Received September 16, 2018, accepted October 5, 2018, date of publication October 16, 2018, date of current version November 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2876395

A Base Station DTX Scheme for OFDMA Cellular Networks Powered by the Smart Grid

QIANG WANG[1,2], FENG ZHAO[1], AND TIEJUN CHEN[2]

[1]Guangxi Colleges and Universities Key Laboratory of Complex System Optimization and Big Data Processing, Yulin Normal University, Yulin 537000, China
[2]School of electronic and Communication Engineering, Yulin Normal University, Yulin 537000, China

Corresponding author: Feng Zhao (zhaofeng@guet.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61871466, in part by the Guangxi Natural Science Foundation Innovation Research Team Project under Grant 2016GXNSFGA380002, and in part by the Projects of Education Department of Guangxi under Grant 2018KY0472.

ABSTRACT Discontinuous transmission (DTX) is an efficient technology to improve the energy efficiency of the wireless cellular networks. DTX enables the deactivation of some components of the base station in sufficient short time, which can decrease the energy consumption without affecting the normal operation of the mobile networks. In addition, we consider distributed smart grid which can power the cellular networks using renewable and conventional energy. The distributed smart grid has many different energy retailers with variant energy resource, such as solar energy, wind energy, and conventional energy. Comparing with conventional energy, the renewable energy is more environmental friendly, but more expensive. As a result, it is necessary to obtain a good tradeoff between the operation cost and greenhouse gas (GHG) emission. In this paper, we jointly optimize the DTX, resource allocation, and smart grid energy procurement to maximize the profit of the network operators and minimize the GHG emission. We formulate the joint optimization problem as a mixed integer programming problem. By exploiting the structure of the coupled constraint of the problem, we propose a suboptimal distributed algorithm based on the Lagrangian dual method, and the algorithm can be performed at cellular network and smart grid alternately, which can significantly decrease the signaling and computational overhead. Simulation results illustrate that the proposed DTX scheme can significantly enhance the energy saving, and further improve the energy efficiency of the cellular networks.

INDEX TERMS DTX, resource allocation, power control, cellular networks, distributed algorithm.

I. INTRODUCTION

With the explosive increase of the number of wireless terminals, the new generation wireless networks will face huge challenge on the energy consumption. High energy consumption will not only cause the increase of operation cost, but also increase the greenhouse gas (GHG) emission of wireless networks. Based on this, the green communication, witch aims to decrease the dependence on conventional energy of wireless networks, becomes a hot topic of the new generation wireless communication technology. Discontinuous Transmission (DTX) is one of the most popular green communication technologies, which can improve the energy saving of the wireless cellular networks by enabling the deactivation of some components of the base station (BS) in sufficient short time. In fact, in the low-load simulation, most of the radio resource unit of the BS is empty which results in significant waste of the energy.

Due the independence of the channel in different time slots, it is necessary to determine that the BS should be switched off in which time slots for a given frame. Reference [1] optimizes the antenna adaptation, power control and DTX to minimize the base station supply power consumption for multi-user MIMO-OFDM. Some recent works study the relationship between the energy-spectrum efficiency and some key system parameters under DTX mode. In [2], Chang and Miao investigate the impact of network traffic load on spectral and energy efficiency of cellular networks with DTX using stochastic geometry. Finally, they obtain the conclusion that as the network load increases, the average link spectral efficiency decreases while the network spectral efficiency increases, and If the sleep-mode power consumption is larger than a threshold, the energy efficiency would monotonically increase as the network load increases. Reference [3] investigates the energy efficiency under finite local delay constraint in the downlink HetNets with the random DTX scheme. Bonnefoi *et al.* [4] consider a joint optimization problem of base station deep-sleep and DTX micro-sleep.

In addition, the integration of the conventional and renewable energy to power the cellular networks is a another hot technology to reduce the energy consumption. In [8], Amirnavaei and Dong propose an online power control scheme to maximize the long-term time-averaged transmission rate with the assumption of a finite battery storage capacity. Reference [9] considers a wireless power transmission scheme from renewable energy source to user. To reduce the interference between the wireless energy link and wireless information link, Zho *et al.* [9] propose a low-complexity algorithm to jointly optimize the subchannel allocation over time, and the power allocation over time and subchannels. Reference [10] considers a multi-hop energy harvesting network. In [10], a power control policy for each node is proposed to minimize the packet drop probability. Reference [11] considers the energy harvesting cognitive radio networks, and uses the evolutionary game approach and the Stackelberg game approach to maximize the residual energy and throughput at the same time. Reference [12] investigates the a multiple-input multiple-output broadcast channel under the energy harvesting constraint and the peak power constrain. Reference [13]–[18] investigates a virtualization networks for infrastructure which can be shared among multiple cellular operators, and the networks are powered by a combination of conventional and renewable energy source. Distributed smart grid can also provide wireless networks with renewable energy, which can also decrease the conventional energy consumption of wireless networks. In distributed smart grid, there are several distributed generator which can provide various distributed energy source, such as solar energy, wind energy and conventional energy. The renewable energy is more green than conventional energy. However, conventional energy is slightly cheaper than renewable energy. Therefore, it is necessary for wireless networks to achieve a trade-off between GHG emission and operation cost. Reference [18] considers the BS sleeping and CoMP technology of cellular networks powered by distributed smart grid. Specially, the BSs need to decide which retailers to procure energy from and the amount to procure from the smart grid. Finally, the systems decision problem has been modeled as a two-level Stackelberg game. In [19], Ghazzai *et al.* investigate the BS sleeping and energy procurement from the smart grid, and formulate the problem as a optimization problem. Then, two different evolutionary algorithms are implied to solve the optimization problem. Reference [20] proposes a new integration architecture for renewable energy-powered cellular networks and the smart grid. In the smart grid considered by [20], the price of electricity depends on the energy load, which will contribute to decreasing the peak consumption and global energy cost.

In our previous works [21]–[23], we investigate the joint BS sleeping strategy and energy procurement scheme from smart grid. Different from the DTX, BS sleeping has a longer time dimension which is inflexible comparing with DTX. In addition, in our previous works, the optimization problem is solved by the particle swarm optimization (PSO) algorithm, which will cause higher overhead due to its population feature.

In this paper, we consider a DTX networks powered by the distributed smart grid. In the considered networks, BS can be switched into DTX mode with the QoS constraint. Meanwhile, each BS can purchase energy from smart grid, and determine the amount of energy to purchase from the smart grid to achieve a trade-off between the GHG emission and operation cost. In addition, we also consider the resource allocation problem in cellular networks to further improve the energy and spectrum efficiency. Finally, we formulate the joint DTX mode, energy procurement and resource allocation problem as a mixed integer programming problem. To solve this problem, we propose a suboptimal distributed algorithm to significantly decrease the computational overhead of the smart control center and the signaling overhead of the wireless cellular network based on the continuous relaxation and the Lagrange dual domain method. In the proposed distributed algorithm, each BS optimizes the power allocation variables and subcarrier assignment variables and the smart grid optimizes the energy procurement variables, alternately. Then, each BS decides whether to be put into DTX mode according to the difference between the operators revenue and the cost of the GHG emissions. Simulation results illustrate the effectiveness of the proposed distributed algorithm to improve the revenue of the operators and decrease the GHG emissions.

The rest of the paper is organized as follows. In section II, the previous related work is presented. Section III introduces the system model. In section IV, we describe the iterative distruibuted algorithm based on Lagrange dual domain method. In section V, simulation results are provided to evaluate the performance of the proposed algorithm. Finally, we conclude this paper in section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

In this paper, we consider a downlink OFDMA cellular network consisting of M BSs. To simplify the expression, we assume that each BS equips a single omnidirectional antenna (i.e., each BS corresponds to one cell). Meanwhile, we assume there are N subcarriers in each cell. We also assume that the number of active users in each cell are different, and there are K_m users in the mth cell. Each scheduling period includes T time slots so that there are NT resource units (RUs) in total. Besides, the wireless cellular network is powered by the smart grid where the renewable resource is integrated into. The wireless cellular network purchases energy from the S retailers of the smart grid with different prices since the energy sources of each retailer are different, such as solar energy, wind energy or conventional energy, and so on. The perfect CSI is considered, and the channel matrices of all cells are independent and stationary in the scheduling period.

We ignore the inter-cell interference even though it is the major interference for the OFDMA system since we assume

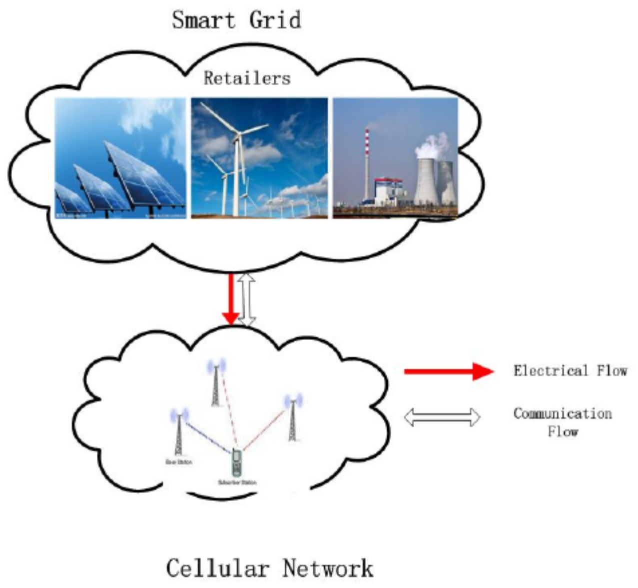

FIGURE 1. Cellular network powered by the smart electrical grid.

the inter-cell interference is managed efficiently with the inter-cell interference control mechanism, such as the Coordinated Multiple Points (CoMP). In this paper, our goal is to determine that each BS should be switched into DTX mode in which time slots of the transmission frame, allocate all NT RUs and power among all K_m users in each cell, and determine each BS should purchase energy from which energy retailers and how much energy should be purchased from each retailer to maximize the operator's profit and minimize the impact on the environment at the same time.

B. DTX POWER MODEL

In this paper, we consider the supply power consumption. The power consumption of each BS includes the power consumption of hardware circuit (such as control units and the baseband processing units) and the signal transmission. In the active mode, the circuit power consumption of the BS is denoted by P_0. The transmission power of the mth BS in the tth time slot is denoted by $P_{m,t} = \sum_{n=1}^{N}\sum_{k_m=1}^{K_m} p_{m,n,k_m}^t$, where p_{m,n,k_m}^t represents the transmit power from the mth BS to the kth user over the nth subcarrier in the tth time slot. When the BS is put into the DTX mode, there is no signal transmission power, and the power consumption of the hardware circuit is in the low level since many components of the base station are turned off. We denote the power consumption of the BS in DTX mode as P_s. Therefore, the power consumption of the mth BS in the tth time slot can be represented as follows:

$$P_{m,t}^{total} = \begin{cases} P_s, & \textit{if } P_{m,t} = 0 \\ P_0 + P_{m,t}, & \textit{otherwise} \end{cases} \tag{1}$$

Since P_s is very little [7], we ignore the energy consumption when the BS is in DTX mode in the following analysis.

C. PROBLEM FORMULATION

We denote the achievable rate of user k_m associated with the mth BS over subcarrier n in the tth time slot as $R_{n,k_m}^{m,t}$. Then, the achievable rate $R_{n,k_m}^{m,t}$ can be given as:

$$R_{n,k_m}^{m,t} = \log(1 + |h_{m,n,k_m}^t|^2 p_{m,n,k_m}^t) \tag{2}$$

where h_{m,n,k_m}^t denotes the channel coefficient from the mth BS to the k_mth user over subcarrier n in the tth time slot; The average rate of the kth user in the mth cell in the frame can be represented as:

$$R_{m,k_m} = \frac{1}{T}\sum_{t=1}^{T}\sum_{n\in N} u_{mnk_m}^t R_{n,k_m}^{m,t} \tag{3}$$

where $u_{mnk_m}^t$ is the subchannel assignment indicator, $\forall\, m$, n, k_m and t. $u_{mnk_m}^t = 1$, if subcarrier n is assigned to user k of the mth cell in the tth time slot; otherwise, $u_{mnk_m}^t = 0$;

Thus, the overall throughput of the mth cell can be given as:

$$R^m = \sum_{t=1}^{T}\rho_{m,t}\sum_{n=1}^{N}\sum_{k=1}^{K_m} u_{mnk_m}^t R_{n,k_m}^{m,t} \tag{4}$$

where $\rho_{m,t}$ is the BS sleeping indicator, $\forall\, m$. If the mth BS is active in the tth time slot, $\rho_{m,t} = 1$; otherwise, $\rho_{m,t} = 0$.

Finally, the overall system throughput can be given as follows

$$R = \sum_{m=1}^{M} R^m \tag{5}$$

Clearly, when the mth BS is put into DTX mode, the throughput of the mth cell is zero. In this case, the network operator has no revenue from the mth cell.

Let ϱ denote the price of the unit throughput. The overall revenue of the network operator can be given as:

$$E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}) = \varrho R = \varrho \sum_{m=1}^{M} R^m \tag{6}$$

where $\mathbf{p} = \{p_{m,n,k_m}^t\}_{M\times N\times K_m\times T}$, $\mathbf{u} = \{u_{mnk_m}^t\}_{M\times N\times K_m\times T}$ and $\boldsymbol{\rho} = \{\rho_{m,t}\}_{M\times T}$.

Intuitively, the network operators should pay more energy cost and pollutant emissions cost to obtain more revenue. It can be readily explained that more throughput consumes more energy, and then more GHG emissions is generated. Next, we introduce the cost of energy consumption and pollutant emission function. The total cost of the energy consumption of the network is expressed as:

$$C(\boldsymbol{\rho}, \mathbf{q}) = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{r=1}^{S} \rho_{m,t}\pi^r q_{m,t}^r \tag{7}$$

where π^r is the cost of unit of energy provided by energy retailer r, q_m^r indicates the amount of energy procured by the mth BS from retailer r, and $\mathbf{q} = \{q_{m,t}^r\}_{M\times T\times S}$.

The pollutant emission function is modeled as follows:

$$F(q_{m,t}^r) = \alpha_r (q_{m,t}^r)^2 + \beta_r q_{m,t}^r \tag{8}$$

where α_r and β_r are the emission coefficient costs of retailer r. For instance, if the retailers energy source is renewable energy, the corresponding emission coefficient costs are small; otherwise, if the retailers energy source is conventional energy, the corresponding emission coefficient costs are large.

Thus, the GHG emission cost function of the network I can be given as follows

$$I(\boldsymbol{\rho}, \mathbf{q}) = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{r=1}^{S} \rho_{m,t} \mathrm{F}(q_{m,t}^r) \tag{9}$$

$I(\boldsymbol{\rho}, \mathbf{q})$ can be regarded as the environment cost of the GHG emissions. To reduce the impact on the environment, the network operators should procure more renewable energy. However, since the renewable energy is more expensive and limited, operators should pay more to procure the clean energy, and when the renewable energy is not enough to cover the need of operators, the operators should procure energy from another retailers owning the conventional energy.

As aforementioned, the operators should achieve a good tradeoff between the revenue of the cellular network and the GHG emission. To this end, the operators should carefully adjust their attitudes toward the revenue and the environment to maximize their profits and minimize the GHG emissions. In the following, the optimization problem can be formulated as

$$\mathbf{P}1 \quad \max_{\mathbf{p},\mathbf{u},\boldsymbol{\rho},\mathbf{q}} \quad w(E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}) - C(\boldsymbol{\rho}, \mathbf{q})) + (1-w)I(\boldsymbol{\rho}, \mathbf{q}) \tag{10}$$

$$s.t. \sum_{t=1}^{T}\sum_{m=1}^{M} \rho_{m,t} q_{m,t}^r \le Q_{max}^r, \quad \forall r \tag{11}$$

$$\sum_{r=1}^{S} q_{m,t}^r = \sum_{n=1}^{N}\sum_{k=1}^{K} p_{m,n,k_m}^t + P_0, \quad \forall m, t \tag{12}$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{k_m=1}^{K_m} p_{m,n,k_m}^t + TP_0 \le P_m, \quad \forall m \tag{13}$$

$$\sum_{k_m=1}^{K} u_{mnk_m}^t = 1, \quad \forall m, n, t \tag{14}$$

$$u_{mnk_m}^t \in \{0, 1\}, \quad \forall m, n, k_m, t \tag{15}$$

$$\rho_{m,t} \in \{0, 1\}, \quad \forall m, t \tag{16}$$

$$\mathbf{p} \succeq 0, \ \mathbf{q} \succeq 0 \tag{17}$$

where w is the weight parameter to be defined and P_m is the peak power of the mth BS; constraints (11) means the overall energy consumed by all BSs from the rth retailer should be not more than the total energy provided by that retailer; constraint (12) indicates that the energy procured by a BS from all retailers should be equal to the overall power consumption of the BS; (13) indicates the overall power consumption of the mth BS should be not more than the peak power of the mth BS; constraint (14) indicates that each subcarrier can be only assigned to one user in each cell.

Indeed, this problem is a multi-objective problem since the two issues (revenue and GHG emissions) are conflicting. Because both the function of the operator revenue and the cost of the GHG emissions can be seen as convex (which will be discussed in the following), the weighted sum method can be adopted to solve the multi-objective problem.

It is worth nothing that the DTX scheme for one certain cell is not dependent on the difference among its channel states of different time slots, since we assume the channel state for each cell is stationary in a short period of time. Instead, in the proposed scenario the DTX scheme is more dependent on the energy procurement. The detail will be illustrated in the next section.

III. OPTIMAL ALGORITHM TO MAXIMIZE THE UTILIZATION FUNCTION

Obviously, problem **P1** is a mixed-integer programming problem which is difficult to solve in general. The common methods to tackle mixed-integer programming problem adopt the continuous relaxation or heuristic algorithm, which are hard to provide an optimal solution. In fact, the continuous relaxation methods only provide an upper bound of the mixed-integer programming problem. In this section, by exploiting the structure of the original problem, we propose an optimal distributed algorithm to solve the problem **P1** which can find out the optimal solution in polynomial time.

Firstly, we introduce some auxiliary variables: $p_{m,n,k_m}^t = \frac{p_{m,n,k_m}^t}{u_{mnk_m}^t}$, $\forall$ $m, n, k_m. t$. These auxiliary variables do not change the original optimization problem [20].

Then, we relax the binary subcarrier assignment variable $\mathbf{u}$ and BS sleeping variable $\boldsymbol{\rho}$ to continuous variables $\widetilde{\mathbf{u}}$ and $\widetilde{\boldsymbol{\rho}}$ in [0, 1] interval, respectively. Thus, the overall revenue, the energy consumption function and the pollutant emission function can be rewritten as:

$$E = \sum_{m=1}^{M} \widetilde{\rho}_{m,t} \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{k=1}^{K_m} \widetilde{u}_{mnk_m}^t \log(1 + |h_{m,n,k_m}^t|^2 \frac{p_{m,n,k_m}^t}{\widetilde{u}_{mnk_m}^t}) \tag{18}$$

$$C = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{r=1}^{S} \widetilde{\rho}_{m,t} \pi^r q_{m,t}^r \tag{19}$$

$$I = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{r=1}^{S} \widetilde{\rho}_{m,t} \mathrm{F}(q_{m,t}^r) \tag{20}$$

Without loss of generality, we let both the weight parameter w and the price of the unit throughput ϱ be 1 to simplify the presentation in the following derivation. Then, substituting $E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho})$, $C(\boldsymbol{\rho}, \mathbf{q})$ and $I(\boldsymbol{\rho}, \mathbf{q})$ into problem **P1**, the original optimization problem can be reformulated as:

$$\mathbf{P}2 \quad \max_{\mathbf{p},\mathbf{u},\boldsymbol{\rho},\mathbf{q}} \quad E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}) - C(\boldsymbol{\rho}, \mathbf{q}) + I(\boldsymbol{\rho}, \mathbf{q}) \tag{21}$$

$$s.t. \sum_{m=1}^{M} \widetilde{\rho}_{m,t} q_{m,t}^r \le Q_{max}^r, \quad r = 1, 2, \cdots, S \tag{22}$$

$$R_{m,k} \geq R_{target}, \quad \forall m, k_m \tag{23}$$

$$\sum_{k_m=1}^{K_m} \widetilde{u}^t_{mnk_m} = 1, \quad \forall m, n, t \tag{24}$$

$$1 \leq \widetilde{\rho}_{m,t} \leq 1, 0 \leq u^t_{mnk_m} \leq 1$$

$$(12), (13), (17) \tag{25}$$

$E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho})$ is not a convex function since its Hessian matrix is not positive definition. In this paper, we propose a suboptimal algorithm to solve the optimization problem. Indeed, if we fix the DTX mode selection variable $\widetilde{\rho}_{m,t}$, the original problem would become a convex optimization problem since $\widetilde{u}^t_{mnk_m}\log(1 + |h^t_{m,n,k_m}|^2 \frac{p^t_{m,n,k_m}}{\widetilde{u}^t_{mnk_m}})$ is a perspective function of $\log(1 + |h^t_{m,n,k_m}|^2 p^t_{m,n,k_m})$. Thus, in the first we can optimize the power allocation, subcarrier assignment and energy procurement with fixed DTX mode selection variable using the Lagrange dual domain method. After optimized these issues, we will optimize the DTX mode selection variable. The detail of the proposed algorithm will be shown in the next subsections.

A. POWER ALLOCATION AND ENERGY PROCUREMENT USING LAGRANGE DUAL METHOD

In this subsection, we solve the problem **P2** using the Lagrange dual domain method. The Lagrange function for (21) can be given as:

$$L(\mathbf{p}, \widetilde{\mathbf{u}}, \boldsymbol{\rho}, \mathbf{q}, \boldsymbol{\lambda}, \boldsymbol{\eta}, \boldsymbol{\mu}, \boldsymbol{\xi})$$

$$= F(\boldsymbol{\lambda}, \boldsymbol{\mu}) + D(\boldsymbol{\eta}, \boldsymbol{\mu}) + \sum_{m=1}^{M} \lambda_m P_m + \sum_{r=1}^{S} \eta_r Q^r_{max} \tag{26}$$

where

$$F = E(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}) - \sum_{m=1}^{M}\sum_{t=1}^{T} \widetilde{\rho}_{m,t}(\lambda_m + \mu_m) \sum_{n=1}^{N}\sum_{k_m=1}^{K} p^t_{m,n,k_m}$$

$$= \max_{\widetilde{\mathbf{u}}, \mathbf{p}, \boldsymbol{\rho}} \sum_{m=1}^{M}\sum_{t=1}^{T} \widetilde{\rho}_{m,t}$$

$$\times [\sum_{n=1}^{N}\sum_{k=1}^{K} \widetilde{u}^t_{mnk_m} \log_2(1 + \frac{p^t_{m,n,k_m}}{\widetilde{u}^t_{mnk_m}} |h^t_{m,n,k_m}|^2)$$

$$-(\lambda_m + \mu_m) \sum_{n=1}^{N}\sum_{k_m=1}^{K_m} p^t_{m,n,k_m}] \tag{27}$$

$$D = \sum_{m=1}^{M}\sum_{t=1}^{T} \widetilde{\rho}_{m,t} \sum_{r=1}^{S} \mathrm{F}(q^r_{m,t}) - C(\boldsymbol{\rho}, \mathbf{q})$$

$$-\sum_{r=1}^{S} \eta_r \sum_{t=1}^{T}\sum_{m=1}^{M} \widetilde{\rho}_{m,t} q^r_{m,t} + \sum_{t=1}^{T}\sum_{m=1}^{M} \widetilde{\rho}_{m,t}\mu_m \sum_{r=1}^{S} q^r_{m,t}$$

$$= \max_{\mathbf{q}, \boldsymbol{\rho}} \sum_{m=1}^{M}\sum_{t=1}^{T} \widetilde{\rho}_{m,t} [\sum_{r=1}^{S} \mathrm{F}(q^r_{m,t}) - \sum_{r=1}^{M} \pi^r q^r_{m,t} - \sum_{r=1}^{S} \eta_r q^r_{m,t}$$

$$+ \mu_m \sum_{r=1}^{S} q^r_{m,t}] \tag{28}$$

Then, we can obtain the dual function:

$$g(\boldsymbol{\lambda}, \boldsymbol{\eta}, \boldsymbol{\mu}) = \max_{\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}, \mathbf{q}} \{L(\mathbf{p}, \mathbf{u}, \boldsymbol{\rho}, \mathbf{q}, \boldsymbol{\lambda}, \boldsymbol{\eta}, \boldsymbol{\mu})\} \tag{29}$$

As aforementioned, the DTX mode selection is fixed in this subsection. Then, we optimize the power allocation and energy procurement variable. Differentiating (26) with respect to p^t_{m,n,k_m} and $q^r_{m,t}$, we can obtain the sufficient and necessary first order condition:

$$\frac{\partial L}{\partial p^{t*}_{m,n,k_m}} = 0, \quad \forall m, n, k_m, t \tag{30}$$

$$\frac{\partial L}{\partial q^{r*}_{m,t}} = 0, \quad \forall m, r, t \tag{31}$$

From (30) and (31), we can obtain the optimal power allocation p^{t*}_{m,n,k_m} and energy procurement $q^{r*}_{m,t}$:

$$p^{t*}_{m,n,k_m} = [\frac{1}{a(\lambda_m + \mu_m)} - \frac{1}{|h^t_{m,n,k_m}|^2}]^+ \widetilde{u}^t_{mnk_m} \tag{32}$$

$$q^{r*}_{m,t} = [\frac{\pi^r - \beta - \eta_r + \mu_m}{2\alpha}]^+ \tag{33}$$

where $\mathrm{a} = 2\ln 2$, $[a]^+ = \max\{0, \mathrm{a}\}$. It can be seen that p^{t*}_{m,n,k_m} is dependent on the channel assignment variable $\widetilde{u}^t_{mnk_m}$. Next, we continue to optimize $\widetilde{u}^t_{mnk_m}$.

B. CHANNEL ASSIGNMENT

Substituting $\mathbf{p}^* \triangleq [p^{t*}_{m,n,k_m}]$ into (28), the power allocation variables can be eliminated. We define

$$\mathrm{A}^t_{mnk_m} = \log_2(1+\frac{p^{t*}_{m,n,k_m}}{\widetilde{u}^t_{mnk_m}}|h^t_{m,n,k_m}|^2)$$

$$-\sum_{m=1}^{M}(\lambda_m+\mu_m)\sum_{n=1}^{N}\sum_{k_m=1}^{K} p^{t*}_{m,n,k_m}$$

It is clear that $\mathrm{A}^t_{mnk_m}$ is dependent on $\widetilde{u}^t_{mnk_m}$.

As aforementioned, we ignore the variable $\widetilde{\rho}_{m,t}$ in this subsection. Then, (27) can be rewritten as:

$$\max_{\widetilde{\mathbf{u}}} \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{k_m=1}^{K_m}\sum_{n=1}^{N} \widetilde{u}^t_{mnk_m} \mathrm{A}^t_{mnk_m} \tag{34}$$

$$s.t. \sum_{k_m=1}^{K} \widetilde{u}^t_{mnk_m} = 1, \quad \forall m, n, t \tag{35}$$

As aforementioned, we ignore the inter-cell interference so that we can allocate the radio resources for each cell independently. Thus, for the mth cell, the corresponding resource allocation problem is given by

$$\max_{\widetilde{\mathbf{u}}} \sum_{t=1}^{T}\sum_{k_m=1}^{K_m}\sum_{n=1}^{N} \widetilde{u}^t_{mnk_m} \mathrm{A}^t_{mnk_m}$$

$$s.t. \sum_{k_m=1}^{K_m} \widetilde{u}^t_{mnk_m} = 1, \quad \forall m, n, t \tag{36}$$

Problem (36) is a linear programming problem, and there always exists a binary optimal solution. In fact, $\mathrm{A}^t_{mnk_m}$ can be regarded as the coefficient of $\widetilde{u}^t_{mnk_m}$ since A^t_{m,n,k_m} is a constant with given λ_m. If there is no tie, only one optimal solution exists, which is that the variable with maximal coefficient is equal to 1, and all another variables are equal to 0. If there is tie, there are infinite optimal solutions. Since we are only interest in the binary optimal solution, arbitrary tie-breaking can be performed which is that a variable with maximal coefficient is randomly selected to be 1, and all another variables are equal to 0. The optimal solution for problem (36) is:

$$\widetilde{u}^{t*}_{mnk_m} = \begin{cases} 1, & if\ k_m = arg \max_{1\le l\le K_m} A^t_{mnl} \\ 0, & otherwise \end{cases} \tag{37}$$

C. DTX MODE SELECTION

In the previous subsections, we have optimized the power allocation, energy procurement decision and the channel assignment. In this subsection, we optimize the DTX mode selection. Substituting $\mathbf{p}^*$, $\mathbf{u}^*$ and $\mathbf{q}^*$ into (26), (26) can be rewritten as:

$$\begin{aligned} L(\boldsymbol{\rho}, \boldsymbol{\lambda}, \boldsymbol{\eta}, \boldsymbol{\mu}) = \max_{\boldsymbol{\rho}} \sum_{m=1}^{M}\sum_{t=1}^{T}(C_1^{m,t} + C_2^{m,t})\widetilde{\rho}_{m,t} \\ + \sum_{m=1}^{M}\lambda_m P_{m,t} + \sum_{r=1}^{S}\eta_r Q^r_{max} \\ 0 \le \widetilde{\rho}_{m,t} \le 1 \end{aligned} \tag{38}$$

where

$$\begin{aligned} C_1^{m,t} &= \sum_{n=1}^{N}\sum_{k_m=1}^{K_m}\widetilde{u}^{t*}_{mnk_m}\log_2(1+\frac{p^{t*}_{m,n,k_m}}{\widetilde{u}^{t*}_{mnk_m}}|h^t_{m,n,k_m}|^2) \\ &\quad -(\lambda_m+\mu_m)\sum_{n=1}^{N}\sum_{k_m=1}^{K_m}p^{t*}_{m,n,k_m} \end{aligned} \tag{39}$$

$$C_2^{m,t} = \sum_{r=1}^{S}\mathrm{F}(q^{r*}_{m,t}) - \sum_{r=1}^{M}\pi^r q^{r*}_{m,t} + \sum_{r=1}^{S}\eta_r q^{r*}_{m,t} - \mu_m\sum_{r=1}^{S}q^{r*}_{m,t} \tag{40}$$

It is obvious that (38) is a linear programming problem, and there are only DTX mode selection variables in Lagrange function when $\boldsymbol{\lambda}$, $\boldsymbol{\eta}$, and $\boldsymbol{\mu}$ are fixed. Then, we can readily obtain the optimal DTX mode selection strategy:

$$\widetilde{\rho}^*_{m,t} = \begin{cases} 1, & if\ C_1^{m,t} + C_2^{m,t} > 0 \\ 0, & otherwise \end{cases} \tag{41}$$

Indeed, for the above solution, there is a more practical explain. For the mth BS, $C_1^{m,t} + C_2^{m,t}$ can be seen as the difference between the revenue and the cost of the GHG emissions of the mth BS in the tth time slot. If this difference is smaller than or equal to 0, it shows that the revenue of the cell is not lager than the cost of the GHG emissions. For this case, the mth BS should be switched into DTX mode in this time slot since this BS can not create "value", or the profits created by the BS is less than the environmental cost of the BS's GHG emissions. Otherwise, if $C_1^{m,t} + C_2^{m,t}$ is larger than 0, the mth BS should be active in the tth time slot for the same reason.

Remark: In this paper, a multi-cell network is considered, in which each cell's DTX mode is dependent on the difference among all the cell's load and channel states rather than the difference among the channel states of different time slots since each cell's channel state is stationary in a short period of time. For one certain cell, if it purchases energy from the renewable source, the energy cost and the GHG emission cost would be reduced which results in more earnings. However, since the renewable energy is limited due to the limited availability and the uncertainty about the timing and the quantity, the smart grid should allocate the limited renewable energy to the cells which can bring more profits.

D. THE DISTRIBUTED ALGORITHM

In the previous subsections, we have optimized the power allocation, subcarrier assignment and energy procurement with fixed $\boldsymbol{\lambda}$, $\boldsymbol{\eta}$, and $\boldsymbol{\mu}$. Generally, the computation procedure is centralized resource allocation scheme which should be implemented in the smart control center (SCC), and it consumes a great deal of signaling and computational overhead. To decrease the computation overhead of the SCC and the signaling overhead of the wireless cellular networks, in this subsection, we propose a distributed algorithm to solve the formulated optimization problem. Meanwhile, the subgradient-based method is used to solve the dual problem to optimize $\boldsymbol{\lambda}$, $\boldsymbol{\eta}$, and $\boldsymbol{\mu}$. The jth iteration of the subgradient-based method is given as follows:

BSs Side Algorithm:

i) Each BS measures the SINR of each subchannel by using pilot signals, and receive the value of μ_j from the smart grid.

ii) BS m determines the subcarrier assignment $u^t_{mnk_m}$, power allocation p^t_{m,n,k_m} and BS sleeping variable $\rho_{m,t}$ according to (37), (32) and (41), respectively.

iii) BS m updates the corresponding Lagrange multiplier λ_m by:

$$\lambda_m(j+1) = \lambda_m(j) - v(j)(P_m - \sum_{n=1}^{N}\sum_{k_m=1}^{K_m}p^t_{m,n,k_m}) \tag{42}$$

Smart Grid Side Algorithm:

At the smart grid side, retailer r updates the corresponding energy procurement $q^r_{m,t}$, Lagrange multipliers η_r and μ_m, and announces the new μ_m to BS m.

i) retailer r updates the energy procurement q^m_r according to (33).

ii) The Lagrange multipliers η_r and μ_m are updated by

$$\eta_r(j+1) = \eta_r(j) + \delta(j)(Q_r - \sum_{t=1}^{T}\sum_{m=1}^{M}q^r_{m,t}) \tag{43}$$

$$\mu_m(j+1) = \mu_m(j) + \theta(j)(\sum_{r=1}q^r_{m,t} - \sum_{n=1}^{N}\sum_{k_m=1}^{K_m}p^t_{m,n,k_m}) \tag{44}$$

where $v(j)$, $\delta(j)$ and $\theta(j)$ are dynamically chosen stepsize sequences.

In the above distributed algorithm, the Lagrange multiplier μ_m has a nice interpretation: μ_m can be interpreted as the price at the smart grid determined by the wireless cellular network load. μ_m plays an important role in the proposed distributed algorithm. In fact, it can be seen as the interactive massage between the BSs side and smart grid side. $\sum_{n=1}^{N}\sum_{k_m=1}^{K_m} p^t_{m,n,k_m}$ can be interpreted as the energy demand of BS m, and $\sum_{r=1} q^r_{m,t}$ can be seen as the energy supply of the smart grid. It is rational that if the energy demand $\sum_{n=1}^{N}\sum_{k_m=1}^{K_m} p^t_{m,n,k_m}$ exceeds the energy supply $\sum_{r=1} q^r_{m,t}$, the price μ_m will go up; otherwise, μ_m will go down.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed DTX scheme and distributed algorithm using simulations. In the first, we introduce the simulation setup. In the simulation, there are four BSs in the wireless network and ten time slots in each transmission frame. Without loss of generality, the unit price of the throughput is set to 1. At the smart grid side, we assume that there are $S = 3$ retailers with 3 different energy sources, respectively, and the cost of unit energy of each retailer are different. Further system parameters in this paper is detailed in Table I, and the prices of the energy is referred from [5]. In this work, 3GPP path loss model is adopted, and the small scale fading is modeled as Rayleigh fading. To evaluate the performance gain of the proposed algorithm, we consider some schemes with simple configurations as benchmarks:

TABLE 1. Simulation parameters.

similation parameter	value
Cell radius	1 Km
Inner boundary radius	0.6 Km
Subcarrier bandwidth	15 KHz
Number of retailers	3
Noise power spectral density	-174 dBm/Hz
Path loss coefficient	4
Peak power of BS	30 dBm
price of the unit throughput	1
price of the unit wind energy	0.5
price of the unit solar energy	0.9
price of the unit conventional energy	0.1

1) Maximum Power Consumption In this case, each BS transmits signals at maximum power, and each subcarrier is allocated to equal power. We only consider the DTX scheme and the energy procurement decision.

2) No DTX Scheme In this case, DTX scheme is not applied, and we only consider the power control, radio resource allocation and the energy procurement decision.

A. SIMULATION RESULTS ANALYSIS

In this subsection, we assess the performance of the proposed algorithm by comparing its performance with the aforementioned benchmarks. Fig.2 compares the different operators' profits of the proposed scheme with that of these benchmarks over different number of users in each cell. From Fig.2, the profits improves with the increase of the number of users in each cell. The result can be easily explained that more users can result in more system throughput which can bring more profits as the result of the multi-user diversity. It also can be observed from Fig.2 that the proposed scheme can achieve more profits than all other benchmarks. The Maximum Power Consumption outperforms the No DTX Scheme. The result of Fig.2 illustrates that the DTX scheme can enhance the energy saving of the wireless cellular network effectively.

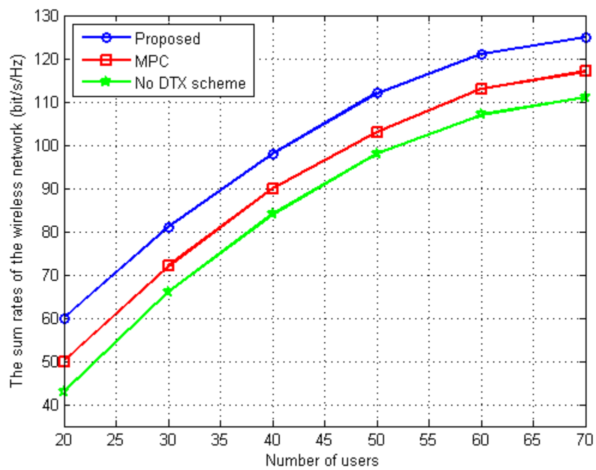

FIGURE 2. Operator's profit vs different number of users. N = 32, M = 4.

The GHG emission performance of the proposed algorithm in comparison to the benchmarks is shown in Fig.3. From Fig.3, it can be observed that the overall GHG emission becomes more and more with the increase of the number of users. The result comes from the fact that more users cause more power consumption which result in the more GHG emissions. We can observe that the proposed scheme outperforms the other benchmarks to decrease the GHG emission. Furthermore, the increasing rate of the curve of the proposed algorithm goes slower and slower with the increase of the number of the users. In fact, it is not necessary to transmit signals in all time slots of the transmission frame to meet the target rates due to the variant channel conditions. That is, the BS can be turned off for a significant portion of its operation time so that No DTX Scheme would waste a lot of power consumption which can generate much extra GHG emission.

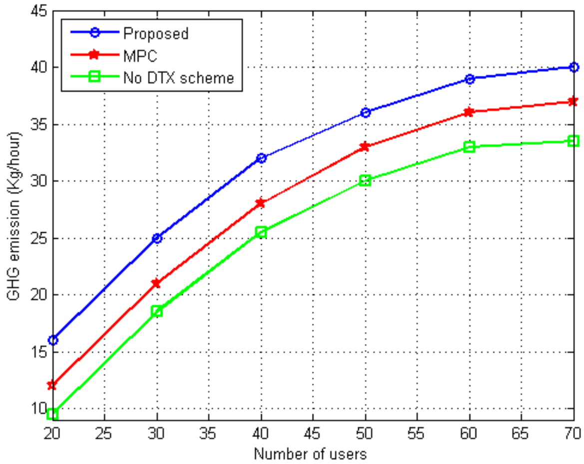

FIGURE 3. Carbon emission vs different number of users. N = 32 M = 4.

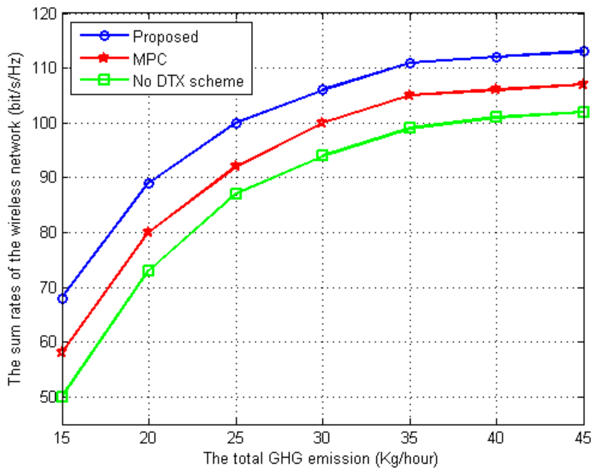

FIGURE 4. Operators' profit vs different carbon emission. N = 32, M = 4, K = 16.

Fig.4 compares the operators' profit of the proposed algorithm with that of the benchmarks. It depicts the relation between the profit and the GHG emission. From Fig.4, it can be seen that the GHG emission increases with the increase of the profit. The result comes from the fact that if the operators want more profit, more GHG would be emitted. Indeed, Fig.4 plots a Pareto front due to the fact that the original problem is a multi-objective optimization problem and the GHG emission and profit of the operators are conflicting. We also observe that the profits obtained by the No DTX Scheme is less than the proposed algorithm and the Maximum Power Consumption scheme with the fixed GHG emission, which illustrates that DTX can significantly enhance the power saving.

B. DTX SCHEME SIMULATION

The proposed scheme in this paper can not only calculate the number of DTX time slots, but also obtain that the BS should be idle in which time slots of the frame. Table 2 shows the BS should be turned into DTX in which time slots in the transmission frame over the increasing average channel condition. It can be shown that the number of DTX time slot in each transmission frame structure decreases with the degradation of the average channel condition. For the worst average channel condition (≤ -10 dB), Table 3 depicts that the BS should be active in all time slots to complete the target rates. When the average channel condition is good enough (≥ 15 dB), a large proportion of all the average time slots is selected for DTX because of the high transmit rate in the good channel condition.

TABLE 2. DTX mode selection in different time slots over the increasing average channel condition.

channel conditions	bad	medium	good
slot 1	on	on	off
slot 2	on	on	on
slot 3	on	off	on
slot 4	on	on	off
slot 5	on	on	off
slot 6	on	off	on
slot 7	on	off	on
slot 8	on	off	off
slot 9	on	on	off
slot 10	on	on	off

TABLE 3. DTX mode selection in different time slots over the increasing user target data rates.

target rates	5 Mbps	15 Mbps	25 Mbps
slot 1	off	on	on
slot 2	on	on	on
slot 3	off	off	on
slot 4	on	on	on
slot 5	on	on	on
slot 6	on	on	on
slot 7	off	off	on
slot 8	off	off	on
slot 9	on	on	on
slot 10	off	on	on

Table 3 shows that when the user target data rates is not high (user target data rates ≤ 15 Mbps), there are a few time slots to be selected for DTX. In fact, it is most likely that the GHG emissions generated by the BS exceeds the profit that it earns in the poor time slots. In this case, it can save more energy to turn off the BS in these time slots. Moreover, the number of the DTX time slots decreases with the increase of the target rates. This result shows that when the target rates is too high, the BS have to work constantly in the poor time slots to meet the target rates.

C. CONVERGENCE PERFORMANCE

Convergence performance is important to the algorithm because of the requirement of lower delay. In this subsection, we intend to evaluate the convergence performance of

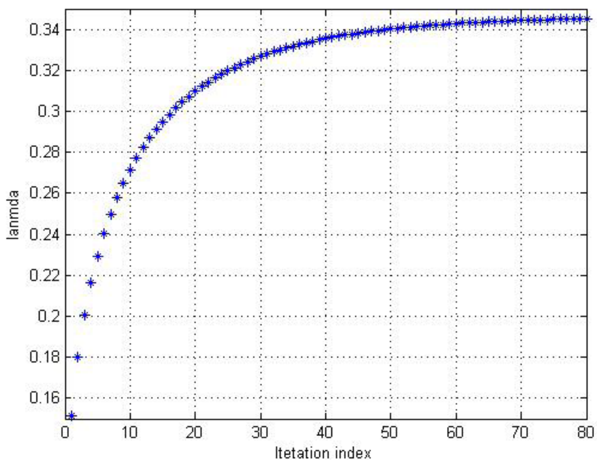

FIGURE 5. Lagrange multiplier vs the number of iterative index. N = 32, M = 4, K = 16.

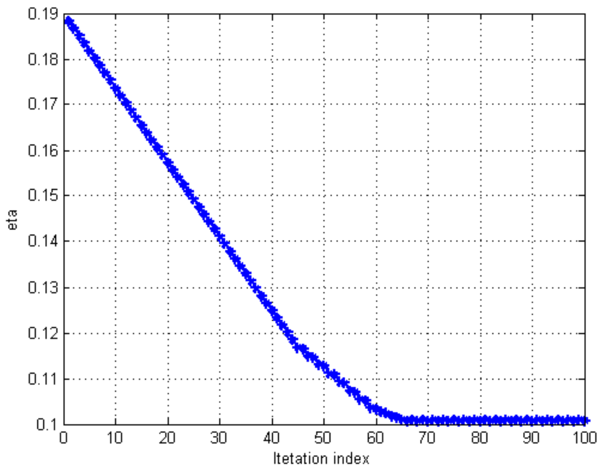

FIGURE 6. Lagrange multiplier vs the number of iterative index. N = 32, M = 4, K = 16.

the proposed algorithm. Fig.5 and Fig.6 show the different Lagrange multipliers versus the iteration indices of the proposed distributed algorithm, respectively. It demonstrates the convergence for the proposed algorithm, and it is also shown that the proposed algorithm converges within 60 iterations.

V. CONCLUSION

In this paper, we investigate the DTX scheme for cellular networks to enhance the energy saving to cope with the requirement of green communication. In addition, the distributed smart grid is considered to power the cellular networks where the renewable energy sources are integrated which can decrease the conventional energy consumption. Generally, comparing with conventional energy, the renewable energy is more expensive, but more environmental friendly. Therefore, it is necessary to optimize the energy procurement to achieve a good tradeoff between the cost and GHG emission. We formulate the DTX scheme, resource allocation and energy procurement as a mixed-integer programming problem. Then, a distributed optimization algorithm based on Lagrangian dual method is proposed to solve the problem, and the proposed algorithm can be performed at cellular networks and smart grid alternately, which can effectively reduce the signaling and computational overhead. Simulation results illustrate that the proposed algorithm can effectively improve the energy efficiency of the cellular networks.

REFERENCES

[1] H. Holtkamp, G. Auer, S. Bazzi, and H. Haas, "Minimizing base station power consumption," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 2, pp. 297–306, Feb. 2014.

[2] P. Chang and G. Miao, "Energy and spectral efficiency of cellular networks with discontinuous transmission," *IEEE Trans. Wireless Commun.*, vol. 16, no. 5, pp. 2991–3002, May 2017.

[3] W. Nie, Y. Zhong, F.-C. Zheng, W. Zhang, and T. O'Farrell, "HetNets with random DTX scheme: Local delay and energy efficiency," *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6601–6603, Aug. 2016.

[4] R. Bonnefoi, C. Moy, and J. Palicot, "New macrocell downlink energy consumption minimization with cell DTx and power control," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–7.

[5] Y. Cui, V. Lau, and Y. Wu, "Delay-aware BS discontinuous transmission control and user scheduling for energy harvesting downlink coordinated MIMO systems," *IEEE Trans. Signal Process.*, vol. 60, no. 7, pp. 3786–3795, Jul. 2012.

[6] S. Tombaz, S.-W. Han, K. W. Sung, and J. Zander, "Energy efficient network deployment with cell DTX," *IEEE Commun. Lett.*, vol. 18, no. 6, pp. 977–980, Jun. 2014.

[7] I. Ashraf, F. Boccardi, and L. Ho, "SLEEP mode techniques for small cell deployments," *IEEE Commun. Mag.*, vol. 49, no. 8, pp. 72–79, Aug. 2011.

[8] F. Amirnavaei and M. Dong, "Online power control optimization for wireless transmission with energy harvesting and storage," *IEEE Trans. Wireless Commun.*, vol. 15, no. 7, pp. 4888–4901, Jul. 2016.

[9] X. Zho, C. K. Ho, and R. Zhang, "Wireless power meets energy harvesting: A joint energy allocation approach in OFDM-based system," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, pp. 3481–3491, May 2016.

[10] M. K. Sharma and C. R. Murthy, "Distributed power control for multi-hop energy harvesting links with retransmission," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 4064–4078, Jun. 2018.

[11] O. Elnahas, M. Elsabrouty, O. Muta, and H. Furukawa, "Game theoretic approaches for cooperative spectrum sensing in energy-harvesting cognitive radio networks," *IEEE Access*, vol. 6, pp. 11086–11110, Feb. 2018.

[12] Z. Chen, P. Fan, D. O. Wu, and K. B. Letaief, "Weighted sum-throughput maximization for MIMO broadcast channel: Energy harvesting with hybrid energy storage," *J. Commun. Netw.*, vol. 19, no. 6, pp. 678–692, Dec. 2017.

[13] M. J. Farooq, H. Ghazzai, E. Yaacoub, A. Kadri, and M.-S. Alouini, "Green virtualization for multiple collaborative cellular operators," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 3, pp. 420–434, Sep. 2017.

[14] A. Bannour, C. Sacchi, and Y. Sun, "MIMO-OFDM based energy harvesting cooperative communications using coalitional game algorithm," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 11166–11179, Dec. 2017.

[15] J. Gong, J. S. Thompson, S. Zhou, and Z. Niu, "Base station sleeping and resource allocation in renewable energy powered cellular networks," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 3801–3813, Nov. 2014.

[16] I. Ahmed, A. Ikhlef, D. W. K. Ng, and R. Schober, "Power allocation for an energy harvesting transmitter with hybrid energy sources," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 6255–6267, Dec. 2013.

[17] Z. Chen, Y. Dong, P. Fan, and K. B. Letaief, "Optimal throughput for two-way relaying: Energy harvesting and energy co-operation," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1448–1462, Mar. 2016.

[18] S. Bu, F. R. Yu, Y. Cai, and X. P. 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.

[19] H. Ghazzai, E. Yaacoub, M.-S. Alouini, and A. Abu-Dayya, "Optimized smart grid energy procurement for LTE networks using evolutionary algorithms," *IEEE Trans. Veh. Technol.*, vol. 63, no. 9, pp. 4508–4519, Nov. 2014.

[20] H. A. H. Hassan, A. Pelov, and L. Nuaymi, "Optimized smart grid energy procurement for LTE networks using evolutionary algorithms," *IEEE Access*, vol. 3, pp. 2755–2770, 2015.
[21] Q. Wang and H.-L. Liu, "Optimized base station sleeping and smart grid energy procurement scheme to improve energy efficiency," in *Critical Developments and Applications of Swarm Intelligence*. Feb. 2018, pp. 357–378.
[22] Q. Wang and H. Liu, "Optimized base station sleeping and renewable energy procurement using PSO," *Int. J. Swarm Intell. Res.*, vol. 8, no. 1, pp. 1–20, 2017.
[23] Q. Wang and H.-I. Liu, "Optimized base station sleeping and renewable energy procurement using PSO," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Sendai, Japan, May 2015, pp. 319–324.

QIANG WANG received the B.S. degree from Qufu Normal University, China, in 2010, and the M.Sc. and Ph.D. degrees from the Guangdong University of Technology, China. He is currently with the Guangxi Colleges and Universities Key Laboratory of Complex System Optimization and Big Data Processing, Yulin Normal University, Yulin, China. His research interests include wireless communications, signal processing, and evolutionary algorithm.

FENG ZHAO received the Ph.D. degree in communications and information systems from Shandong University, China, in 2007. He is currently a Professor with the Guangxi Colleges and Universities Key Laboratory of Complex System Optimization and Big Data Processing, Yulin Normal University, Yulin, China. His research interests include wireless communications, signal processing, and information security.

TIEJUN CHEN received the B.S. degree from the University of Electronic Science and technology of China, China, in 1988, and the M.Sc. degree from the Guilin University of Electronic Technology, China, in 2007. He is currently with the School of Electronic and Communication Engineering, Yulin Normal University, Yulin, China, and also the Senior Member of the China Electronics Society. His research interests include wireless communications, signal processing, and embedded system.