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

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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, which 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. Ref. [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], the authors 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. Ref. [3] investigates the energy efficiency under finite local delay constraint in the downlink HetNets with the random DTX scheme. The authors in [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 hot technology to reduce the energy consumption. In [8], the authors propose an online power control scheme to maximize the long-term time-averaged transmission rate with the assumption of a finite battery storage capacity. Ref. [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, the authors in [9] propose a low-complexity algorithm to jointly optimize the subchannel allocation over time, and the power allocation over time and subchannels. [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. Ref. [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. [12] investigates the a multiple-input multiple-output broadcast channel under the energy harvesting constraint and the peak power constraint. Ref. [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. Ref. [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 system's decision problem has been modeled as a two-level Stackelberg game. In [19], the authors 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. Ref. [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 operator's 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 distributed 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 $m$th 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.
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 $m$th BS in the $t$th time slot can be represented as follows:

$$P_{m,t}^{\text{total}} = \begin{cases} P_s, & \text{if } P_{m,t} = 0 \\ P_0 + P_{m,t}, & \text{otherwise} \end{cases}$$  \hspace{1cm} (1)$$

Since $P_s$ is very little \cite{7}, we ignore the energy consumption when the BS is in DTX mode in the following analysis.

\section*{C. PROBLEM FORMULATION}

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

$$R_{m,k_m}^{m,t} = \log(1 + \left|h_{m,n,k_m}^t\right|^2 P_{m+n,k_m}^{m,t})$$  \hspace{1cm} (2)$$

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

$$R_{m,k_m} = \frac{1}{T} \sum_{t=1}^{T} \sum_{n \in \mathcal{N}} u_{m,n,k_m}^{t} R_{m,n,k_m}^{m,t}$$  \hspace{1cm} (3)$$

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

Thus, the overall throughput of the $m$th cell can be given as:

$$R^m = \sum_{t=1}^{T} \rho_{m,t} \sum_{n=1}^{N} \sum_{k=1}^{K_m} u_{m,n,k_m}^{t} R_{m,n,k_m}^{m,t}$$  \hspace{1cm} (4)$$

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

Finally, the overall system throughput can be given as follows:

$$R = \sum_{m=1}^{M} R^m$$  \hspace{1cm} (5)$$

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

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

$$E(p, u, \varrho) = \varrho R = \varrho \sum_{m=1}^{M} R^m$$  \hspace{1cm} (6)$$

where $p = \{p_{m,n,k_m}^{t}\}^{M \times N \times K_m \times T}$, $u = \{u_{m,n,k_m}^{t}\}^{M \times N \times K_m \times T}$ and $\varrho = \{\varrho_{m,t}\}^{M \times T}$.

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:

$$ C(\rho, \bar{q}) = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{r=1}^{S} \rho_{m,t} \pi_r q_{m,t}^r $$  \hspace{1cm} (7) $$

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

The pollutant emission function is modeled as follows:

$$ F(q_{m,t}^r) = \alpha_r (q_{m,t}^r)^2 + \beta_r q_{m,t}^r $$  \hspace{1cm} (8) $$

where $\alpha_r$ and $\beta_r$ are the emission coefficient costs of retailer $r$. For instance, if the retailer's energy source is renewable energy, the corresponding emission coefficient costs are small; otherwise, if the retailer's 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:

$$ I(\rho, \bar{q}) = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{r=1}^{S} \rho_{m,t} F(q_{m,t}^r) $$  \hspace{1cm} (9) $$

$I(\rho, \bar{q})$ 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

$$ \textbf{P1} \max_{\rho, u, \bar{q}} \quad w(E(u, \bar{q}) - C(\rho, \bar{q})) + (1 - w)I(\rho, \bar{q}) $$ \hspace{1cm} (10) $$

s.t. \hspace{1cm} \sum_{t=1}^{T} \sum_{m=1}^{M} \rho_{m,t} q_{m,t}^r \leq Q_{\text{max}}, \forall r $$ \hspace{1cm} (11) $$

$$ \sum_{r=1}^{S} q_{m,t}^r = \sum_{n=1}^{N} \sum_{k=1}^{K} p_{m,n,k}^t + P_0, \forall m, t $$ \hspace{1cm} (12) $$

$$ \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} p_{m,n,k}^t + TP_0 \leq P_{m,t} \forall m, t $$ \hspace{1cm} (13) $$

$$ \sum_{k_{mn}m}^{K} u_{m,n,k_{mn}}^t = 1, \forall m, n, t $$ \hspace{1cm} (14) $$

$$ u_{m,n,k_{mn}}^t \in \{0,1\}, \forall m, n, k_{mn}, t $$ \hspace{1cm} (15) $$

$$ \rho_{m,t} \in \{0,1\}, \forall m, t $$ \hspace{1cm} (16) $$

where $w$ is the weight parameter to be defined and $P_{m,t}$ is the peak power of the $m$th BS; constraints (11) means the overall energy consumed by all BSs from the $r$th 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 $m$th BS should be not more than the peak power of the $m$th BS; constraint (14) indicates that each subcarrier can be only assigned to one user in each cell. Then, we give the details of the variables of problem \textbf{P1} in the table I.

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 \textbf{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 \textbf{P1} which can find out the optimal solution in polynomial time.

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

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

$$ E = \sum_{m=1}^{M} \bar{\rho}_{m,t} \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} \bar{u}_{m,n,k_{mn}}^t \log(1 + h_{m,n,k_{mn}}^t \frac{P_{t}^m n_{mn}}{\bar{u}_{m,n,k_{mn}}^t}) $$ \hspace{1cm} (18) $$

$$ C = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{r=1}^{S} \bar{\rho}_{m,t} \pi_r q_{m,t}^r $$ \hspace{1cm} (19) $$
I = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{r=1}^{S} \tilde{p}_{m,t} 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 \( \varrho \) be 1 to simplify the presentation in the following derivation. Then, substituting \( E(p, u, \rho, \lambda, \eta) \) and \( I(p, \lambda, \eta) \) into problem \( \text{P1} \), the original optimization problem can be reformulated as:

\[
P_2 \quad \max_{p,u,\rho,q} \quad E(p, u, \rho) - C(\rho, q) + I(\rho, q) \tag{21}
\]

s.t.

\[
\sum_{m=1}^{M} \tilde{\rho}_{m,t} q_{m,t}^r \leq Q_{\text{max}}^r, r = 1, 2, \cdots, S \tag{22}
\]

\[
R_{m,k} \geq R_{\text{target}}, \forall m, k \tag{23}
\]

\[
\sum_{k_m=1}^{K_m} \tilde{u}_{m,n,k_m} = 1, \forall m, n, t \tag{24}
\]

\[
1 \leq \tilde{\rho}_{m,t} \leq 1, 0 \leq u_{m,n,k_m} \leq 1 \tag{25}
\]

\[(12), (13), (17)\]

\( E(p, u, \rho, \lambda, \eta) \) is not a convex function since its Hessian matrix is not positive definite. In this paper, we propose a suboptimal algorithm to solve the optimization problem. Indeed, if we fix the DTX mode selection variable \( \tilde{\rho}_{m,t} \), the original problem would become a convex optimization problem since \( \tilde{u}_{m,n,k_m} \log(1 + |h_{m,n,k_m}|^2) \) is a perspective function of \( \log(1 + |h_{m,n,k_m}|^2) \). Thus, in the first step 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 \( \text{P2} \) using the Lagrange dual domain method. The Lagrange function for (21)

\[
L(p, \tilde{u}, \rho, \eta, \lambda, \mu, \xi) = F(\lambda, \mu) + D(\eta, \mu) + \sum_{m=1}^{M} \lambda_m P_m + \sum_{r=1}^{S} \eta_r Q_{\text{max}}^r
\]

where

\[
F = E(p, u, \rho) - \sum_{m=1}^{M} \sum_{t=1}^{T} \tilde{\rho}_{m,t} (\lambda_m + \mu_m) \sum_{n=1}^{N} \sum_{k_m=1}^{K_m} \rho_{m,n,k_m}^t \tag{26}
\]

\[
= \max_{u,p,\rho} \sum_{m=1}^{M} \sum_{t=1}^{T} \tilde{\rho}_{m,t} \sum_{n=1}^{N} \sum_{k_m=1}^{K_m} \rho_{m,n,k_m}^t \log_2 (1 + \frac{\rho_{m,n,k_m}^t}{\hat{u}_{m,n,k_m}^t} |h_{m,n,k_m}^t|^2) - (\lambda_m + \mu_m) \sum_{n=1}^{N} \sum_{k_m=1}^{K_m} \rho_{m,n,k_m}^t
\]

\[
- \lambda_m \sum_{m=1}^{M} \sum_{t=1}^{T} \rho_{m,t} \sum_{n=1}^{N} \sum_{k_m=1}^{K_m} \rho_{m,n,k_m}^t \tag{27}
\]

\[
D = \max_{q} \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{r=1}^{S} F(q_{m,t}^r) - C(\rho, q)
\]

Then, we can obtain the dual function:

\[
g(\lambda, \eta, \mu) = \max_{p,u,\rho,q} \{ L(p, u, \rho, q, \lambda, \eta, \mu) \} \tag{29}
\]

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 \( p_{m,n,k_m}^t \) and \( q_{m,t}^r \), we can obtain the sufficient and necessary first order condition:

\[
\frac{\partial L}{\partial p_{m,n,k_m}^t} = 0, \forall m, n, k_m, t \tag{30}
\]

\[
\frac{\partial L}{\partial q_{m,t}^r} = 0, \forall m, n, t \tag{31}
\]

From (30) and (31), we can obtain the optimal power allocation \( p_{m,n,k_m}^* \) and energy procurement \( q_{m,t}^r \):

\[
p_{m,n,k_m}^* = \frac{1}{a(\lambda_m + \mu_m)} - \frac{1}{h_{m,n,k_m}^t |h_{m,n,k_m}^t|^2} \hat{u}_{m,n,k_m}^t \tag{32}
\]

\[
q_{m,t}^r = \frac{\pi_r - \beta - \eta_r + \mu_m}{2a} \tag{33}
\]

where \( a = \text{2ln}2, [a]^+ = \max\{0,a\} \). It can be seen that \( p_{m,n,k_m}^* \) is dependent on the channel assignment variable \( \tilde{u}_{m,n,k_m}^t \). Next, we continue to optimize \( \hat{u}_{m,n,k_m}^t \).

### B. CHANNEL ASSIGNMENT

Substituting \( p = [p_{m,n,k_m}^*] \) into (28), the power allocation variables can be eliminated. We define

\[
A_{m,n,k_m}^t = \log_2 (1 + \frac{\rho_{m,n,k_m}^t}{\hat{u}_{m,n,k_m}^t} |h_{m,n,k_m}^t|^2) - \sum_{m=1}^{M} (\lambda_m + \mu_m) \sum_{n=1}^{N} \sum_{k_m=1}^{K_m} p_{m,n,k_m}^t
\]

\[
A_{m,n,k_m}^t \text{ is dependent on the channel assignment variable } \tilde{u}_{m,n,k_m}^t.
\]
It is clear that \( A_{mnk}^t \) is dependent on \( \bar{u}_{mnk}^t \).

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

\[
\max_{u} \sum_{m=1}^{M} \sum_{k=1}^{K_m} \sum_{n=1}^{N} u_{mnk}^t A_{mnk}^t \tag{34}
\]

s.t. \( \sum_{k=1}^{K_m} \bar{u}_{mnk}^t = 1, \forall m, n, t \)

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

\[
\max_{u} \sum_{t=1}^{T} \sum_{k=1}^{K_m} \sum_{n=1}^{N} u_{mnk}^t A_{mnk}^t \tag{36}
\]

s.t. \( \sum_{k=1}^{K_m} \bar{u}_{mnk}^t = 1, \forall m, n, t \)

Problem (36) is a linear programming problem, and there always exists a binary optimal solution. In fact, \( A_{mnk}^t \) can be regarded as the coefficient of \( u_{mnk}^t \) since \( A_{mnk}^t \) is a constant with given \( \lambda_m \). 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:

\[
\bar{u}_{mnk}^t = \begin{cases} 1, & \text{if } k_m = \arg \max_{1 \leq k \leq K_m} A_{mnl}^t \\ 0, & \text{otherwise} \end{cases} \tag{37}
\]

\[\text{C. DTX MODE SELECTION}\]

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 \( p^* \), \( u^* \) and \( q^* \) into (26), (26) can be rewritten as:

\[
L(p, \lambda, \eta, \mu) = \max_p \sum_{m=1}^{M} \sum_{t=1}^{T} (C_{1,m,t} + C_{2,m,t}) \bar{\rho}_{m,t} \tag{38}
\]

\[
+ \sum_{m=1}^{M} \lambda_m P_{m,t} + \sum_{r=1}^{S} \eta_r Q_{max}^r \\
0 \leq \bar{\rho}_{m,t} \leq 1
\]

where

\[
C_{1,m,t} = \sum_{n=1}^{N} K_m \frac{n}{N} u_{mnk}^t \log_2 \left( 1 + \frac{P_{m,n,k}^t h_{m,n,k}^t}{u_{mnk}^t} \right)^2 \\
(\lambda_m + \mu_m) \sum_{n=1}^{N} \sum_{k=1}^{K_m} \bar{p}_{m,n,k}^t \\
C_{2,m,t} = \sum_{r=1}^{S} F(q_{m,t}^r) - \sum_{r=1}^{M} \pi_r q_{m,t}^r + \sum_{r=1}^{S} \eta_r q_{m,t}^r - \mu_m \sum_{r=1}^{S} q_{m,t}^r 
\]

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

\[
\bar{\rho}_{m,t}^* = \begin{cases} 1, & \text{if } C_{1,m,t} + C_{2,m,t} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{41}
\]

Indeed, for the above solution, there is a more practical explain. For the \( m \)th 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 \( m \)th BS in the \( t \)th 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 \( m \)th BS should be switched into DTX mode in this time slot since 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 \( m \)th BS should be active in the \( t \)th 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 differences 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.

\[\text{D. THE DISTRIBUTED ALGORITHM}\]

In the previous subsections, we have optimized the power allocation, subcarrier assignment and energy procurement with fixed \( \lambda, \eta, \) and \( \mu \). 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 \( \lambda, \eta, \) and \( \mu. \) The \( j \)th iteration of the subgradient-based method is given as follows:

**BSs side Algorithm:**

- Each BS measures the SINR of each subchannel by using pilot signals, and receive the value of \( \mu_j \) from the smart grid.
- BS \( m \) determines the subcarrier assignment \( u_{m,n,k}^t \), power allocation \( p_{m,n,k,m}^t \), and BS sleeping variable \( \rho_{m,t} \) according to (37), (32) and (41), respectively.
- BS \( m \) updates the corresponding Lagrange multiplier \( \lambda_m \) by:

\[
\lambda_m(j+1) = \lambda_m(j) - v(j) (P_m - \sum_{n=1}^{N} \sum_{k,m=1}^{K_m} p_{m,n,k,m}^t) \tag{42}
\]

**Smart Grid side Algorithm**

At the smart grid side, retailer \( r \) updates the corresponding energy procurement \( q_{m,t}^r \). Lagrange multipliers \( \eta_r \) and \( \mu_m \), and announces the new \( \mu_m \) to BS \( m. \)

- Retailer \( r \) updates the energy procurement \( q_{m,t}^r \) according to (33).
- The Lagrange multipliers \( \eta_r \) and \( \mu_m \) are updated by

\[
\eta_r(j+1) = \eta_r(j) + \delta(j) (Q_r - \sum_{t=1}^{T} \sum_{m=1}^{M} q_{m,t}^r) \tag{43}
\]

\[
\mu_m(j+1) = \mu_m(j) + \theta(j) (\sum_{r=1}^{R} q_{m,t}^r - \sum_{n=1}^{N} \sum_{k,m=1}^{K_m} p_{m,n,k,m}^t) \tag{44}
\]

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

In the above distributed algorithm, the Lagrange multiplier \( \mu_m \) has a nice interpretation: \( \mu_m \) can be interpreted as the price at the smart grid determined by the wireless cellular network. \( \mu_m \) plays an important role in the proposed distributed algorithm. In fact, it can be seen as the interactive message between the BSs side and smart grid side. \( \sum_{m=1}^{N} \sum_{k,m=1}^{K_m} p_{m,n,k}^t \) can be interpreted as the energy demand of BS \( m \), and \( \sum_{r=1}^{R} q_{m,t}^r \) can be seen as the energy supply of the smart grid. It is rational that if the energy demand \( \sum_{m=1}^{N} \sum_{k,m=1}^{K_m} p_{m,n,k,m}^t \) exceeds the energy supply \( \sum_{r=1}^{R} q_{m,t}^r \), the price \( \mu_m \) will go up; otherwise, \( \mu_m \) 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:

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.

<table>
<thead>
<tr>
<th>Simulation Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell radius</td>
<td>1 Km</td>
</tr>
<tr>
<td>Inner boundary radius</td>
<td>0.6 Km</td>
</tr>
<tr>
<td>Subcarrier bandwidth</td>
<td>15 KHz</td>
</tr>
<tr>
<td>Number of retailers</td>
<td>3</td>
</tr>
<tr>
<td>Noise power spectral density</td>
<td>-174 dBm/Hz</td>
</tr>
<tr>
<td>Path loss coefficient</td>
<td>4</td>
</tr>
<tr>
<td>Peak power of BS</td>
<td>30 dBm</td>
</tr>
<tr>
<td>price of the unit throughput</td>
<td>1</td>
</tr>
<tr>
<td>price of the unit wind energy</td>
<td>0.5</td>
</tr>
<tr>
<td>price of the unit solar energy</td>
<td>0.9</td>
</tr>
<tr>
<td>price of the unit conventional energy</td>
<td>0.1</td>
</tr>
</tbody>
</table>

### TABLE I: Simulation Parameters
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 2: Operator's profit vs different number of users. N = 32, M = 4](image1)

![Figure 3: Carbon emission vs different number of users. N = 32, M = 4](image2)

![Figure 4: Operators' profit vs different carbon emission. N = 32, M = 4, K = 16](image3)

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

<table>
<thead>
<tr>
<th>channel conditions</th>
<th>bad</th>
<th>medium</th>
<th>good</th>
</tr>
</thead>
<tbody>
<tr>
<td>slot 1</td>
<td>on</td>
<td>on</td>
<td>off</td>
</tr>
<tr>
<td>slot 2</td>
<td>on</td>
<td>on</td>
<td>on</td>
</tr>
<tr>
<td>slot 3</td>
<td>on</td>
<td>off</td>
<td>on</td>
</tr>
<tr>
<td>slot 4</td>
<td>on</td>
<td>on</td>
<td>off</td>
</tr>
<tr>
<td>slot 5</td>
<td>on</td>
<td>on</td>
<td>off</td>
</tr>
<tr>
<td>slot 6</td>
<td>on</td>
<td>off</td>
<td>on</td>
</tr>
<tr>
<td>slot 7</td>
<td>on</td>
<td>off</td>
<td>on</td>
</tr>
<tr>
<td>slot 8</td>
<td>on</td>
<td>off</td>
<td>off</td>
</tr>
<tr>
<td>slot 9</td>
<td>on</td>
<td>on</td>
<td>off</td>
</tr>
<tr>
<td>slot 10</td>
<td>on</td>
<td>on</td>
<td>off</td>
</tr>
</tbody>
</table>

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 II 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 ($\leq -10$ dB), Table III depicts that the BS should be active in all time slots to complete the target rates. When the average channel condition is good enough...
Table III shows that when the user target data rates is not high (user target data rates $\leq 15$ 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 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


