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Hybrid Energy Supply based Energy Efficiency and Spectral Efficiency Tradeoff for Green Cellular System

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Abstract

The tradeoff between energy efficiency (EE) and spectral efficiency (SE) under the smart grid with joint energy harvesting and grid power supply is considered. The price factor in economics is used to propose the economic EE and SE. Then a new EE-SE tradeoff metric called the EE-SE adaptive tradeoff (ESAT) is built under the fluctuating harvesting energy. Furthermore, the offline optimization problem is put forward and the solution is discussed. The offline solutions based on the branch-and-bound algorithm and the Lagrange dual decomposition method are discussed to analyze the influence of renewable energy quantity on the proposed structure. Numerical results indicate that the proposed ESAT framework is efficient to the tradeoff between EE and SE.

Keywords*: Energy efficiency, spectral efficiency, resource efficiency, smart grid*

1. Introduction

Energy-efficient communications as one of the promising technologies for 5G wireless communication systems have gained great attention. The traditional studies on the spectral efficiency (SE) have met the bandwidth requirement of emerging high data rate wireless applications, which also lead to a dramatic increase of energy consumption. This trend has significant financial implications for service providers due to the rapidly increasing cost of energy. The electricity bill has become a significant portion of the operational expenditure for cellular operators. Green communications, which aim at enhancing energy efficiency (EE) for the wireless networks, have received considerable attention. Unfortunately, the increasing EE performance often leads to decreasing SE performance and vice verse [1]. Hence, it is often urgent to build a tradeoff between EE and SE. The relationship of EE and SE has been characterized firstly in various scenarios, such as the point-to-point link [1] and the heterogeneous networks [2]. Then the tradeoff frameworks of EE and SE are established based on the multi-objective optimization method [3-4], which is mainly to improve the resource utilization efficiency of energy and spectrum. Furthermore, one metric of EE or SE is also maximized with the constraint of another metric [5-6].

On the other hand, the smart grid as the energy supplier of cellular network integrates more renewable energy sources such as the wind energy source and the solar energy source to produce green energy. But these renewable energy sources are highly intermittent in nature and often uncontrollable. So the integration of the renewable energy resources and the traditional power grid is very useful for guaranteeing the data transmission.

Recently, in both downlink and uplink cellular networks with orthogonal frequency division multiple access (OFDMA), [7] studies the energy-efficient resource allocation and develops a suboptimal but low-complexity approach by exploring the inherent structure and property of the energy-efficient design. In the next-generation cellular networks, [8] analyzes the energy efficiency of small cell through adopting a random spatial network model, where BSs and users are modeled as two independent spatial Poisson point processes. Under the statistical quality of service (QoS) provisioning, [9] formulates the resource allocation problem as a maximization of effective capacity based bits-per-joule capacity. For the multicell OFDMA networks, [10] investigates the distributed power allocation by taking both the energy efficiency and the intercell interference mitigation into account. In order to realize the users' fairness, [11] proposes a bisection-based optimal power allocation to maximize EE and guarantee proportional data rates for users in a downlink OFDM-based mobile communication system.

However, there are only limited works on energy efficient issues with smart grid in wireless cellular networks [12-18]. [12] Studies the optimizing green energy utilization with both the traditional power grid and green energy in cellular networks. [13-15] formulate the cellular network and multiple power retailers as a two-level Stackelberg game. [16] Studies the energy efficiency resource allocation in OFDMA systems powered by hybrid renewable energy. [17] Considers the optimization of point-to-point data transmission by maximizing the throughput and minimizing the transmission completion time. Further, [18] studies the problem as minimizing the grid power consumption with random energy harvesting and data arrival. In the above research, the tradeoff framework problem of EE and SE with hybrid energy supplies has not been studied, which can be more conducive to the tradeoff and hence the main focus of this paper. The harvesting renewable energy is green energy relative to the traditional power grid, which can be utilized to realize the tradeoff of SE and EE. However, the resource quantity or cost of bandwidth and energy have not be considered fully, which is related to the resource utilization efficiency.

The main contributions of this paper are as follows: the renewable energy quantity based EE and SE adaptive tradeoff (ESAT) metric is put forward firstly. The tradeoff framework can put more weight on SE adaptively when the harvesting energy quantity is sufficient. Then the offline ESAT optimization model is designed especially. Further, the branch-and-bound algorithm based solution and the Lagrange dual decomposition method are proposed for the ESAT optimization. Through the simulation analysis, the renewable energy quantity based adaptive tradeoff model can adjust the relation between EE and SE properly.

The rest of this paper is organized as follows. In Section 2, the system model is described. In Section 3, the EE-SE adaptive tradeoff metric is proposed. Then the average ESAT optimization problem is presented and the solution is discussed in Section 4. In Section 5, the numerical results are provided. Finally, we summarize the paper with some concluding remarks in Section 6.

2. System Model

Consider a single BS cellular network, which is powered by the smart grid with both energy harvesting and traditional power grid. Assume one active user in the BS service region with the lowest rate requirement R_{min} and the downlink bandwidth budget W_{bud}. The system is operated in a time-slotted manner with L frames and frame length τ seconds. In each frame, the renewable energy is charged and consumed for the frame data transmission. Suppose that W_{bud} is same for each frame and the channel varies from frame to frame, but keeps constant during each frame. The data buffer of BS for the user is assumed to be always full and there are no empty scheduling slots.

Assume that the BS has perfect knowledge of channel state information between the BS's transmitter and the user's receiver. Denote the bandwidth consumption as W_i in the frame $i \in \{1, \ldots, L\}$, the achievable upper transmission rate r_i is as follows

$$r_i = W_i \log_2\left(1+\frac{p_i\left|h_i\right|^2}{N_0 W_i}\right) \quad (1)$$

where h_i is the channel gain from the BS to the user's receiver. p_i is the transmission power consumption. N_0 is the noise power spectral density of additive white Gaussian noise with zero mean and unit variance.

Denote P_i as the power consumption of BS, which generally contains the transmission power and the circuit energy consumption. We assume the circuit energy consumption as P_C. Thus the energy consumption of BS can be expressed as

$$P_i = p_i + P_C \quad (2)$$

The maximum transmission power of BS for downlink transmission is represented as a constant P_{max}, thus the power budget of BS also is constant, which is modeled as

$$P_{bud} = P_{\max} + P_C \quad (3)$$

In the frame i, because the transmission rate, the bandwidth consumption and the energy consumption are constant, define frame SE as the ratio of the transmission bits to the bandwidth consumption, frame EE as the transmission bits per unit of power consumption, which are given respectively as

$$\eta_{SE}^{fra} = \frac{r_i}{W_i} = \log_2\left(1+\frac{p_i\left|h_i\right|^2}{N_0 W_i}\right) \quad (4)$$

$$\eta_{EE}^{fra} = \frac{r_i}{P_i} = \frac{W_i \log_2\left(1+\frac{p_i\left|h_i\right|^2}{N_0 W_i}\right)}{p_i + P_C} \quad (5)$$

The incoming energy is collected by an energy harvester. Due to the instability of the renewable energy, the harvested energy always is buffered in a battery before it is used for data transmission. The battery has the limited capacity constraint with the maximum amount of energy storage capacity E_{max}. Because the data rate can be increased if the energy is used in advance instead of overflowed, the storage capacity is enough for the harvested energy, *i.e.* the energy overflow is not considered here [18].

Denote E_0 as the initial battery energy, and E_i, $i = 1, . . .,L -1$, as the harvested energy in the frame i. The energy consumption of BS for one frame may be higher or lower than the stored energy, there we mainly consider the case that the harvested energy is insufficient or equal to the energy consumption of BS. If the energy in the battery is insufficient, the transmitter will use the energy of traditional power grid to guarantee the user's QoS. Thus denote the consumed power supplied by the battery as $P_{B,i}$, the other supplied by the traditional power grid as $P_{G,i}$. Generally the supply of the traditional power grid is stable and enough for single consumer, so the traditional power grid constraint is ignored [18]. Due to the energy causality, the harvested energy cannot be consumed before its arrival, meanwhile the battery overflow is not considered, so we have the following two energy constraints [17-18].

$$\sum_{i=1}^{l} \tau P_{B,i} \le \sum_{i=0}^{l-1} E_i, \quad l = 1,2,\cdots,L \quad (6)$$

$$\sum_{i=0}^{l} E_i - \sum_{i=1}^{l} \tau P_{B,i} \le E_{\max}, \qquad l = 1, 2, \cdots, L-1 \tag{7}$$

3. EE-SE Adaptive Tradeoff Metric

In order to maximize the frame EE and the frame SE simultaneously, the scalarization method in the multi-objective optimization is often applied. It is important to make all object functions comparable, but the unit for frame EE is bits/Joule while that for frame SE is bits/s/Hz. The multi-objective optimization is always as follows

$$\max_{P} \quad \left\{ \eta_{EE}^{fra}, \eta_{SE}^{fra} \right\} \tag{8}$$

Similar to [4], we utilize the ratio of bandwidth budget and power budget as the unit normalizer for frame SE and frame EE, which is modeled as

$$\eta_{SE}^{norm} = \eta_{SE}^{fra} \cdot \frac{W_{bud}}{P_{bud}} \tag{9}$$

We can see that the unit of η_{SE}^{norm} is also bits/Joule, which is same as frame EE. So the multi-objective optimization can be applied on the frame EE and the normalized frame SE, which is defined as

$$\varsigma = (1-\gamma)\eta_{EE}^{fra} + \gamma \eta_{SE}^{norm} \tag{10}$$

where $\gamma \in [0, 1]$, is a weight factor to control the balance of frame EE and frame SE, such that weighted sum of the objectives optimize frame EE when $\gamma = 0$ but optimize frame SE when $\gamma =1$. Generally, there it is up to the decision maker to choose appropriate weights [4].

Considering the available renewable energy quantity is fluctuating, when the available renewable energy quantity increases, the energy in the battery increases, which can be more used to emphasize on frame SE and lower the demand of frame EE. Whereas when the available renewable energy quantity decreases, the energy of traditional power grid should be more used, so as to improve the demand of frame EE and save the traditional energy. Thus in order to reflect the influence of the available renewable energy quantity on the frame EE-SE tradeoff, we introduce a renewable energy ratio factor to instead of γ, which is defined as the ratio of the renewable energy quantity and the total power budget for one frame

$$\gamma = \frac{E_i}{\tau P_{bud}} \tag{11}$$

When the charged renewable energy quantity is insufficient or equal to the total power budget, i.e. $E_i \le \tau P_{bud}$, the ratio factor implies the potential of the renewable energy to meet the demand of energy consumption. Then a novel EE-SE tradeoff metric called EE and SE adaptive tradeoff (ESAT) metric can be defined as

$$\varsigma = \left(1 - \frac{E_i}{\tau P_{bud}}\right)\eta_{EE}^{fra} + \frac{E_i}{\tau P_{bud}} \eta_{SE}^{fra} \cdot \frac{W_{bud}}{P_{bud}} \tag{12}$$

Based on the ESAT metric, the EE-SE tradeoff problem can be formulated as following offline system optimization model under the constraints of required data transmission, causality of harvested energy, battery capacity and nonnegative power allocation.

4. The Problem Presentation

Assume that the energy and bandwidth allocation policy is constant during each frame slot. In each frame, the non-causal knowledge of energy arrival and channel gains are certain. Due to the fluctuating renewable energy arrivals and channel gains of all the frames, the system optimization of EE-SE tradeoff for L frames can be realized through the adjustment of renewable energy among the L frames. Thus the average frame EE and frame SE tradeoff performance among all the frames is the appropriate optimization object. But for the causality of harvested energy and the unpredictable channel gain, we design an offline system resource allocation model by assuming the availability of non-causal knowledge of energy arrivals and channel gains, that is

$$\max_{p_i, W_i, P_{B,i}, i=1,\ldots,L} \frac{1}{L}\sum_{i=1}^{L}\left[W_i \log_2\left(1+\frac{p_i |h_i|^2}{N_0 W_i}\right)\right]\left[\frac{\left(1-\frac{E_i}{\tau P_{bud}}\right)}{p_i+P_C}+\frac{W_{bud}E_i}{\tau {P_{bud}}^2 \cdot W_i}\right]$$

$$s.t. C1 \quad r_i \ge R_{\min}, \quad i=1,2,\cdots,L$$

$$C2 \quad p_i + P_C \le P_{bud}, \quad i=1,2,\cdots,L$$

$$C3 \quad p_i \ge 0, \quad i=1,2,\cdots,L \qquad (13)$$

$$C4 \quad \sum_{i=1}^{l}\tau P_{B,i} \le \sum_{i=0}^{l-1} E_i, \quad l=1,2,\cdots,L$$

$$C5 \quad \sum_{i=0}^{l} E_i - \sum_{i=1}^{l}\tau P_{B,i} \le E_{\max}, \quad l=1,2,\cdots,L-1$$

$$C6 \quad 0 \le P_{B,i} \le p_i + P_C, \quad i=1,2,\cdots,L$$

For the offline problem formulation (13), the consumed bandwidth quantity and energy quantity are both uncertain. it is a fractional programming problem which contains a sum of a finite number of fractional functions. According to [19], the sum of linear ratios problem is nonconvex. By utilizing a transformation and a two-part linearization method, a sequence of traditional programming relaxations of the initial nonconvex programming problem can be derived which are embedded in a branch-and-bound algorithm. In addition, we can also solve the offline problem (13) by using Lagrange dual decomposition as in [4], where the problem is transformed to the dual problem with the given energy consumption of BS. Then the dual problem can be solved iteratively where the BS solves L subproblems as inner loop in parallel and solves the master problem as outer loop with the gradient method.

Through analyzing the offline problem formulation structure of (13), the online system optimization solution of multiple frames can be obtained by the dynamic programming which is similar to [16].

5. Numerical Results

In this section, numerical results are provided to validate the effectiveness of our proposed ESAT model. Assume that P_{max} = 1W, P_C = 0.25W, W_{bud} = 2MHz, R_{min} = 6Mbits/s and the noise power is 10^{-13}W. The channel gain h is modeled as independent, identically distributed Rayleigh random variables with an average of 0 dB. Assume the frame length τ=5ms and L = 100 frames. The harvested energy is assumed with non-negative uniform distribution with mean 1W. The battery capacity is M times of the average arrived energy in one frame [18], and we set M = 3 in this setup. All results are average of 1500 monte carlo simulation for each parameter setup. These simulation parameters are chosen to demonstrate the effectiveness of ESAT for simplicity, which can be modified easily to other values for different scenarios.

Figure 1 shows the impact of renewable energy quantity to the frame EE and the normalized frame SE. For each frame with increasing renewable energy quantity, the frame EE decreases gradually while the frame SE increases gradually. This is because increasing renewable energy quantity results in putting more weight on frame SE, and more energy is consumed which reduces the frame EE. Thus the adaptive tradeoff structure plays an important role with the renewable energy quantity based weighting factor.

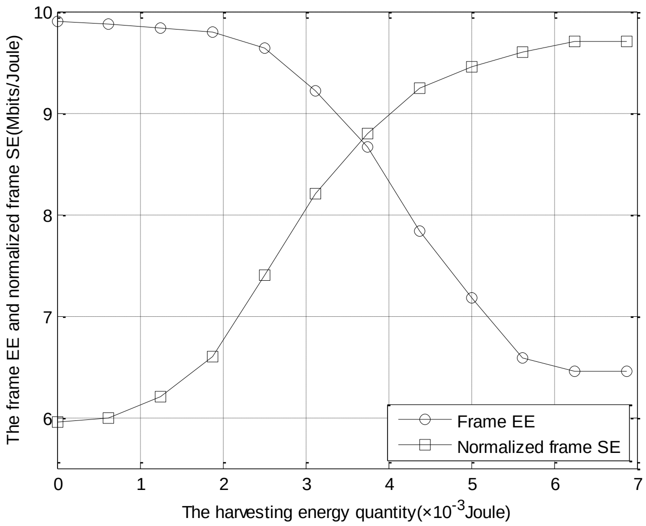

Figure 1. The Impact of Renewable Energy Quantity to the EE-SE Tradeoff Structure

We also verify the average maximum ESAT versus the power budget for the different lowest rate requirements. At the beginning of P_{bud} (i.e., P_{bud} < 0.85W for R_{min} = 6Mbits/s) in Figure 2, the ESAT curve increases quickly with the increasing P_{bud}. But when P_{bud} is comparably high, there has been sufficient power budget, the ESAT curve decreases gradually. The turning point of ESAT curve is P_{bud} =0.9W for R_{min} = 6Mbits/s, and 1.15W for R_{min} = 8Mbits/s. The higher the lowest rate requirement needs more the power budget, which results in the lower maximum achievable ESAT. It is very important for green cellular networks, as we can save much energy consumption by setting the power budget properly.

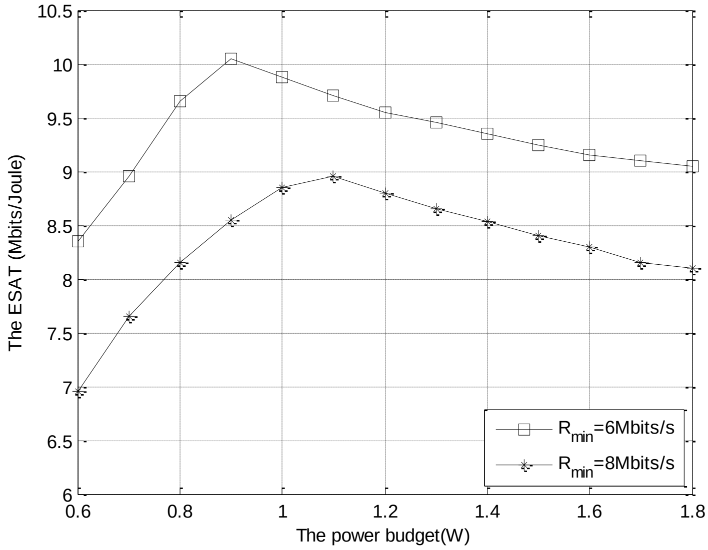

Figure 2. The Maximum Achievable ESAT versus Different Power Budget

6. Conclusion

This paper introduces the tradeoff frameworks of EE and SE with hybrid energy supplies under the smart grid environment. The EE and SE adaptive tradeoff metric based the renewable energy quantity for cellular network is put forward. Then an offline average ESAT optimization of the power and subcarrier allocation is formulated mathematically, under the influence of the fluctuating renewable energy supply, the constraint of power budget and rate requirements. To solve the proposed sum of linear ratios problem, the branch-and-bound algorithm and Lagrange dual decomposition method based solutions are discussed. For practicality, the online ESAT optimization is also discussed based on the offline optimization method. The numerical simulation results imply that, the proposed ESAT metric can adjust the relation of EE and SE properly, and the power budget has more relation with the rate requirements, which is practical to plan the green cellular networks.

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