Joint Energy and Data Storage Management for Cost Reduction in Renewable Cellular Networks

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Keywords: Energy harvesting communications, Renewable energy, Energy and data storage management, Cost minimization.

Abstract. The future integration of renewable energy in mobile cellular networks promises to significantly reduce the energy generation cost and the carbon emission using conventional fuel generators. Nevertheless, the random nature of renewable energy generation and data traffic energy demand makes efficient usage of renewable powered communications difficult. In particular, unregulated renewable power generation can either be over- or under-supplied in the short-term compared to the load demand, which can result in energy waste due to battery overcharging or higher electricity cost due to the use of more expensive grid power. In this paper, we propose to make use of both energy and data storages to tackle the instantaneous mismatch between renewable energy generation and energy demand. By exploiting the delay tolerance in the data traffic, we propose a threshold-based energy and data storage management method to minimize the long-term energy cost of cellular system operator. Simulation results show that the proposed method can effectively improve the utilization of renewable energy and reduce the energy cost.

Introduction

The rapid growth of mobile communication service towards wide-band and high data-rate wireless access in the recent decades has transformed the modern lifestyle. In practice, this also brings tremendous electricity generation cost and carbon emission increase on powering the mobile cellular facilities, such as base station tower and air-conditioning devices. Based on some recent survey [1], Information and Communication Technology (ICT) industry is responsible for 2% of global CO₂ emissions, where mobile communication system constitutes a large part. As predicted in [2], the amount of data traffic will increase by 61% annually from 2016 to 2020. Therefore, we can expect significant surge in power consumption and carbon emission on mobile facilities in the next few years. This not only increases the operational expenditure of mobile operators, but also causes environmental concerns on global warming problem [3].

Thanks to the development of renewable technologies, carbon footprint can be effectively reduced to a large extent with the usage of green energy (such as solar and wind energy) in distributed electricity generation. These distributed renewable generators are often installed at the site of the cellular base stations to reduce the cost of power transfer. However, due to the intermittent and unpredictable nature of these renewable resources, the increasing penetration of renewable energy sources will bring considerable uncertainty to the grid [4]. To tackle this problem, the integration of
storage systems with intelligent monitoring, communication and control is widely used in [5], which can store the excessive renewable energy and withdraw the power when needed.

In practice, due to its extensive installation cost, energy storage is often very limited in size. Therefore, it is necessary to design efficient battery charging and discharging management techniques [6]. There have been extensive studies on energy storage management for renewable generations. For instance, the work [7] solves the optimal charging/discharging control from the consumer side amidst time-varying prices. In [8], the authors consider using coordinated charging of Plug-in Hybrid Electric Vehicles (PHEVs) to store electric energy for coping with high demand and intermittent generation of renewable sources. In [9], the authors consider the problem of minimizing the time average electricity cost, subject to a stable demand backlog queue, in the presence of renewable sources.

Besides the randomness of renewable generations, the randomness of data traffic creates another layer of challenge to the battery management. The independent random arrival of data is likely to cause instantaneous mismatch between the renewable energy available and required to process the data, e.g., unexpected high data traffic during off-peak solar power generation period or low data traffic when the renewable generation power is high. The short-term mismatch may directly lead to high electricity cost from the use of expensive grid power when renewable generation is insufficient, or energy waste when the battery storage is full and can no longer store the excessively generated renewable energy. Nonetheless, we can still exploit the delay tolerance of data traffic to mitigate the imbalance. Intuitively, some delay-sensitive data (such as audio and video data streams) needs to be processed and sent to the mobile users immediately after arrived at the base station; while some other data can be delay-tolerant from several seconds to minutes, such as webpage and email. In [10] and [11], the concept of delay tolerant users is applied, in which a fraction of the users may witness an additional delay before accessing the network. The electricity bill is reduced by 27% through the cooperation between mobile networks and the smart grid. Accordingly, by leveraging data storage in addition to energy storage, we have the potential to achieve a balance between the random renewable energy generation and random energy demand from data traffic.

As most of the existing works exploit the energy and data storages separately in energy management for renewable powered cellular network, we consider in this paper a joint energy and data storage management framework in renewable powered cellular network. In particular, we propose a practical threshold-based energy and data storage management algorithm that determines the energy plan, e.g., using renewable or grid power, and data transmission plan, e.g., the amount of data to be transmitted, in each time slot. Specifically, we exploit the delay tolerance in the data traffic. By delaying the transmission of some delay-tolerant data traffic and the use of renewable energy, we can effectively tackle the short-term energy mismatch between renewable generation and traffic demand. By jointly optimize the thresholds of the energy and data storages, we show in simulations that the proposed method can significantly improve the renewable utilization and reduce the electricity cost of a renewable powered base station.

**System Model**

We show in Fig.1 the structure of the considered renewable powered base station (BS), which has a renewable generator and serves a set of mobile subscribers in the downlink.
Due to the intermittency and time-varying nature of renewable generations, the BS is also connected to the conventional power grid, such that it can withdraw electricity power from the main grid when necessary. Energy storage with finite capacity is used to store either the excessive renewable energy or grid power. Besides, it can also be used to power the data transmissions in the downlink. On the other hand, the downlink user data arrives at random and can be stored in data storage of finite capacity. In this paper, the data and energy storages are jointly managed through a central control unit, which decides the amount of data to be transmitted and the amount of energy to be consumed in real time.

![Figure 1. The schematic modules of the considered renewable base station.](image)

In particular, we consider a slotted system that operates in consecutive transmission slot each of duration $T$. Specifically, we assume that the user data packets are of fixed length and arrive according to a Poisson process with rate $\lambda_D$ within a slot. Each data packet $i$ is associated with a delay tolerance $d_i$, where $d_i = 1, 2, \ldots$ representing the number of transmission slots that can be delayed before transmission. The distribution of $d_i$ can be a general distribution. Without loss of generality, we also assume that transmitting a data packet consumes exactly one unit of energy. For simplicity, we assume that the BS had sufficient bandwidth such that it can always transmit the data packets arrived or in the storage within a transmission slot. In other words, the data queue in the storage is caused only by deliberate delay of the packet transmission as a result of transmission scheduling. The capacity of the data storage is denoted by $D_n$. On the other hand, we assume a discrete renewable energy model that on average $\lambda_E$ units of energy can be harvested by the BS within a slot, where the arrival process follows a Poisson process. To avoid trivial solution, we assume $\lambda_E < \lambda_D$, such that the energy-harvesting BS is energy-constrained in data transmission. The capacity of the energy storage is denoted by $E_n$. In addition, we consider a constant grid electricity price, where the cost of a unit of grid energy is denoted as $c$ dollars and we assume no limit to the energy that can be withdrawn from the power grid within a slot. The cost of using renewable energy is neglected. As we consider a constant electricity price, the BS has no incentive to store the energy withdrawn from the main grid. Therefore, the energy storage is only used for storing the renewable energy when needed. Here, we use $d_i'$ to denote the residual delay...
tolerance of the $i$-th packet in the $t$-th time slot, where $d^{i+1}_t = \max \{d^i_t - 1, 0\}$ holds for any $t$. Then, depending on the value of $d^i_t$, the user traffic is categorized as either emergent or non-emergent in the $t$-th time slot. Specifically, an emergent data packet with $d^i_t = 1$ needs to be transmitted in the current slot while non-emergent data ($d^i_t > 1$) can be stored in data storage for later transmissions. Let $S_E(t)$ and $S_D(t)$ denote the amount of renewable energy and data stored in the energy and data storages at the beginning of the $t$-th time slot. We denote $D_e(t)$ as the amount of emergent data to be transmitted at the $t$-th slot, which consists of both newly arrived data and the data stored in the storage with $d^i_t = 1$. $D_{ne}(t)$ is used to denote the amount of non-emergent data to be transmitted in the $t$-th time slot, which can be either newly arrived data or data stored in the storage with $d^i_t > 1$. We denote $E(t)$ and $D(t)$ as the amount of renewable energy and user data generated in the $t$-th time slot, and $G(t)$ as grid power consumed.

Then, the amount of grid energy consumed is related as

$$G(t) = \max \{D_{ne}(t) + D_e(t) - S_E(t) + E(t), 0\}. \tag{2}$$

Meanwhile, $S_D(t+1)$ can be expressed as

$$S_D(t+1) = \min \{S_D(t) + D(t) + D_e(t) - D_{ne}(t), 0\}. \tag{3}$$

Note that in each time slot, the system operator only needs to decide the amount of non-emergent data to be transmitted given the data and energy storage states, and the amount of newly arrived data and renewable energy generated. The objective is to minimize the use of grid power to minimize the electricity cost

$$C = c \cdot \sum_{t=1}^{N} G(t), \tag{4}$$

where $N$ denotes the total number of time slots considered and $c$ is the energy price (dollar per unit).

In Fig.2 and 3, we use two simple examples to illustrate the advantage of applying data and energy storages for energy conservation in a base station. In Fig.2, we first consider three consecutive time slots, where initially there are two non-emergent packets in the data storage at the beginning of the first time slot, while the energy storage is empty. We assume one unit of renewable energy is generated in each of the first two slots and no new data packet is generated within the three slots. Consider first a greedy transmission scheme in Fig.2(a-c) that the base station transmits the two packets in the first slots, in total it needs to withdraw from the power grid one unit of energy, however leaving one unit of renewable energy unused at last. Instead, if we delay the transmissions of the two packets by one slot as in Fig.2 (d-f), the transmissions of the two packets can be successfully powered by the additional renewable energy generated in the second slot. Evidently, the second case that uses data storage to delay the transmissions of non-emergent data enjoys a lower electricity cost.

We then consider in Fig.3, where there are one unit of renewable energy and one non-emergent packet in the energy and data storages at the beginning of the first slot. Besides, one unit of renewable energy is generated in the second slot, and two emergent
data packets arrive in the second slot as well. In this case, the greedy method (Fig.3(a-c)) first transmits the existing packet in the first slot, and then withdraw one unit of grid power to transmit the two newly arrived packets in the second slot. Instead, in Fig.3(d-f), by delaying the usage of renewable energy in the first slot, we can transmit the two emergent data in the second slot without withdrawing any grid power. The remaining non-emergent data can be transmitted after waiting for a period of time when there is enough green energy generated.

From the above illustration, we can see that the use of energy and data storages can effectively mitigate the short-term mismatch between renewable energy generation and data arrivals, and thus reduces the electricity cost. In general, based on the different system state, the data and energy storages should be jointly managed by carefully
selecting the amount of non-emergent data to be transmitted in each time slot, i.e., $D_{ne}(t)$.

**Threshold-Based Data and Energy Storage Management Algorithm**

In this section, we present a threshold-based method to manage the energy and data storages. From the illustrations in Fig.2 and Fig.3, we can see that it is not preferable to transmit all the data packets by exhausting all the remaining energy in the storage. Intuitively, this is achievable by setting a data threshold $T_D$ and an energy threshold $T_E$, such that the system transmits the remaining data only when both the remaining data and energy in the storages exceed the thresholds. Specifically, for the $t$-th time slot, we first define $E_f(t)$ as the amount of remaining energy after all the emergent data has been transmitted, i.e.,

$$E_f(t) = S_E(t) + E(t) - D_e(t).$$

Note that $E_f(t)$ can be negative, indicating that the remaining energy is not sufficient to transmit all the emergent data. Besides, we denote $D_f(t)$ as the amount of remaining non-emergent data after emergent data has been transmitted, i.e.,

$$D_f(t) = S_D(t) + D(t) - D_e(t),$$

where $D_f(t) \geq 0$ always holds. Then, depending on the values of $E_f(t)$ and $D_f(t)$, we separate our discussions into the following cases:

1) Case 1: $E_f(t) < 0$ and $D_f(t) < T_D$. In this case, the system only needs to withdraw grid power to transmit the rest of the emergent data. Therefore, we have $G(t) = -E_f(t)$ and $D_{ne}(t) = 0$. Accordingly, we have $S_E(t+1) = 0$ and $S_D(t+1) = D_f(t)$.

2) Case 2: $E_f(t) < 0$ and $D_f(t) \geq T_D$. Besides transmitting the rest of the emergent data, the system operator also needs to transmit additional non-emergent data to maintain the data queue below the threshold $T_D$. Accordingly, we have

$$G(t) = D_f(t) - T_D - E_f(t),$$

and $D_{ne}(t) = D_f(t) - T_D$. The states of the energy and data storage are updated as $S_E(t+1) = 0$ and $S_D(t+1) = T_D$, respectively.

3) Case 3: $E_f(t) \geq 0$ and $D_f(t) < T_D$. In this case, there is a surplus of renewable energy in the energy storage after transmitting emergent energy, while the remaining data is below the threshold. Then, depending on the value of $E_f(t)$, the system operator can either transmit the non-emergent data or not. Specifically, when $E_f(t) \geq T_E$, we deem the energy is sufficient, such that $(E_f(t) - T_E)$ amount of energy can be used to transmit non-emergent data. Therefore, the amount of non-emergent data transmitted is

$$D_{ne}(t) = \min\{E_f(t) - T_E, D_f(t)\},$$

and the grid power consumption $G(t) = 0$. Otherwise, if $E_f(t) < T_E$, the energy should be stored to cope with future random arrivals of emergent data. Therefore, we have $D_{ne}(t) = G(t) = 0$. 


4) Case 4: $E_f(t) > 0$ and $D_f(t) \geq T_D$. In this case, the data queue is considered too long, thus should be reduced to $T_D$ by the remaining renewable energy, i.e., transmitting $(D_f(t) - T_D)$ amount of non-emergent data. Therefore, when $E_f(t) \geq D_f(t) - T_D$, it is feasible to reduce the data queue in the storage to $T_D$ using only the renewable energy. That is, $D_{ne}(t) = D_f(t) - T_D$ and $G(t) = 0$. Otherwise if $E_f(t) < D_f(t) - T_D$, we need to withdraw additional grid power to achieve the target, where we have

$$G(t) = D_f(t) - T_D - E_f(t),$$

and $D_{ne}(t) = D_f(t) - T_D$.

For the simplicity of reference, we plot the diagram of the proposed threshold-based data and energy storage management method in Fig.4.

![Diagram of the proposed threshold-based method](image)

**Simulation Results**

In this section, we use simulations to evaluate the considered threshold-based data and energy storage management algorithm. Without loss of generality, we consider a data storage of 2000 units capacity and an energy storage of 1000 units capacity, and both data and energy storages are initially empty. Besides, we consider a time slot duration $T = 6$ minutes, and assume that the number of arrivals of the renewable energy $E(t)$ follows a Poisson process with mean equals to $\lambda_E$ per slot. Besides, the arrivals of the data packets also follow a Poisson process with mean $\lambda_D$ per slot, where the arrival rates of the emergent and non-emergent data packets are $\alpha \lambda_D$ and $(1-\alpha) \lambda_D$, respectively ($0 < \alpha < 1$). Without loss of generality, we assume the delay tolerance of each non-emergent data as $d_n = 12$. In practice, $\lambda_E$ and $\lambda_D$ are different in different periods of a day. We use the parameters listed in Table 1 to model the arrivals of user data traffic and renewable energy within a day. In particular, the renewable energy may correspond to a typical renewable base station with hybrid solar and wind harvesting...
devices, such that the peak energy harvesting rate is at noon and the valley is at night. Besides, the arrival rates of user data correspond to a residential area with peak usage arrives after working time and before bed time. Unless otherwise stated, we set $\alpha = 0.8$, $T_E = 500$ and $T_D = 1000$. For simplicity of illustration, we assume that the energy cost of grid power is $c = 1$ dollar per unit. For performance comparison, we also consider a greedy algorithm, which always transmits all the remaining non-emergent data regardless of the remaining renewable energy. Each point in the figures is an average of 20 independent simulations.

| Time periods [hour] | Arrival rates [per time slot] |
|--------------------|-------------------------------|
| T(0, 6]            | $\lambda_E = 1, \lambda_D = 5$ |
| T(6, 11]           | $\lambda_E = 3, \lambda_D = 7$ |
| T(11, 16]          | $\lambda_E = 5, \lambda_D = 6$ |
| T(16, 19]          | $\lambda_E = 3, \lambda_D = 7$ |
| T(19, 24]          | $\lambda_E = 1, \lambda_D = 9$ |

In Fig.5, we first fix $T_D = 1000$ and investigate the impact of data and energy arrival rates to the optimal energy threshold that minimizes the average cost within 1 hour. Specifically, we vary the data arrival rate from $\lambda_D = 5$ to 10, and consider energy arrival rate $\lambda_E \in \{1, 3, 5\}$. Evidently, we can see that the optimal $T_E^*$ increases proportionally with $\lambda_D$. This is because the system operator needs to save more energy in the battery to transmit the higher data traffic in the future. Besides, with a higher $\lambda_E$, we can afford to have a smaller threshold $T_E^*$ to save less renewable energy for future consumption.

![Figure 5. The optimal threshold of different $\lambda_E$ when $\lambda_D$ changes.](image)

We then compare the average accumulated electricity cost achieved by different algorithms within a day in Fig.6. For the proposed threshold based method, we set a fixed $T_D = 1000$ and consider two ways to set the thresholds $T_E$. One is to select the optimal $T_E^*$ based on the empirical experiment obtained like in Fig.5. The other is to
simply set $T_E = 500$, i.e., half of the capacity. We can see that the proposed threshold based energy and data management method can effectively reduce the energy cost compared to the greedy method. In particular, the threshold method with simple $T_E = 500$ can save 24% energy cost than the greedy method. The one with the optimal $T^*_E$ can save 27% of the cost than the greedy method. We can see that the performance improvement of using an optimal threshold over that of a simple $T_E = 500$ is limited. We can also see that cost saving is especially effective between 12:00 to 19:00 when the energy and data arrival rates are close. However, the saving becomes less evident when the energy arrival rate $\lambda_E$ is much smaller than $\lambda_D$, like the time period within 20:00 to 6:00 in the morning.

Figure 6. The accumulated electricity cost comparison of different algorithms during one day.

Figure 7. The accumulated electricity cost comparisons under different pair of $(\lambda_E, \lambda_D)$. 
To further investigate this effect, we plot in Fig.7 the average energy cost with a five-hour period under different $\lambda_e$ and $\lambda_d$. Here, we consider the two most representative periods in Fig.6: the one that $\lambda_e$ is similar to $\lambda_d$ in 11:00-16:00. And the one that $\lambda_e$ is much smaller than $\lambda_d$ in 19:00-24:00. We can see in Fig.7(a) that when $\lambda_e \ll \lambda_d$, the performance gain of the proposed method over greedy algorithm is not evident, where the proposed method with $T_e = 500$ and optimal $T_e^*$ can save 17% and 29% of the cost of greedy method, respectively. However, when $\lambda_e$ and $\lambda_d$ are similar, the cost reduction can be around 29% and 41% for the proposed threshold-based method with $T_e = 500$ and optimal $T_e^*$, respectively. The result shows that our method is most effective when the energy and data arrival rates are similar, such that short-term energy mismatch can be largely mitigated with the data and energy storages.

Conclusion

In this paper, we proposed to make use of both energy and data storages to tackle the instantaneous mismatch between renewable energy generation and energy demand. By exploiting the delay tolerance in the data traffic, we proposed a threshold-based energy and data storage management method to minimize the long-term energy cost of cellular system operator. Simulation results show that the proposed method can effectively improve the utilization of renewable energy and reduce the energy cost, especially when the energy and data arrival rates are similar such that short-term energy mismatch can be largely mitigated with the data and energy storages.

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