including deployment and operation of networks.

B. SMALL CELL DEPLOYMENTS AND OPERATIONS WITHOUT EH

Optimizing the locations and operations of small cells is one of the most fundamental problems of network planning. Three main directions are taken in the small cells without EH to cope with these challenges. The first category formulates an optimization problem of small cell deployment and operation towards typical or amorphous network topology. The joint optimization problem is decoupled into cluster formation of deployment and resource management for deriving the optimization variables [33], [34]. A new economical model and low-complex solutions are proposed to solve the problem of small cell deployment and backhaul alleviating based on the characteristics of isolated rural communities and information [35]. Considering the static small cells cannot be flexible deployment, the concept of mobile small cell is introduced in [36] and [37]. A joint resource allocation and location updating scheme of small cell is proposed towards amorphous network topology [36]. Furthermore, Chou *et al.* [37] provide a series of realistic parameters as the inputs for the deployment algorithm of mobile small cell.

Second, amorphous deployment scheme can lead to more flexible and evolvable, however, it poses a significant risk affecting network performance due to the severe interference [38]–[40]. Utilizing interference and environment knowledge, Guo *et al.* [38] propose a small cell deployment scheme based on the stochastic geometry and Monte Carlo simulations. Reference [39] presents a coordinated multiple point (CoMP) transmission algorithm for assisting the dense small cell deployment. Considering the realistic interference environment and traffic load distribution, the placement location of small cells derived from a joint interference and load deployment strategy in [40].

Moreover, due to ultra-dense deployment, the overall energy consumption of small cells may be more larger than the traditional MBSs. The massive deployment of SCBSs inevitably triggers a tremendous escalation of energy consumption [41]–[49]. Cai *et al.* [41] and Peng *et al.* [42] propose effective control modes that adaptively regulate the operating states (ON or OFF) of the SCBSs for reducing the overall energy cost. Reference [43] proposes a self-organized resource allocation scheme (SO-RAS) to reduce energy consumption. Reference [44] evaluates various small cell discovery techniques tailored for energy-efficiency detection of small cells. Pervaiz *et al.* [45] consider a joint spectrum efficiency and energy efficiency balancing tradeoff as a multiple objectives optimization toward green heterogeneous networks. Considering the delay-constrained service requirements and battery-limited mobile terminals, the authors propose an energy-aware multipath transport protocol to minimize energy consumption [46], [47] and present bandwidth-efficient multipath transport protocol to maximize network goodput [48], [49] respectively.

III. PRELIMINARIES AND STATISTICAL ANALYSIS

In order to capture the key statistical characteristics of both traffic and energy availability, this section provides an analytical framework considering various traffic load distributions and environmental energy models across spatio-temporal fluctuation in realistic network scenarios.

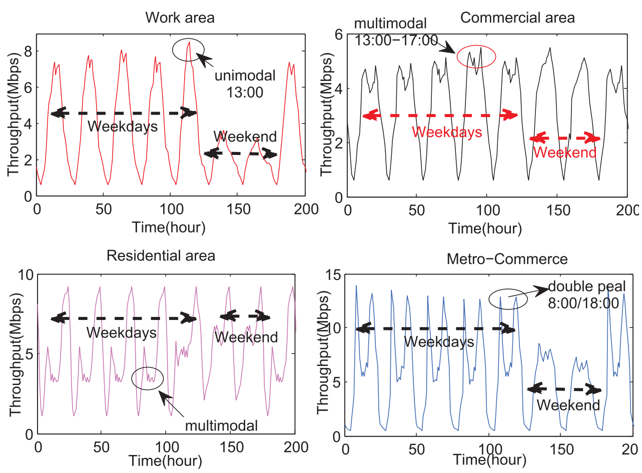


FIGURE 1. Illustration of dynamics of spatio-temporal fluctuating network throughput. The data information dates from 15 days in December 2013 at 387 base stations in Hong Kong for LTE-FDD networks [50].

A. FEATURE OF TRAFFIC LOAD

The trajectory of mobile users has a considerable impact on the space-time distribution of traffic load due to the user social attribution. Fig. 1 reflects some basic characteristics of realistic traffic load under four typical hot-spot areas over a week in Hongkong [50]. Firstly, the characteristic of maximal overall throughput demonstrates several difference among areas distinctly, i.e., at working areas and residential areas the highest peak of traffic load appears the unimodal feature while the other two areas experience the double peak and multimodal respectively. Secondly, the traffic load under a certain area also experiences massive variations across time scale. For an instance, the traffic load in residential area is very high at night, especially from 20:00 to 23:00 at weekdays. Moreover, the light traffic load experiences across the most time of daytime. In sharp contrast, the situation is vice versa at weekends. Therefore the distribution of the traffic load, i.e., the amount of users associated to any EH-SCBS, following the only one typical distribution cannot fully capture the user requirements. In this paper, we assume that the traffic load follows the distribution vector $W = \{\omega_1, \omega_2, \ldots, \omega_W\}$ across the time scales.

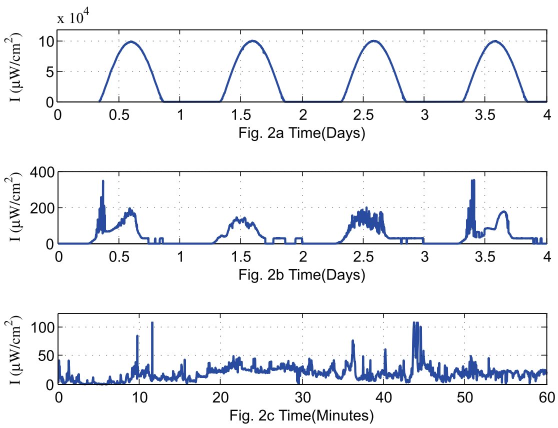


FIGURE 2. **Illustration of energy harvesting characteristics in different environment. Fig. 2a: periodic and deterministic energy arrival (Las Vegas, outdoors [51]), Fig. 2b: periodic and partially predictable energy arrival (New York, a static indoor node [51]), Fig. 2c: completely stochastic energy arrival (New York, a mobile scenario in Times Square at nighttime [52]).**

B. ENVIRONMENTAL ENERGY MODEL

The energy harvesting process is the most fundamental property for analyzing the network performance for EH-HetNets. It is no doubt that the harvestable energy largely depends on different parameters such as locations and natural environment, energy harvesting facilities, and the network devices' mobility. Practically, energy harvesting rates in general can be determined or predicted in rural areas by assistance of the weather forecast. However, in metropolis with massive buildings, the energy harvesting process may fully stochastic. Fortunately, the work [51], [52] gives the guidelines of radiant energy sources with various parameters. Fig. 2 illustrates the energy harvesting process of radiant energy sources in various environment. Fig. 2a shows the stable and periodic energy arrival process in outdoors environment. Fig. 2b gives the characteristic of energy availability when a static device locates at indoors. It is observed that the statistical analysis of harvesting process satisfies the periodicity but hard to predict at short time granularity. Moreover, Fig. 2c shows the energy arrival process of mobile device seemed as the time-independent stochastic variance. Based on Fig. 2, the energy harvesting process can be categorized as the deterministic, partially predicable and fully stochastic energy arrival.

IV. SYSTEM MODEL AND PROBLEM DEFINITION

Combining the characteristic of traffic load and energy harvesting process, the objective of this paper aims to design an efficient small cell deployment scheme for maximizing the total system utility of both users and network operators. In this section, we first presents a valuable network model where the traffic load and energy availability of EH-SCBSs experience the dynamic characteristics with spatio-temporal variation in small heterogeneous cells. Then, we take the the preference relation between users and EH-SCBSs into consideration and provides the individual utility function respectively. Last, the problem of joint location deployment and mobility management of EH-SCBSs is formulated as an optimization problem which is provided a feasibility analysis for optimal solution.

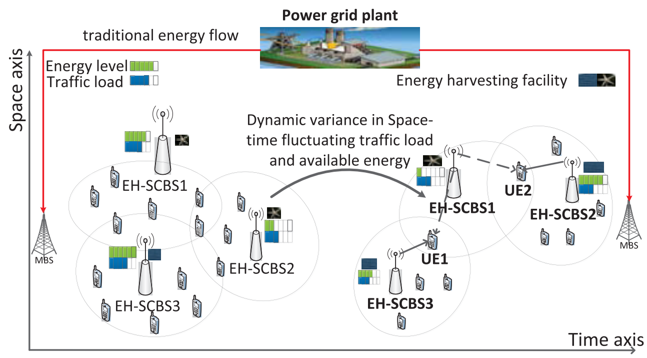


FIGURE 3. **A graphical illustration of network model that the problem of location deployment and mobility management of small cells faces several intractable challenges across spatio-temporally fluctuating traffic load and energy availability in HetNets with EH. To match traffic and available energy, EH-SCBSs update their locations and form various cooperation clusters among adjacent small cells adaptively for improving the total system utility.**

A. NETWORK MODEL

We consider a small heterogeneous cellular networks which consists of M macro-base stations (MBSs), K small cell base stations (SCBSs) and N users. All the MBSs are powered by the traditional power grid and all the SCBSs are solely powered by the renewable energy from natural environment. Fig. 3 shows an example that the traffic load and energy level of EH-SCBSs experience the dynamics with spatio-temporal variation. If the users' location or/and EH-SCBSs' energy availability changes, the cooperative region aligned by the adjacent EH-SCBSs will change correspondingly. For example, the EH-SCBS1 with renewable energy surplus can sever more users at 13:00, however at the next time period (e.g., at 15:00), EH-SCBS1 with energy deficit will offload its existed traffic links (dotted line) to the other adjacent EH-SCBS2 or EH-SCBS3 with energy surplus and light traffic load (solid line). Considering the massive small cells, an efficient deployment and management scheme is necessary to adaptively match the traffic load and energy availability.

B. UTILITIES OF NETWORK NODES

Users' utility: We assume that the deployed location and region matrix of EH-SCBSs is defined as $S=[s_1, s_2, \ldots, s_K] \in \Re^{K\times 2}$ and $D = [d_1, d_2, \ldots, d_k]$ respectively, where $s_i \in d_i$ stands that the location deployment of EH-SCBS i including the horizonal and vertical axis needs to be deployed at the region d_i. Supposed that each EH-SCBS is solely powered by various renewable energy harvesting facilities equipped with a finite capacity of energy storage. We adopt the linear approximation of the power consumption model [15] and the total power consumption of EH-SCBS i for a transmission is stated as

$$p_i(s_i) = p_i^{st} + \beta_i p_i^{tr}(s_i) \tag{1}$$

where p_i^{st} is static power consumption of EH-SCBS i including baseband processing, radio frequency (RF) power expenditure, etc., $p_i^{tr}(s_i)$ is the transmission power of EH-SCBS i, β_i is the amplification factor of the energy consumption [15].

When the user j associates to EH-SCBS i in the downlink heterogeneous networks, the capacity (bits) of the user j is given by

$$\vartheta_{ij}(s_i) = \log(1 + SINR_{ij}(s_i)) \tag{2}$$

$$SINR_{ij}(s_i) = \frac{g_{ij}(s_i)p_i^{tr}(s_i)}{\sum_{k\in K, k\neq i} g_{kj}(s_k)p_k^{tr}(s_k) + \delta^2} \tag{3}$$

where δ^2 is additional white Gaussian noise power, wireless channel can be modeled as finite state markov channels which not only consider the pass loss but also include slow fading and fast fading [53], [54]. The channel gain between EH-SCBS i and user j can be expressed as $g_{ij} = \xi\gamma_{ij}\varsigma_{ij}L_{ij}^{-\varphi}(s_i)$, where ξ, φ is interpreted as the path loss constant and exponent respectively, γ_{ij} is the slow shading factor following log-normal distribution, ς_{ij} is the fast shading factor following exponential distribution, and $L_{ij}^{-\varphi}(s_i)$ is the distance function between EH-SCBS i and user j.

In order to represent users' utility, we not only consider the differentiated transmission requirements but describe the individual satisfaction for the desired spectrum resources as well. Considering service transmission requirement, we assume that the η_j (bits) denotes the size of data requesting of user j. Under a given transmission requirement, any user $j \in N$ selects a EH-SCBS $i \in K$ aiming to optimize its channel capacity in (2). For the perspective of user individual satisfaction, we use the welfare model defined by chen *et al.* [55]. Thus, one suitable utility which reflects the preference of a typical user j associated with a EH-SCBS i is given by

$$U_{ij}(s_i, y_{ij}^{rb}) = \frac{\vartheta_{ij}(s_i)}{\eta_j}\exp\left[-\frac{\left(y_{ij}^{rb} - B_j\right)^2}{2B_j^2}\right] \tag{4}$$

where η_j is the size of requesting transmission data, $\vartheta_{ij}(s_i)$ is channel capacity in (2), y_{ij}^{rb} is the actual bandwidth of user j allocated by EH-CSBS i and B_j is the desired bandwidth of user j. Under a given location s_i, the utility function has the characteristics including strictly concave and differentiable.

EH-SCBSs' utilities: The EH-SCBSs will experience massive variations over space and time in terms of stochastic energy arrival and various traffic load distribution. We assume that the maximum storage capacity of each EH-SCBS is $C = \left(C_1^{\max}, C_2^{\max}, \ldots, C_K^{\max}\right)$. The harvested renewable energy of EH-SCBSs in a certain period is assumed as $S = (C_1, C_2, \ldots, C_K)$. The ratio of current energy availability and total power consumption in (1) is defined as the available operating interval (s) to evaluate the energy availability of EH-CSBS i. Thus, the metric of available operating interval is stated as

$$I(s_i) = \frac{C_i(s_i)}{p_i(s_i)} \tag{5}$$

Inherently, within a small heterogeneous cells with energy harvesting capability, the EH-SCBSs have two objectives. 1) Energy efficiency for overall system: EH-SCBSs offload the traffic from the MBSs to reduce the traditional power consumptions, as well try to satisfy the stringent QoS requirements; 2) Energy-load tradeoff among small cells: the energy consumption and traffic load should be balanced due to asymmetrical energy availability and traffic load distribution among small heterogeneous cells. In order to satisfy these objectives, we present the similar utility which is widely used in field theory [56]. The utility function which is interpreted as the preference of EH-SCBS i to serve user j is defined as

$$Y_{ij}(s_i) = \frac{I_i(s_i)}{\ell_{mj}U_{ij}^{re}(s_i, y_{ij}^{rb})} \tag{6}$$

$$\Psi_{ij}^{th} \le \Psi_{ij} = \frac{\left(\sum_{j\in N} Y_{ij}\right)^2}{N\sum_{j\in N} Y_{ij}^2} \le 1 \tag{7}$$

where $U_{ij}^{re}(s_i, y_{ij}^{rb}) = \frac{\eta_j}{y_{ij}^{rb}\vartheta_{ij}(s_i)}$ is defined as the service transmission interval (s) to guarantee the user QoS requirement. Unlike the user' utility $U_{ij}(s_i, y_{ij}^{rb})$ in (4), $U_{ij}^{re}(s_i, y_{ij}^{rb})$ only reflects the serving ability of EH-SCBS i allocating resource blocks to user j. $\ell_{mj} = \frac{I_m}{U_{mj}^{re}}$ is represented as the utility of MBS m when user j is associated with MBS m, $m \in \{1, 2, \ldots, M\}$, where I_m represents the available operating interval powered by the traditional power gird and U_{mj}^{re} is the service transmission interval allocated by MBS m to user j.

Obviously, a worse ℓ_{mj} implies that EH-SCBS i can achieve more rewards by offloading user j from the MBS m due to reduce traditional energy consumption. Otherwise, user j associates with the MBS m for the better satisfaction of QoS requirements. In addition, the utility function in (6) can obtain energy consumption and traffic load balancing by the association of EH-SCBSs intending to serve the users according to current energy availability and traffic load distribution.

It is noted that although unlike traditional metric of energy efficiency ($bits/J$), the dimensionless utility of EH-SCBSs in (6) is equivalent to the performance evaluation of energy efficiency due to energy-load balancing tradeoff. The constraint of Jain's Fairness Index (JFI) described in (7) is interpreted to guarantee the fairness for the number of users associating with EH-SCBS i.

C. THE OPTIMIZATION PROBLEM

We formulate the joint location deployment and association of EH-SCBSs as an optimization problem for maximizing total system utility of both users and EH-SCBSs. According to the characteristics of traffic load distribution and renewable energy arrival, we use the summation of discounted utility of EH-SCBSs and users over a finite time horizon as the long term reward. We first give the notation definition and total system utility, and then interpret the optimization problem.

We assume Ω to be a $K \times N$ association matrix with element of the association indicator $x_{ij} = \{0, 1\}$, where $i \in \{1, 2, \ldots, K\}$ and $j \in \{1, 2, \ldots, N\}$. Each association indicator $x_{ij} = 1$ denotes the association between EH-SCBS i and user j, otherwise the association indicator $x_{ij} = 0$. Each user is assigned to one and only one EH-SCBS, while each EH-SCBS can associate at most $Z = \{z_1, z_2, \ldots, z_K\}$ simultaneously, z_i is the maximum quota of EH-SCBSs i. Thus, we have two constrains, i.e., $\sum_{i=1}^{K} x_{ij} \leq 1$ and $\sum_{j=1}^{N} x_{ij} \leq z_i$.

For a given time period t and traffic load distribution ω_w, the sum utility of users and EH-SCBSs is stated as

$$\phi^t(s_i, \omega_w) = \sum_{j=1}^{N}\sum_{i=1}^{K} U_{ij}^t(s_i) x_{ij}^t \tag{8}$$

$$\varphi^t(s_i, \omega_w) = \sum_{i=1}^{K}\sum_{j=1}^{N} Y_{ij}^t(s_i) x_{ij}^t \tag{9}$$

where $U_{ij}^t(s_i)$ and $Y_{ij}^t(s_i)$ is given by (4) and (6), respectively. Furthermore, the optimization problem for the locations deployment and users association of EH-SCBSs is stated as

$$\max_{s,x} \sum_{t=1}^{T} \chi^t \left\{ \sum_{w=1}^{W} q^t(\omega_w)\varphi^t(s_i, \omega_w) + \partial \sum_{w=1}^{W} q^t(\omega_w)\phi^t(s_i, \omega_w) \right\} \tag{10}$$

$$s.t. \sum_{i=1}^{K} x_{ij} \leq 1, \quad \sum_{j=1}^{N} x_{ij} \leq z_i, \quad x_{ij} = \{0, 1\} \tag{11}$$

$$SINR_{ij}^{\min}(s_i) \leq SINR_{ij}(s_i) \tag{12}$$

$$C_i \leq C_i^{\max}, \quad p_i^{tx} \leq p_i^{max}, \ \forall i \in K \tag{13}$$

$$\Psi_{ij}^{\min} \leq \Psi_{ij} \leq 1, \quad \forall i \in K, \ \forall j \in N \tag{14}$$

where χ is the discount factor, ∂ is a configurable parameter as the weight value to adjust the impact of preference utility between EH-CSBSs and users, p_i^{max} is the maximal transmission power and $q(\omega_t)$ is the probability when traffic load following the distributions ω_w at given time period t.

The above joint optimization problem is a Mixed-Integer Nonlinear Programming (MINLP) problem. Specifically, the determination of location of small cells will depend on decisions of other EH-SCBSs due to interdependent interference, thus it is difficult to derive the closed analytical expression. Moreover, the computational complexity under a given location will exponentially increase with the number of users and EH-SCBSs, especially in the ultra-dense networks. In order to tackle these challenges, the joint optimization problem is solved as in two stages: online location updating of EH-SCBSs stage and association and self-organizing cooperation of EH-SCBS stage. Firstly, the realistic measurements of traffic load and energy availability provide the important inputs for the proposed two stages algorithms. Secondly, in location updating stage approach, locations matrix can be updated by comparing the action-utility function through iteration method. Finally, having a determined location derived from the first stage approach, the second stage approach is modeled as a Hospital/Residents (HR) matching game for achieving the optimal user association vector as well developing the self-organizing cooperation scheme to improve the overall energy efficiency. In the next sections, we first present association and self-organizing cooperation of EH-SCBS stage and then illustrate the online location updating of EH-SCBSs stage.

V. HOSPITAL/RESIDENTS GAME FOR EH-SCBSs ASSOCIATION AND COOPERATION

In this section, the problem of association and cooperation of EH-SCBSs is modeled as a Hospital/Residents (HR) matching game. We first provide the basic terminologies in HR matching theory, and then describe the proposed Stable Hospital/Residents (SHR) algorithm. Furthermore, according to the stable matching result partitioned to the various clusters (the different subsets of users in N associated with EH-SCBSs in K), some adjacent EH-SCBSs may have incentive for cooperation based on the traffic load and energy availability. The self-organizing cooperation strategy is presented to avoid the resource waste and improve overall system energy efficiency.

A. HR GAME FORMULATION AND PREFERENCE

Within the studied EH-SCBSs in heterogeneous networks, we formulate a Hospital/Residents problem [57], also known as many-to-one matching game, defined by three components: 1) we define the set K of EH-SCBSs acting as the hospitals, and each EH-SCBS has a certain quota z_i that is the most users associated by EH-SCBSs i simultaneously; 2) we denote the set N of users acting as the residents; 3) each hospital (EH-SCBS) i ranks the $j \in N$ residents into a preference list. Meanwhile, each resident (user) j ranks the $i \in K$ hospitals into a preference list. Actually, the implementation of this HR game is regarded as a two-sides assignment model between the hospitals and residents subject to their QoS requirements.

Preference relation $\prec_j$ for each resident is denoted as a transitive binary relation over the set of all hospitals. Each resident $j \in N$ determines a subset of hospitals in strictly descending order based on the utility function in (4). For any two hospitals, $i, k \in K,\ i \neq k$, the preference relation is stated as

$$i \prec_j k \;\Leftrightarrow\; U_j(i) < U_j(k) \tag{15}$$

where $U(\cdot)$ is given by (4). Based on the traffic load distribution and energy availability, each hospital $i \in K$ determines a preference relation $\prec_k$ for each resident. Such as, for any two residents $j, q \in N,\ j \neq q$, the preference relation is given by

$$j \prec_i q \Leftrightarrow Y_i(j) < Y_i(q) \tag{16}$$

where $Y(\cdot)$ is given by (6). Consequently, each EH-SCBS accepts the subset formed by users in N based on the Jain's Fairness Index in (7) if there are more than one subset associated with the same EH-SCBS.

The classical Gale and Shapely algorithm in [58] solves the matching problem (e.g., one-to-one marriage match problem) with low-complexity. Under a given location matrix derived from the first stage approach described in next section, an extended algorithm can well apply to the many-to-one HR matching problem, called as the Stable Hospital/Resdients Matching (SHRM) algorithm. We first introduce the comprehensive definition for this SHRM algorithm, and then give an illustration of one round of the proposed HR matching process.

Definition 1 (Stable Hospital/Reisdents Matching (SHRM)): The problem is illustrated as to find a stable association of users and EH-SCBSs based on the quota of the EH-SCBSs. In this case an assignment of users to EH-SCBSs with matching Φ will be called stable association if there are no any two users $j \in N$ and $q \in N$ who are assigned to EH-SCBSs $i \in K$ and $k \in K$, respectively, although j prefers k to i and k prefers j to q simultaneously [58].

Having a determined locations matrix of EH-SCBSs calculated by the first stage approach, each user calculates the utility function in (4) in terms of each EH-SCBS and builds its preference list according to the strictly descending order. Correspondingly, each EH-SCBS executes the same operation to build its preference list. At beginning of matching process, each user first applies for the most favorite EH-SCBS based on its preference list. When all users complete their proposals, EH-SCBS i will check whether or not the number of applicants $\sum_{i\in K} x_{ij}$ exceed the quota z_i. If $\sum_{i\in K} x_{ij} > z_i$, the EH-SCBS i will accept these applicants subject to the Jain's Fairness Index in (7) and rejects the others. Otherwise, all the applicants will be accepted and arranged in the candidate list with strict descending order. In next iteration, the users first will remove the EH-SCBSs which rejected their in previous applications and will update the preference lists. Then, the rejected users propose most preferred EH-SCBSs in updating preference lists again respectively. Repeated the previous round of assignment, the stable matching association result is formed until the all the applicants in the candidate list. The details of matching process is showed in the Phase I of Algorithm 1.

Algorithm 1 Stable HR Matching Algorithm of Small Cells Association With Self-Organizing Cooperation

1: **Input:** Having a determined a location matrix: $S^t = \{s_1^t, s_2^t, \ldots, s_K^t\}$.
2: **Output:** The stable association matching result between users and EH-SCBSs.
3: **Phase I Deployment and association without cooperation :**
4: **for** $\omega_l \in W, l = 1$ *to* L **do**
5: Construct the preference lists of EH-SCBSs and users respectively.
6: **for** $j = 1$ *to* N **do**
7: **if** the user j is accepted by the previous requesting **then**
8: go to step 6 for executing the next requesting
9: **else**
10: Delete the EH-SCBS which rejects user j from the preference list and submit the second preferred EH-SCBS.
11: **end if**
12: **end for**
13: **for** $i = 1$ *to* K After all the users finish their request **do**
14: **if** $\sum_{j\in N} x_{ij} > z_i$ **then**
15: Select the users based on Equation (7).
16: **else**
17: Rank the users and create candidate list on the z_i, and reject others.
18: **end if**
19: **end for**
20: Until All the users are on the candidate lists, and we have the stable association between users and EH-SCBSs.
21: **Phase II Cooperative self-organizing scheme:**
22: Within the partition $\Lambda = \{\Lambda_1, \Lambda_2, \ldots, \Lambda_K\}$ from the Phase I. All the EH-SCBSs can meet flexible cooperation based on the proposed rule.
23: **for** $i = 1$ *to* K **do**
24: Calculates the active probability and the average energy level based on the CMTC in (18) and (19).
25: Follow the cooperation rules, user is accepted or rejected by cooperative EH-SCBSs.
26: **end for**
27: **Until** Coverage a stable cooperation result.
28: **end for**

B. COOPERATIVE SELF-ORGANIZING STRATEGY

According the two-side preference relation in (15) and (16), a stable association of SHRM game can be seen as a partition Λ of the set N such as $\Lambda = \{\Lambda_1, \ldots, \Lambda_K\}$, where

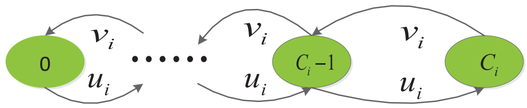


FIGURE 4. Birth-Death process describing the energy variation of EH-SCBS *i*.

$\Lambda_i \cap \Lambda_k = \emptyset$, $i \neq k$ and $\cup_{i=1}^{K} \Lambda_i = N$. Each $\Lambda_i \subseteq N$ is denoted as a cluster formed by the subset of users in N associated with EH-SCBS i, $i \in \{1, \ldots, K\}$, $\Lambda_i \neq \emptyset$. Otherwise, Λ_i=$\emptyset$ represents that EH-SCBS i has no users assigned to it.

In order to formulate dynamic cooperation among adjacent EH-SCBSs, we propose a self-organizing strategy (e.g., residents transfer from the previous hospital to another as the better conditions or incentive) to solve the problem. First, the dynamics of energy storage level is modeled by the discontinuous time markov chain (DTMC) that achieves the stationary state distribution. According to [14], we assume EH-SCBS i has an energy harvesting module and a finite storage with maximum capacity of $C_i^{\max}$ energy units. Practically, the variation of energy level in general is more slowly than the traffic load variations derived from cell association and service requesting. Correspondingly, the time scale of implementing energy arrival process of all EH-SCBSs can be formulated as an independent poisson process. With regard to the energy arrival rates and consumption rates, we use the realistic data that the average available energy is 1517 $J/cm^2/day$, the standard variance is 787 and an energy consumption rate to transmit data is $1nJ/bits$ respectively [59]. In this paper, we assume that the overall energy consumption at each EH-SCBS is approximately proportional factor to the average number of users associated with EH-SCBS i following the traffic load distribution with average value v. To simplify the analysis, we define the proportional factor is 1. Specifically, we assume that EH-SCBS i is active if it can serve corresponding with traffic load under current energy availability. Otherwise, EH-SCBS i utilizes the cooperative strategy for offloading its requests to other adjacent EH-SCBSs with sufficient energy storage level. Furthermore, we indicate the energy levels each EH-SCBS i as $C_i = [0, 1, 2, \ldots, C_i]$ and model the temporality and dynamics as a birth-death process as shown in Fig. 4. The probability of EH-SCBSs active is given by [14]

$$\rho = 1 - \left(\frac{1 - \frac{u}{v}}{1 - \left(\frac{u}{v}\right)^{C_i + 1}} \right) \tag{17}$$

If the C_i is finite and $C_i \gg 1$. Then, equation (17) can be equivalent to

$$\rho = \begin{cases} \frac{u}{v} & u \leq v \\ 1 & u > v \end{cases} \tag{18}$$

Practically, the energy consumption rate in general is larger than the energy arrival rate, $v > u$. Therefore, the average energy level is given by

$$E = \left(\frac{u}{v - u} \right) \tag{19}$$

An efficient self-organizing cooperation strategy can avoid wasting energy resource and improving the overall system energy efficiency. We define a cooperative rule among the clusters that are identified by the pair (N, Υ) where N is the set of users and Υ is a mapping that assigns for every cluster $\Lambda_a \subseteq \Lambda$. A reward vector V that each element $V_{ij} = U_{ij} + Y_{ij}$ is defined as the utility of both user j and EH-SCBS i as per (4) and (6). Here, each cluster $\Lambda_a \subseteq N$ represents a group of users associated by a EH-SCBS $a \in K$. Furthermore, we define the function $V(\Lambda_a) = \sum_{j \in \Lambda_a} V_{ij}$ as the total social welfare generated by a cluster Λ_a. For a given cooperation, we denote $V(\Lambda_a \backslash \{j\}) + V(\Lambda_b \cup \{j\}) > \varepsilon \{V(\Lambda_a) + V(\Lambda_b)\}$ as the incentive factor to determine users j whether or not transfer from cluster a to cluster b, where the $a, b \in K$ and $\varepsilon = [0\ 1]$ is the balance factor. The prime objective of cooperative strategy is to improve the energy efficiency, so the balance factor can be dynamically adjust according the traffic load and energy availability subject to the users QoS requirements. When self-organized cooperation is triggered, the following steps should be executed:

1) Decide whether the self-organizing cooperation rules are fulfilled. Only if there is a certain EH-SCBS i that must be active (Equation (18)) and the average availability of EH-SCBS i described in (19) must larger than a predefined threshold. Meanwhile, the number of users in EH-SCBS i which accepts the new users from other EH-SCBS does not exceed the maximal quota.

2) Determine which users for handover. The prime objective of the self-organizing cooperation scheme is to automatically regulate the operating state (ON/OFF) of EH-SCBSs for reducing the overall system energy consumption. Therefore, one user will be selected from a predefined condition according to the current traffic load.

3) Find a suitable EH-SCBS as the target. The EH-SCBS with most spare energy and spectrum resource will be selected as the target EH-SCBS for the user handover.

The detailed cooperative self-organizing cooperation algorithm is illustrated in the Phase II of Algorithm 1.

C. COMPLEXITY ANALYSIS

In Algorithm 1, the worst case happens on Phase I of Algorithm 1 when all users choose the least favorite EH-SCBS after receiving $(K-1)$ rejection from all the other EH-SCBSs. In the situation, each user first provide the applicant to $(K-1)$ most favorite EH-SCBS and then receive the rejections from all EH-SCBSs. The number of proposals requested by N users is $N(K-1)$ in this case. Within the partition Λ of the set N such that $\Lambda = \{\Lambda_1, \ldots, \Lambda_K\}$ on phase II of Algorithm 1, the worst case happens when each cluster $\Lambda_a \subseteq \Pi$ compares with each other whether or not they satisfy cooperative rule. In this case, all the clusters K execute the maximal number of iterations expressed as the $K(K-1)$. Therefore, the complexity of Algorithm 1 is $O(W(N(K-1) + K(K-1)))$ in the worst case.

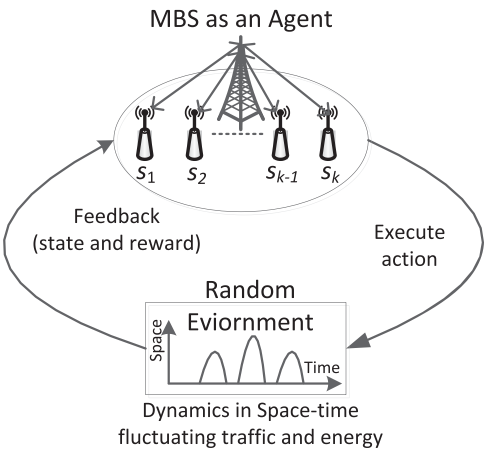


FIGURE 5. Illustration of interaction between multiple EH-SCBSs and external random environment.

Practically, K can be regarded as a small fixed integer, thus the complexity is equivalent to the $O(N(K-1)+K(K-1))$.

VI. ONLINE LOCATION UPDATING SCHEME

In this section, we develop an online location updating algorithm to achieve two objectives: 1) to improve elasticity among EH-SCBSs with cooperation; and 2) to enhance robustness under random environment where each EH-SCBS can only keep track of the current available energy without any priori-knowledge. Fig. 5 gives an illustration how the mutual relationship between multiple EH-SCBSs and external environment is executed to meet the location updating of self-adaption [60]. In this framework, we assume the MBS as an agent is responsible to update the deployment locations based on the inputs from the external random environment (e.g., traffic load and energy availability). Meanwhile, the determined location matrix provides the key inputs of Algorithm 1 described in the second stage approach.

A. MBS AS AN AGENT

In a practical network, considering the communication overhead, small cells only need to periodically report their location information, traffic load and energy availability to MBSs. In this paper, the time frame of running the algorithm is assumed to one hour according to the characteristic of energy availability and traffic load analyzed in previous section. In the proposed online location updating algorithm, the prime objective of agent is to take an optimal policy such that it captures an acceptable EH-SCBSs' location matrix to improve the system utility. Specifically, a policy function $\pi^*(S) \rightarrow A$ is formulated for mapping the system state S to a set of location updating action A. However, a closed analytical expression for policy function is difficult to be derived due to be lack of the training samples, i.e., $\langle s, a\rangle$. Alternatively, an instantaneous reward sequence $r(s, a)$ can substitute for the policy function as the metric on location updating decisions. Therefore, we define a tractable action-utility function that indirectly captures the optimal policy. The MBS takes the policy of location updating through comparing the action-utility function. It can be interpreted mathematically by the following parameters: $\{S, A, T, \Pi, R\}$, where $s_i \in S$ is a finite set of system states of EH-SCBS i, $a_i \in A$ is action set with members as the finite number of actions taken by the EH-SCBS i, T is the time period of execution, $\pi_i \in \Pi$ is the policy set for EH-SCBSs i, and $r_i \in R$ is the instantaneous reward given by the environment.

B. RANDOM ENVIRONMENT

During the interactive process between agent and randomly external environment, the agent executes online learning algorithm with respect to the certain input parameters from external environment. Mathematically, the random environment can be defined as $\langle A, S, R\rangle$, where A is input parameters derived from the agent, S and R are the output parameters passed to the agent as the feedback including updated system state and instantaneous reward. After execution of each iteration, these parameters are updated and may be taken by the agent to make the optimal decisions.

C. DESIGN OF ACTION-UTILITY FUNCTION

Based on aforementioned analysis, the proposed online algorithm only has to keep track of the current traffic load and available energy left at the EH-SCBSs. We design an action-utility function $\hat{Q}(s, a)$ as the criterion to evaluate the utility how the agent takes a certain action. Specifically, the $\hat{Q}(s, a)$ can be interpreted as a list where each row interprets a system state matrix and each column represents an action taken by agent. Thus, the action-utility function maps the tuple $\langle s, a\rangle$ to a utility value to evaluate current the policy. At the beginning of the online location updating algorithm, the $\hat{Q}(s, a)$ is initialized the arbitrary value in the list. Agent observes the current system state s and takes a certain action a repeatedly. Then, the agent observes the instantaneous reward $r(s, a)$ and the next system state $\langle s', a'\rangle$. Moreover, the action-utility function $\hat{Q}(s, a)$ has been updated according to following rule

$$\begin{aligned}\hat{Q}^t\{(s_i, s_{-i}), a\} \leftarrow\ & (1-\alpha) * \hat{Q}^t\{(s_i, s_{-i}), a\} \\ & + \alpha * \left\{r + \gamma \max_a \hat{Q}^{t+1}\left((s'_i, s_{-i}), a'\right)\right\}\end{aligned} \tag{20}$$

$$r((s_i, s_{-i}), a) = \exp\left(-\left(\frac{U(s_i, s_{-i})}{I(s_i, s_{-i})}\right)^2\right) \tag{21}$$

where s_{-i} is the location matrix of all EH-SCBSs except EH-SCBSs i, (s', a') is the two-tuple formed by state-action pair in the next time period, $r((s_i, s_{-i}), a)$ is the instantaneous reward sequence for $r \in R$ and $|r| < c$, c is a bounded positive number, α is the learning rate, γ is the discount factor, and the $U(\cdot)$ and $I(\cdot)$ as per (4) and (6) reflects the current traffic load and energy availability respectively. According to the updating rule in (20) and (21), the larger learning rate α shows that the previous training samples have less impact on action-utility function updating. The more larger discount factor γ means more greater weight on action-utility updating related to $\max_a \hat{Q}^{t+1}\left((s'_i, s_{-i}), a'\right)$ which stands the maximal the utility under the next system-action pair $\langle s', a'\rangle$. The detailed online location updating algorithm is illustrated in the Algorithm 2.

Algorithm 2 Online Location Updating Algorithm

1: **Initialization:** $t = 0$, $S^0 = \{s_1^0, s_2^0, \ldots, s_K^0\}$, $U(S^0)$, $I(S^0)$, $\hat{Q}^0(s, a) = 0$.
2: **From** $t = 1$ **to** T
3: Observe the current state $S^t_{cur} = S^{t-1}$, $\hat{Q}^t_{cur}(s, a) = \hat{Q}^{t-1}(s, a)$
4: **for** $i = 1$ to K, select an action and execute its decision **do**
5: Calculate the instantaneous reward $r((s_i, s_{-i}), a)$ as per (21) and observe the new the state s'_i after executing each decision with external environment.
6: Update the action-utility function of $\hat{Q}(s, a)$ by the Equation (20).
7: **if** $\hat{Q}^t\{(s_i, s_{-i}), (a_i, a_{-i})\} < \hat{Q}^t_{cur}\{(s_i, s_{-i}), (a_i, a_{-i})\}$ **then**
8: $S^t_{cur} = S^{t-1}$ and $\hat{Q}^t_{cur}(s, a)$ does not change
9: **else**
10: $(s_i, s_{-i}) \leftarrow (s'_i, s_{-i})$ and $\hat{Q}^t_{cur}(s, a) \leftarrow \hat{Q}^t(s, a)$
11: **end if**
12: **Repeat** the step 4 until completed location updating at current time.
13: **end for**
14: Execute the updating location matrix as the input for the second stage approach.
15: **Continue** Step 2.
16: **Until** $\left|\hat{Q}^{t+1}(s', a') - \hat{Q}^t(s', a')\right| \leq \Delta$, Δ is a small positive number.

D. CONVERGENCE AND COMPLEXITY ANALYSIS

The execution of the proposed online algorithm is a round-robin iteration with random environment. Algorithm 2 converges to an optimal policy after finite of iterations as it satisfies the following conditions [60]: 1) the deterministic and finite system state set S and action set A; 2) a bounded instantaneous reward r, that is, for all two-tuple $\langle s, a\rangle$ obey the condition of the inequality $|r(s, a)| < c$; and 3) each system state s and reward r could be infinitely accessed by agent. More importantly, in given internal environment, the amount of computing iterations is key metric for evaluating the performance of offline algorithm. In contrast, the executive time and cost of each action with random environment have considerable impact on the efficiency of online algorithm rather than computing consumption. Therefore, the complexity of the online location updating algorithm is $O(TK)$ in the worst conditions.

VII. PERFORMANCE EVALUATION

This section provides numerical simulations evaluating the performance of the algorithms of location deployment and mobility management for small heterogeneous cells with energy harvesting. We mainly consider a two-tier heterogeneous network which is composed of $M = 3$ MBSs and various amount of EH-SCBSs, i.e., (5/10/15/20) respectively. Correspondingly, the coverage area of each MBS is a square area of 3 km $\times$ 3 km and each MBS is deployed at the center coordinate. Considering EH-SCBSs with different transmission power and energy harvesting rates, without loss of generality, we assume the coverage area from 20 m $\times$ 20 m to 100 m $\times$ 100 m. The transmission powers of all MBSs and EH-SCBSs is set to 43 dBm and 26 dBm respectively, the static powers of all MBSs and EH-SCBSs is set to 728 W and 10.6 W respectively. In addition, all the noise plus interference level and the propagation loss is set to -110 dBm and $\varphi = 3$ respectively. With regard to the energy harvesting rates, we use the realistic value including the available energy mean $\bar{u} = 1517\ J/cm^2/day$, the standard variance $\sigma(u) = 787$ and energy consumption rate $1nJ/bits$. Unless stated otherwise, the packet size is set to $\eta = 128/256/512/1024$ bits and the quota of the EH-SCBSs is set the typical value $z_i = 8, \forall i \in K$.

For simplifying description, the Phase I and Phase II of our proposed algorithms is described the SHRM and SHRM with cooperation scheme individually. Moreover, in order to validate the efficiency of our proposed algorithms, we compare the performance of our proposed SHRM and SHRM with cooperation schemes with the Random Association of Only Utility of users Concerned (RA-OUC) algorithm and as well as a slightly simplified version of the SHRM scheme - Best User Utility (BUU) algorithm. In the BUU algorithm, only utilities of users are considered during the association process while the utilities of EH-SCBSs are not taken in account.

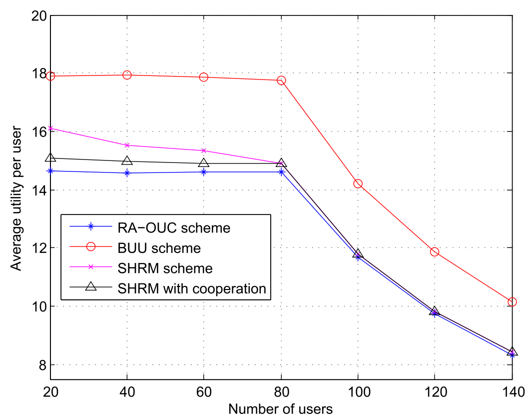


FIGURE 6. Average utility per user under different algorithms.

In Fig.6 and Fig.7 we show the average utility per user and average system utility with RA-OUC, BUU, SHRM and SHRM with cooperation algorithms, for a small heterogeneous cells with K=10 EH-SCBSs, $z_i = 8, \forall i \in K$ and $\eta = 256(bits)$. It can be observed the average utility per user of all algorithm decreases as the number of users increase due

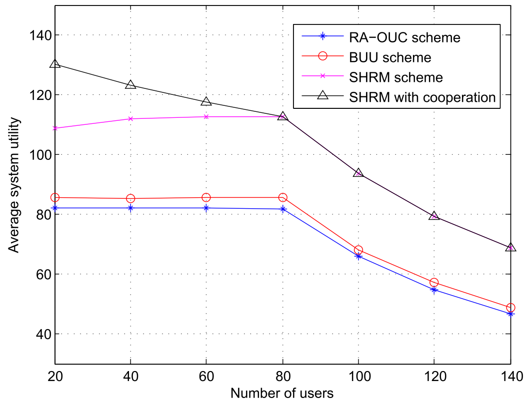


FIGURE 7. **Average system utility under different algorithms.**

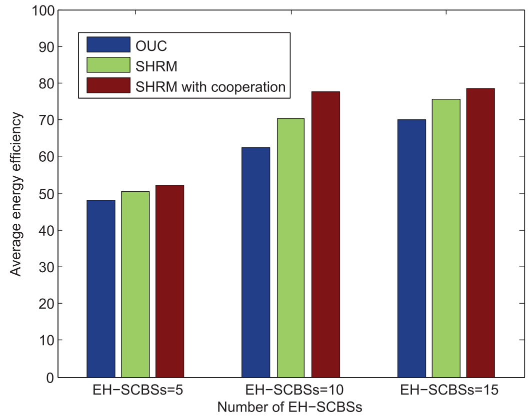


FIGURE 8. **Average system utility in different EH-SCBSs cases.**

to the limited energy and bandwidth resources. Furthermore, Fig. 6 demonstrates the performance of our proposed algorithms are slightly better than RA-OUC algorithm. That can be explained by that the objective of both SHRM and SHRM with cooperation algorithms aims to balance the energy consumption and traffic load among small cells. In contrast, the BUU algorithm just greedily associates a certain EH-SCBS based on the individual preference in Equation (4) while does not take the over system energy efficiency into consideration. Therefore the average utility for per user is better than other schemes. In Fig. 7, it can be observed that our proposed SHRM and SHRM with cooperation algorithms are obviously better than RA-OUC and BUU algorithms. The most essential reason is that our proposed schemes not only consider the utility of per user as a part of the optimization objective, but also treat the overall system utility of network operators with high importance. Furthermore, our proposed SHRM with cooperation scheme can improve the average system utility when the demand of users association is unsaturated. That can be explained that the operating state (ON/OFF) of EH-SCBSs can be regulated automatically based on the amount of users for reducing system power consumption. However, when there are substantially large amount of associated requests, the average system utility of both SHRM with/without cooperation schemes are same due to terminate self-organized the cooperation strategy. In this paper, we primely consider the delay-tolerant transmission, if delay-constrained services requirement cannot be guaranteed by small cells with energy harvesting, MBSs that are powered by traditional power grid keep on ensuring the stringent QoS requirement.

Fig. 8 compares the performance of the average system utility with different amount of EH-SCBSs cases, for a small heterogeneous cells with $N = 80$, $z_i = 8$, $\forall i \in K$ and $\eta = 1024(bits)$. It is obvious that the available energy and bandwidth resources increase with the number of EH-SCBSs so that each user can get more opportunities to be associated and scheduled. Through comparative analysis, the SHRM with/without cooperation algorithms get minor improvement of average system utility compared with the RA-OUC and BUU algorithms with the few amount of EH-SCBSs. This is because that SHRM with cooperation has less contribution for performance improvement due to the far distance among EH-SCBSs. However, as the number of EH-SCBSs increases, effective cooperation among the EH-SCBSs can significantly improve the system utility.

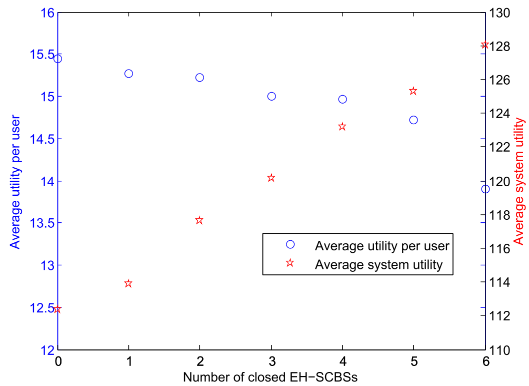


FIGURE 9. **Average utility per users and system utility tradeoffs as the number of closed EH-SCBSs changes.**

Fig. 9 shows the trade-off between the average user utility and average system utility balancing with the variation of number of EH-SCBSs under the OFF state. In this paper, the user utility just represents the user' transmission requirement while the system utility describes the overall energy efficiency from network operators' perspective for reducing the total energy consumption. As shown in Fig. 9, the SHRM with cooperation algorithm determines the number of EH-SCBSs under the OFF state while significantly effect on balancing the trade-off between user utility and system utility. Therefore, it is important to adaptively adjust the cooperation strategy according to the practical environment.

Fig. 10 illustrates the average number of iterations with applying the proposed algorithm as the number of users increase and K varies. For each EH-SCBS, we assume the $z_i = 7$. When the number of users are smaller than the maximal quota corresponding to its EH-SCBS, the average number of iterations are obviously increasing as the N increases. From Fig. 10, we find the change of number of iterations keeps flat and nearly equals to a constant with $K = 5$

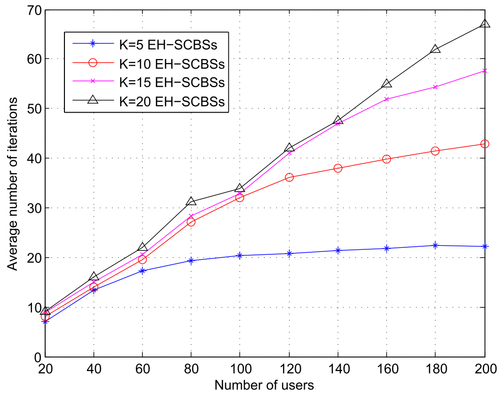


FIGURE 10. **Average number of iterations in SHRM algorithm.**

and $K = 10$. That can be explained by that as the number of users N becomes large relative to K, the users will still submit their most favorite EH-SCBS according to preference list at the each iteration. Therefore, the iterative result finally converges a stable state. Furthermore, it is observed that the gap of average number of iterations obviously increase for different EH-SCBSs when the number of users greater than the maximal quota particularly. That can be explained that the more associated requests will be rejected when the number of users larger than the maximal quota with two-side matching scheme.

VIII. CONCLUSION AND FUTURE WORK

This paper proposes a new deployment and mobility management scheme in HetNets which consists of MBSs and EH-SCBSs. For maximizing the overall system utility of both users and network operators, the problem of location deployment and mobility management are formulated as a joint optimization. Due to the high complexity and interdependent interference among EH-SCBSs, the formulated problem is solved in two stages approach including location updating stage and the association and cooperation of small cells stage. The proposed location updating algorithm adaptively updates their locations that only keep tack of the current available energy and traffic load left in the EH-SCBSs. Having the determined deployment locations, the optimal user association vector will be recalculated according to the two-side matching algorithm. Simulation results demonstrate that the overall system utility is obviously improved by the proposed algorithms.

The dense deployment of small heterogeneous cells can further shorten the distance between users and EH-SCBSs, thus the utilization of wireless energy transfer (WET) technique is becoming a reality to transfer energy to mobile terminals. Our future work can be extended to introduce the deployment and mobility management in this network scenario for prolonging the lifetime of terminals battery. Beside this, the deployment and management of mobile ''drop and play'' small cell with energy harvesting faces a number of intractable challenges due to capacity-constrained wireless backhual.

REFERENCES

[1] X. Zhang *et al.*, ''Energy-efficient multimedia transmissions through base station cooperation over heterogeneous cellular networks exploiting user behavior,'' *IEEE Wireless Commun.*, vol. 21, no. 4, pp. 54–61, Aug. 2014.

[2] K. Zhang *et al.*, ''Energy-efficient offloading for mobile edge computing in 5G heterogeneous networks,'' *IEEE Access*, vol. 4, pp. 5896–5907, Aug. 2016.

[3] G. Piro *et al.*, ''HetNets powered by renewable energy sources: Sustainable next-generation cellular networks,'' *IEEE Internet Comput.*, vol. 17, no. 1, pp. 32–39, Jan. 2013.

[4] S. Bu, F. Richard Yu, Y. Cai, and P. Xiaoping Liu, ''When the smart grid meets energy-efficient communications: Green wireless cellular networks powered by the smart grid,'' *IEEE Trans. Wireless Commun.*, vol. 11, no. 8, pp. 3014–3024, Aug. 2012.

[5] W. Zhong, R. Yu, Y. Zhang, Y. Gao, and S. Gjessing, ''Adaptive rate control in smart grid heterogeneous communications networks,'' in *Proc. IEEE CIT/IUCC/DASC/PICOM*, Oct. 2015, pp. 12–17.

[6] L. Silu, ''The green CDMA base station,'' in *Huawei Communication*, no. 45, 2009. [Online]. Available: http/www.huawei.com/link/en/download/HW_082746.

[7] E. Hossain and M. Hasan, ''5G cellular: Key enabling technologies and research challenges,'' *IEEE Instrum. Meas. Mag.*, vol. 18, no. 3, pp. 11–21, Jun. 2015.

[8] Nokia Siemens Networks. *Multiradio Base Station Makes Network Evolution Easier and Greener Than Ever, Press Release, Nokia Siemens Networks*. [Online]. Available: http://www.nokiasiemensnetworks.com/sites/default/files/document/Nokia SiemensNetworks_2009_02_05_enFlexiMultiradioBTS.pdf

[9] M. Gorlatova, A. Wallwater, and G. Zussman, ''Networking low-power energy harvesting devices: Measurements and algorithms,'' in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2011, pp. 1602–1610.

[10] K. Tutuncuoglu and A. Yener, ''Optimum transmission policies for battery limited energy harvesting nodes,'' *IEEE Trans. Wireless Commun.*, vol. 11, no. 3, pp. 1180–1189, Mar. 2012.

[11] Y. Luo, J. Zhang, and K. B. Letaief, ''Optimal scheduling and power allocation for two-hop energy harvesting communication systems,'' in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2013, pp. 4180–4184.

[12] M. Antepli, E. Uysal-Biyikoglu, and H. Erkal, ''Optimal packet scheduling on an energy harvesting broadcast link,'' *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1721–1731, Aug. 2011.

[13] R. Yu *et al.*, ''An optimal replenishment strategy in energy harvesting wireless networks with a mobile charger,'' in *Proc. Int. Conf. Heterogeneous Netw. Quality, Rel., Secur. Robustness (QSHINE)*, Aug. 2015, pp. 433–439.

[14] H. S. Dhillon, Y. Li, P. Nuggehalli, Z. Pi, and J. G. Andrews, ''Fundamentals of heterogeneous cellular networks with energy harvesting,'' *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2782–2797, May 2014.

[15] P.-S. Yu, J. Lee, Q. S. Tony Quek, and Y.-W. Peter Hong, ''Traffic offloading in heterogeneous networks with energy harvesting personal cells-network throughput and energy efficiency,'' *IEEE Trans. Wireless Commun.*, vol. 15, no. 2, pp. 1146–1161, Feb. 2016.

[16] Y. Mao, Y. Luo, J. Zhang, and B. Khaled Letaief, ''Energy harvesting small cell networks: Feasibility, deployment, and operation,'' *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 94–101, Jun. 2015.

[17] J. Xu, L. Duan, and R. Zhang, ''Cost-aware green cellular networks with energy and communication cooperation,'' *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 257–263, May 2014.

[18] Y. Liu, Y. Zhang, R. Yu, and S. Xie, ''Integrated energy and spectrum harvesting for 5G wireless communications,'' *IEEE Netw.*, vol. 29, no. 3, pp. 75–81, May/Jun. 2015.

[19] K. Zhang *et al.*, ''Incentive-driven energy trading in the smart grid,'' *IEEE Access*, vol. 4, pp. 1243–1257, Apr. 2016.

[20] Y. Xiao, D. Niyato, Z. Han, and A. Luiz DaSilva, ''Dynamic energy trading for energy harvesting communication networks: A stochastic energy trading game,'' *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2718–2734, Dec. 2015.

[21] R. Yu *et al.*, ''Price-based energy control for V2G networks in the industrial smart grid,'' in *Proc. Int. Conf. Ind. Netw. Intell. Syst. Commun. (INISCOM)*, Mar. 2015, pp. 107–112.

[22] D. Liu *et al.*, ''User association in 5G networks: A survey and an outlook,'' *IEEE Commun. Surveys Tut.*, vol. 18, no. 2, pp. 1018–1044, Jan. 2016.

[23] S. Jangsher, H. Zhou, V. O. K. Li, and K. C. Leung, ''Joint allocation of resource blocks, power, and energy-harvesting relays in cellular networks,'' *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 482–495, Mar. 2015.

[24] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-efficient resource allocation in OFDMA systems with hybrid energy harvesting base station," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3412–3427, Jul. 2013.

[25] Y. Guo, J. Xu, L. Duan, and R. Zhang, "Joint energy and spectrum cooperation for cellular communication systems," *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3678–3691, Oct. 2014.

[26] A. H. Sakr and E. Hossain, "Analysis of multi-tier uplink cellular networks with energy harvesting and flexible cell association," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2014, pp. 4525–4530.

[27] A. M. Siddiqui, L. Musavian, and Q. Ni, "Energy efficiency optimization with energy harvesting using harvest-use approach," in *Proc. IEEE Int. Conf. Commun. Workshop (ICC Wkshps)*, Jun. 2015, pp. 1982–1987.

[28] A. H. Sakr and E. Hossain, "Analysis of K-tier uplink cellular networks with ambient RF energy harvesting," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 10, pp. 2226–2238, Oct. 2015.

[29] X. Zhang, Y. Zhang, R. Yu, W. Wang, and M. Guizani, "Enhancing spectral-energy efficiency forLTE-advanced heterogeneous networks: A users social pattern perspective," *IEEE Wireless Commun.*, vol. 21, no. 2, pp. 10–17, Apr. 2014.

[30] T. K. Thuc, E. Hossain, and H. Tabassum, "Downlink power control in two-tier cellular networks with energy-harvesting small cells as stochastic games," *IEEE Trans. Commun.*, vol. 63, no. 12, pp. 5267–5282, Dec. 2015.

[31] J. Kang *et al.*, "Toward secure energy harvesting cooperative networks," *IEEE Commun. Mag.*, vol. 53, no. 8, pp. 114–121, Aug. 2015.

[32] J. Li *et al.*, "Social-aware energy harvesting device-to-device communications in 5G networks," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 20–27, Aug. 2016.

[33] H.-Y. Hsieh, S.-E. Wei, and C.-P. Chien, "Optimizing small cell deployment in arbitrary wireless networks with minimum service rate constraints," *IEEE Trans. Mobile Comput.*, vol. 13, no. 8, pp. 1801–1815, Aug. 2014.

[34] J. Xu *et al.*, "Cooperative distributed optimization for the hyper-dense small cell deployment," *IEEE Commun. Mag.*, vol. 13, no. 4, pp. 61–67, May 2014.

[35] A. Martinez-Fernandez *et al.*, "The TUCAN3G project: Wireless technologies for isolated rural communities in developing countries based on 3G small cell deployments," *IEEE Commun. Mag.*, vol. 57, no. 7, pp. 36–43, Jul. 2016.

[36] A. Dong, X. Luo, and Q. Du, "A small cell deployment strategy towards amorphous coverage in the cellular network," in *Proc. IEEE Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Aug. 2015, pp. 745–750.

[37] S.-F. Chou, T.-C. Chiu, Y.-J. Yu, and A.-C. Pang, "Mobile small cell deployment for next generation cellular networks," in *Proc. IEEE Global Commun., (GLOBECOM)*, Dec. 2014, pp. 4852–4857.

[38] W. Guo, S. Wang, X. Chu, J. Zhang, J. Chen, and H. Song, "Automated small-cell deployment for heterogeneous cellular networks," *IEEE Commun. Mag.*, vol. 51, no. 5, pp. 46–53, May 2013.

[39] W. Zuo, H. Xia, and C. Feng, "A novel coordinated multi-point transmission in dense small cell deployment," in *Proc. IEEE 26th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Aug./Sep.2015, pp. 1872–1877.

[40] Y. Park *et al.*, "Effective small cell deployment with interference and traffic consideration," in *Proc. IEEE Veh. Technol. Conf. (VTC Fall)*, Sep. 2014, pp. 1–5.

[41] S. Cai *et al.*, "Green 5G heterogeneous networks through dynamic small-cell operation," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1103–1115, Jan. 2016.

[42] C.-T. Peng, L.-C. Wang, and C.-H. Liu, "Optimal base station deployment for small cell networks with energy-efficient power control," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2015, pp. 1863–1868.

[43] L. Cheng, Y. Gao, Y. Li, D. Yang, and X. Liu, "A cooperative resource allocation scheme based on self-organized network in ultra-dense small cell deployment," in *Proc. IEEE 81st Veh. Technol. Conf. (VTC Spring)*, May 2015, pp. 1–5.

[44] A. Prasad *et al.*, "Energy-efficient inter-frequency small cell discovery techniques for LTE-advanced heterogeneous network deployments," *IEEE Commun. Mag.*, vol. 5, no. 5, pp. 72–81, May 2013.

[45] H. Pervaiz, L. Musavian, Q. Ni, and Z. Ding, "Energy and spectrum efficient transmission techniques under QoS constraints toward green heterogeneous networks," *IEEE Access*, vol. 3, pp. 1655–1671, Sep. 2015.

[46] J. Wu, C. Yuen, B. Cheng, M. Wang, and J. Chen, "Energy-minimized multipath video transport to mobile devices in heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1160–1178, Apr. 2016.

[47] J. Wu, B. Cheng, and M. Wang, "Energy minimization for quality-constrained video with multipath TCP over heterogeneous wireless networks," in *Proc. IEEE Int. Conf. Distr. Comput. Syst. (ICDCS)*, Jun. 2016, pp. 487–496.

[48] J. Wu, C. Yuen, B. Cheng, Y. Yang, M. Wang, and J. Chen, "Bandwidth-efficient multipath transport protocol for quality-guaranteed real-time video over heterogeneous wireless networks," *IEEE Trans Commun.*, vol. 64, no. 6, pp. 2477–2493, Nov. 2016.

[49] J. Wu, C. Yuen, B. Cheng, Y. Yang, M. Wang, and J. Chen, "Adaptive flow assignment and packet scheduling for delay-constrained traffic over heterogeneous wireless networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 10, pp. 8781–8787, Nov. 2015.

[50] Z. Yi, Y. Peng, T. Wang, X. Zhang, and W. Wang, "Traffic scenario recognition and analysis for wireless cellular system: From social network perspective," in *Proc. IEEE Can. Conf. Elect. Comput. Eng. (CCECE)*, May 2016, pp. 1–5. [Online]. Available: http://www.ee.nthu.edu.tw/cychi/index.html

[51] United States Department of Energy. (2013). *Measurement and Instrumentation Data Center, National Renewable Energy Laboratory (NREL)*. [Online]. Available: http://www.nrel.gov/midc

[52] M. Gorlatova, A. Wallwater, and G. Zussman, "Networking low-power energy harvesting devices: Measurements and algorithms," *IEEE Trans. Mobile Comput.*, vol. 12, no. 9, pp. 1853–1865, Jul. 2012.

[53] H. S. Chang, P. J. Fard, S. I. Marcus, and M. Shayman, "Multitime scale Markov decision processes," *IEEE Trans. Autom. Control*, vol. 48, no. 6, pp. 87–976, Jun. 2003.

[54] H. S. Whang and N. Moayeri, "finite-state Markov channel-a useful model for radio communication channels," *IEEE Trans. Veh. Technol.*, vol. 44, no. 1, pp. 71–163, Feb. 1995.

[55] Y.-H. Chen, N.-Y. Yang, C.-J. Chan, and F.-C. Ren, "A utility function-based access selection method for heterogeneous WCDMA and WLAN networks," in *Proc. IEEE Annu. Int. Symp. Pers., Indoor Mobile Radio Commun., (PIMRC)*, Sep. 2007, pp. 1–5.

[56] J. Maldacena, "The large-N limit of superconformal field theories and supergravity," *Int. J. Theoretical Phys.*, vol. 2, no. 4, pp. 1113–1133, 1997.

[57] D. F. Manlove, *The Hospitals/Residents Problem With Ties*. Springer, vol. 7, no. 18, pp. 390–394, 2008.

[58] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *Amer. Math. Monthly*, vol. 69, no. 1, pp. 9–15, Jan. 1962.

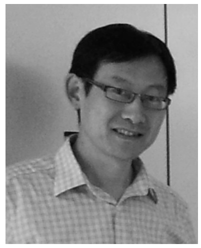
[59] M. Gorlatova, P. Kinget, I. Kymissis, D. Rubenstein, X. Wang, and G. Zussman, "Energy harvesting active networked tags (EnHANTs) for ubiquitous object networking," *IEEE Wireless Commun.*, vol. 17, no. 6, pp. 18–25, Dec. 2010.

[60] T. M. Mitchell, *Machine Learning*. McGraw-Hill, Mar. 1997.

GUANHUA QIAO (S'16) is currently pursuing the Ph.D. degree with the School of Communication and Information Engineering, University of Electronic Science and Technology of China. His interests have focused on the key technologies and resource allocation issue in wireless heterogeneous network with energy harvesting.

SUPENG LENG (M'06) received the Ph.D. degree from Nanyang Technological University (NTU), Singapore. He is currently a Professor with the School of Communication and Information Engineering, University of Electronic Science and Technology of China, Chengdu, China. He has been a Research Fellow with the Network Technology Research Center, NTU. He has authored over 100 research papers. His research interests include resource, spectrum, energy, routing and networking in broadband wireless access networks, vehicular networks, Internet of Things, next-generation mobile networks, and smart grids. He serves as an Organizing Committee Chair and a Technical Program Committee Member for many international conferences, and a Reviewer for over ten international research journals.

KE ZHANG is currently pursuing the Ph.D. degree with the University of Electronic Science and Technology of China. He is currently a Lecturer with the University of Electronic Science and Technology of China, and a Visiting Researcher with Simula Research Laboratory, Fornebu, Norway. His research interests include energy management and communications in the smart grid, design and optimization of next-generation wireless networks, and Internet of Things.



KUN YANG (SM'08) received the M.Sc. and B.Sc. degrees from the Computer Science Department, Jilin University, China, and the Ph.D. degree from the Department of Electronic & Electrical Engineering, University College London (UCL), U.K. He was with UCL on several European Union (EU) research projects for several years. He is currently a Chair Professor with the School of Computer Science & Electronic Engineering, University of Essex, and leading the Network Convergence Laboratory, U.K. He is also an Affiliated Professor with the University of Electronic Science and Technology of China, China. He has published over 100+ journal papers. His main research interests include wireless networks, future Internet technology and network virtualization, mobile cloud computing, and networking. He serves on the editorial boards of the IEEE and the non-IEEE journals. He is a fellow of IET since 2009.