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Optimal power management under delay constraint in cellular networks with hybrid energy sources

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ABSTRACT

In cellular networks, energy provision contributes up a significant fraction of the total operational cost. To address this problem, service providers have started considering the deployment of renewable energy sources. Due to the variability of renewable energy source, conventional grid energy sources is still required to provide steady service for users. In this paper, Base Stations (BSs) equipped with hybrid energy sources and limited energy storages are considered. We investigate a joint power allocation and battery management scheme to cut down electricity cost under electricity markets, which is ignored by previous studies. Considering the random data arrival, link quality, renewable energy and electricity price, a stochastic program which minimizes the time-average expected electricity cost while stabilizing the network is formulated. Based on the Lyapunov optimization technique, we design an online algorithm to approximately obtain the optimal solution. Especially, our algorithm can guarantee the worst delay through introducing virtual queues. Furthermore, theoretical analysis shows that our algorithm offers an explicit tradeoff between cost saving and delay performance. Numerical simulation results demonstrate the effectiveness of our algorithm.

1. Introduction

The upsurge in mobile data traffic as a result of explosive growth in data demand and the popularity of smart phones, has presented cellular network operators with several challenges. One of the challenges is economic challenge caused by the energy consumption increase, which presents operators with high operational expenditures (OPEX) through increased electricity bills. It is estimated that energy consumption rises at 15–20% per year and double every five years in the field of Information and Communication Technology (ICT). The direct result is a collective cellular network OPEX of $22 billion in 2013 [1]. Thus, reining back the spiraling OPEX is crucial to the continuing success of operators.

One natural solution to cut down OPEX is to improve energy-efficiency in all components of cellular networks, especially Base Stations (BSs) which consume a significant portion of energy, reported to amount to about 60–80% [2]. Power allocation is one traditional way to achieve huge green gain by reducing the transmission power intelligently while maintaining the system performance [3–5]. The authors of [3] try to minimize a weighted sum of the expenditure power and the average delay. Hasan et al. [4] maximizes the energy efficiency for downlink orthogonal frequency division multiple access networks through power allocation. Meshkati et al. [5] studies the Quality of Service (QoS) constrained power and rate control in multiple-access networks using a game theoretic framework. In recent years, the deployment of renewable energy

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sources, such as solar panels and wind turbines, has started being considered as another effective solution [6,7]. Due to the variability of renewable energy sources, conventional energy sources such as power grid is still required to guarantee User Equipments' (UEs') QoS. What's more, energy storages such as battery can be introduced to avoid energy waste when the energy harvested is more than the energy needed. Therefore, BSs equipped with hybrid energy sources (conventional grid and renewable energy sources) and finite energy storages will be common in the near future and have gotten a lot of researchers' attention [8–13]. In this trend, Zheng et al. investigate the OPEX saving problem from the perspective of network planning framework in [8]. Chia et al. [9] and Han and Ansari [10] minimize average grid energy consumption via battery management and BS cell size adaptation, respectively. Gong et al. [11] minimizes average grid energy consumption while satisfying UEs' outage probability requirement through resource allocation. Gong et al. propose a multi-stage water filling policy to achieve the optimal power allocation of a single-link wireless communication in [12]. Xu and Zhang [13] studies the throughput-optimal transmission policies for energy harvesting wireless transmitters with the non-ideal circuit power.

Obviously, all the above works [3–5,8–13] have not considered the influence of electricity markets. A grid operator may charge different prices for conventional grid energy at different times of a day, especially when the smart grid is applied. One typical example is the widely used peak-valley electricity price. The data set obtained from the publicly available government sources [14] also shows that electricity price may change every several minutes unpredictably. If the real-time electricity market is considered, the traditional minimization of electricity consumption may not be equivalent to that of the electricity cost. Based on the above analysis, Guo and Fang [15] and Guo et al. [16] adopt energy storages to overcome the variability of real-time electricity price under electricity markets and minimize the average electricity cost at data centers and in the smart grid, respectively.

Motivated by Guo and Fang [15] and Guo et al. [16], in this paper, we discuss the problem of minimizing the electricity cost of BSs, equipped with hybrid energy sources and finite battery energy storages, under electricity markets. Different from [15,16] which just consider energy supplement control through battery management, we additionally control the energy requirement through power allocation in cellular networks. On the one hand, we can allocate less power and delay some data to be transmitted when the electricity price is low or the available harvested energy is much enough. On the other hand, due to the time-varying link quality, we can reduce the power consumption through delaying data to be transmitted when link quality is good enough. Therefore, with joint battery management and power allocation, we can further achieve OPEX saving gain by sacrificing delay performance. However, it is challenging to stabilize the system and ensure the delay performance, especially when we consider the variability and unpredictability of renewable energy, electricity price, business data and link quality. Facing such random processes with possibly unknown statistics, we formulate the problem as a stochastic program. Based on the Lyapunov optimization technique which is extremely useful in the development of stable queue control algorithms [17–19], we design an online algorithm to approximately obtain the optimal solution. Our contributions are summarized as follows:

- From the perspective of service provider, we take the first step to investigate the problem of minimizing the electricity cost under electricity markets by joint power allocation and battery management for BS equipped with hybrid energy sources and finite energy storages. When electricity price is constant, our problem can be degenerated into the conventional grid energy minimization problem.
- We formulate the problem as a stochastic program which minimizes the time-average expected electricity cost while stabilizing the system. Besides, we propose an online algorithm based on the Lyapunov optimization technique to approximately obtain the optimal solution without the knowledge of future information. Especially, our algorithm can guarantee the worst delay experienced by UEs through introducing virtual queues.
- Through theoretical analysis, we show that our algorithm can offer an explicit tradeoff between the cost saving and worst delay performance. Besides, numerical simulation results demonstrate the effectiveness of our proposed algorithm.

The rest of the paper is organized as follows: We present the system model and formulate our problem in Section 2. In Section 3, we propose an online algorithm to approximately solve our problem. Theoretical analysis and discussions on the performance of our algorithm are given in Section 4. Numerical simulation results are presented and discussed in Section 5. Finally, we conclude our work in Section 6.

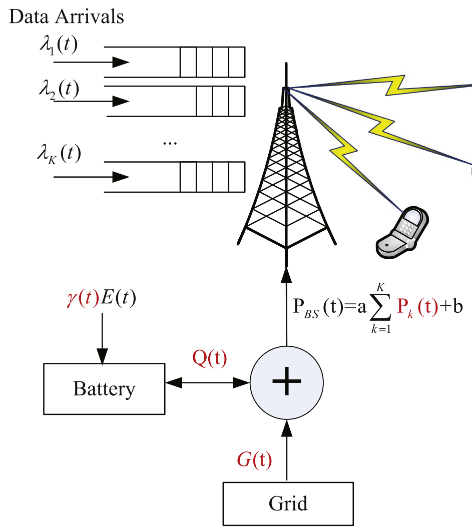


Fig. 1. System model.

2. System model and problem formulation

2.1. System model and assumptions

As shown in Fig. 1, we consider a single-cell time-slotted system where K UEs are served by a BS. Without loss of generality, BS allocates specific channel whose bandwidth is W to each UE. The time-varying channel is considered and we denote $H_k(t)$ as the Channel State Information (CSI) acquired through the uplink dedicated pilots from UE k at the beginning of time slot t.

Energy model. To reduce the grid energy consumption and provide reliable service, the BS is equipped with hybrid energy sources and finite energy storages (take battery as an example). Let $E(t)$ denote the amount of renewable energy harvested in slot t. This energy is first stored in the battery before it can be used in the next time slots. There is a maximum value constraint for practical condition, that is $0 \leqslant E(t) \leqslant E_{\max}$. In order to prevent battery overflow, we need a controller to regulate the portion $\gamma(t)$ of the energy harvested stored into battery for each slot t. The other portion $1-\gamma(t)$ is spilled. Obviously, we have

$$0 \leqslant \gamma(t) \leqslant 1. \tag{1}$$

With battery equipment, we can manage the battery, i.e., control the charge or discharge behavior, to utilize the time diversity of electricity prices. For example, in the intuition, when the battery is not overflow and the electricity price is low, we can recharge the battery, vice versa. Let $Q(t)$ denote the power charged to $(Q(t) > 0)$ or discharged from $(Q(t) < 0)$ the battery during period t. The battery usually has an upper bound on the charge and discharge rate. Therefore, we have the following constraint on $Q(t)$:

$$-Q_{\min} \leqslant Q(t) \leqslant Q_{\max}. \tag{2}$$

Combining the renewable energy stored into battery $\gamma(t)E(t)$ and the charging or discharging action $Q(t)$, we can model the dynamics of the battery as:

$$B(t+1) = B(t) + Q(t) + \gamma(t)E(t), \tag{3}$$

where $B(t)$ is the battery energy level at slot t. It should be always nonnegative and cannot exceed the battery capacity $B_{\max}$. Thus,

$$0 \leqslant B(t) \leqslant B_{\max}. \tag{4}$$

From constraints (2)–(4), we get the following equivalent constraint for $Q(t)$:

$$\min\{Q_{\max}, B_{\max} - B(t)\} \geqslant Q(t) \geqslant -\min\{Q_{\min}, B(t)\}. \tag{5}$$

Traffic model. The data of each UE arrives at the end of each slot into an infinite data queue. Let $X_k(t)$ denote the queue length of UE k at slot t. We model the dynamics of the data queue length as:

$$X_k(t+1) = [X_k(t) - \mu(P_k(t), H_k(t))]^+ + \lambda_k(t), \tag{6}$$

where $[x]^+ = x$ if $x > 0$ or 0 otherwise, $\lambda_k(t)$ and $\mu(P_k(t), H_k(t))$ are the newly arrived data and transmitted data during period t. In practical system, $0 \leqslant \lambda_k(t) \leqslant \lambda_{\max}$ and $0 \leqslant \mu(P_k(t), H_k(t)) \leqslant \mu_{\max}$. The transmitted data $\mu(P_k(t), H_k(t))$ is dependent on the channel state $H_k(t)$ and power allocated to the UE $P_k(t)$. One typical relation can be expressed as:

$$\mu(P_k(t), H_k(t)) = W \log(1 + P_k(t)H_k(t)). \tag{7}$$

The power allocated to each UE usually should be always nonnegative and cannot exceed an upper $P_{\max}$, that is:

$$0 \leqslant P_k(t) \leqslant P_{\max}. \tag{8}$$

We consider the delay-tolerant traffic and let d be the delay constraint for UE. Using Little's Law, we can write the average delay in terms of mean queue-length, that is, the time-average data queue $\bar{X}_k$ should satisfy the following condition:

$$\bar{X}_k = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{X_k(t)\} < d\mathbb{E}\{\lambda_k(t)\}. \tag{9}$$

Electricity cost model. The system electricity cost is dependent on the total power consumption and the electricity price. We build the power consumption model of BS as $P_{BS}(t) = a\sum_{k=1}^{K} P_k(t) + b$, where a stands for power consumption that scales with the average radiated power and the term b models the static power consumed by signal processing, battery backup and cooling. Due to the introduction of energy storage, the total amount of energy $G(t)$ drawn from the conventional grid during time period t is given by:

$$G(t) = Q(t) + P_{BS}(t) = Q(t) + a\sum_{k=1}^{K} P_k(t) + b. \tag{10}$$

Obviously, the following constraint should always be satisfied:

$$Q(t) + a\sum_{k=1}^{K} P_k(t) + b \geqslant 0. \tag{11}$$

We assume a time-varying electricity price $C(t)$ with the maximum value $C_{\max}$ and the minimum value $C_{\min}$. It can be a constant value, double values in peak-valley electricity markets and unpredictable values in wholesale electricity markets as shown in [14]. When it is a constant value, the electricity cost problem discussed in this paper can be degenerated into the conventional grid energy consumption minimization problem in [9–11].

It should be mentioned that we do not consider the battery leakage. In practical system, the battery leakage is usually far smaller than the static power consumed by the BS, which makes the battery leakage negligible. Consider a worst case where the battery energy leakage c always exists no matter whether $B(t)$ is larger than c or not. We can treat the battery leakage as one part of BS's static power. Then the influence of battery leakage can be ignored comparing with the original static power b.

2.2. Problem formulation

In this paper, we are interested in minimizing the time-average expected electricity cost while stabilizing the system through choosing the following two control decisions: (1) control the energy requirement through power allocation, i.e., $\vec{P}(t)$; (2) control the energy supplement through battery management, i.e., $\gamma(t)$ and $Q(t)$. Thus, our problem can be formulated as the following stochastic program, called **P1**:

$$\underset{Q(t),\vec{P}(t),\gamma(t)}{\text{minimize}} \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{C(t)G(t)\},$$

subject to constraints (1), (3), (5), (6), (8), (9), (11). It should be noted that only if d in (9) is finite, the system can be stable [17].

One challenge to solve the above stochastic optimization problem is the unawareness of future data arrival $\vec{\lambda}(t)$, link quality $\vec{H}(t)$, energy harvested $E(t)$ and electricity price $C(t)$. Fortunately, Lyapunov theory which combines stability and optimization techniques has been extremely useful in the development of stable queue control algorithms [18,19]. Through minimizing a drift-plus-penalty function, an algorithm can be developed to stabilize the system and drive the object to an optimal value without knowledge of future information. Based on this point, we develop a robust algorithm in next section. Especially, we will show that our algorithm can guarantee the worst delay experienced by UEs through introducing virtual queues.

3. Proposed solution

3.1. Relaxed problem

The constraint (5) on $B(t)$ brings the time-coupling property to our problem. Thus, we firstly relax **P1** by eliminating this constraint on $B(t)$, which can help us design our control policy.

Define the time-average expected values of utilized renewable energy and charging/discharging rate under any feasible control policy of **P1** as follows:

$$\overline{\gamma E} = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{\gamma(t)E(t)\}, \quad \overline{Q} = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{Q(t)\}.$$

Summing (4) over all $t \in \{0,1,2,\ldots,T-1\}$, taking expectation on both sides, dividing both sides with T and taking $T \to \infty$, we have $\overline{Q} + \overline{\gamma E} = 0$. Hence, we obtain the following relaxed problem, called **P2**:

$$\underset{Q(t),\vec{P}(t),\gamma(t)}{\text{minimize}} \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{C(t)G(t)\}$$

subject to constraints (1), (2), (8), (9), (11) and

$$\overline{Q} + \overline{\gamma E} = 0.$$

Denote the optimal objective values of **P1** and **P2** as R^*_{ori} and R^*_{rel}, respectively. From the discussion above, we observe that any feasible solution to **P1** is also a feasible solution to **P2**. Thus, $R^*_{rel} \leqslant R^*_{ori}$. As given by the following Lemma, it is easier to find the optimal solution to **P2** because of the removal of the constraints on $B(t)$.

Lemma 1. *If $\vec{\lambda}(t)$, $\vec{H}(t)$, $E(t)$ and $C(t)$ are i.i.d. over slots, then there exists a stationary, randomized policy that takes control decisions $\hat{Q}^{stat}(t)$, $\hat{\vec{P}}^{stat}(t)$, $\hat{\gamma}^{stat}(t)$ every period t purely as a function (possibly randomized) of current system state $\vec{\lambda}(t)$, $\vec{H}(t)$, $E(t)$ and $C(t)$ while satisfying the constraints of* **P2** *and providing the following guarantees:*

$$\begin{aligned}&\mathbb{E}\{C(t)\hat{G}^{stat}(t)\} = R^*_{rel},\\&\mathbb{E}\{\hat{Q}^{stat}(t) + \hat{\gamma}^{stat}(t)E(t)\} = 0,\\&\mathbb{E}\{\mu(\hat{P}^{stat}_k(t), H_k(t))\} \geqslant \mathbb{E}\{\lambda_k(t)\}, \quad \forall 0 \leqslant k \leqslant K,\end{aligned} \tag{12}$$

where the expectations are w.r.t. the stationary distribution of $\vec{\lambda}(t)$, $\vec{H}(t)$, $E(t)$ and $C(t)$ and the control decisions.

The proof is similar to that in [16] and follows the framework of Lyapunov optimization in [17], which is omitted here for brevity. With Lemma 1, we can use the existence of such a stationary, randomized policy to help us design our control policy and derive the performance results for our algorithm.

3.2. Key queues

As mentioned before, we will propose an online algorithm based on the Lyapunov optimization technique to approximately obtain the optimal solution. Lyapunov optimization technique can stabilize all network queues while optimizing some performance objectives. The queues are cores of Lyapunov theory. Through designing different queues to be stabilized, we can achieve different performance assurances in different application scenarios. In this subsection, we introduce three kinds of problem-specific key queues for different purposes, which will help us design our algorithm in next subsection.

Firstly, we modify the data queue (6) with α and define a new modified data queue as follows:

$$D_k(t+1) = \left[D_k(t) - \frac{\mu(P_k(t), H_k(t))}{\alpha}\right]^+ + \frac{\lambda_k(t)}{\alpha}, \tag{13}$$

where α is a key control parameter which builds the relationship between the cost saving and delay performance as discussed later. The purpose of introducing α is to build a bridge between the transmitted data and energy consumption.

Secondly, we use the ξ−persistent queue technique and additionally define the following virtual queue $Z_k(t)$ to guarantee the worst case delay for any buffered data in the queue:

$$Z_k(t+1) = \left[Z_k(t) - \frac{\mu(P_k(t), H_k(t))}{\alpha} + \xi 1_{\{D_k(t)>0\}}\right]^+, \tag{14}$$

where $1_{\{D_k(t)>0\}}$ is an indicator function that is 1 if $D_k(t) > 0$ or 0 otherwise. ξ is a fixed positive parameter to be specified later. Obviously, $Z_k(t)$ has the same service process as $D_k(t)$, but has an arrival process that adds ξ whenever the actual backlog is nonempty, which can ensure that $Z_k(t)$ grows if there is remaining data. The following Lemma reveals that if we can control the system to ensure that the queues $D_k(t)$ and $Z_k(t)$ have finite upper bounds, then any data of UE k can be transmitted within the worst case delay.

Lemma 2. *Suppose we can control the system to ensure that $Z_k(t) \leqslant Z_{\max}$ and $D_k(t) \leqslant D_{\max}$ for all slots t, where $Z_{\max}$ and $D_{\max}$ are some positive constants, then the worst case delay for all buffered data is upper bounded by $\delta_{\max}$ where*

$$\delta_{\max} \triangleq \left\lceil \frac{D_{\max} + Z_{\max}}{\xi} \right\rceil. \quad (15)$$

Proof. The proof follows directly from the framework of Lyapunov optimization [17]. Consider any slot t for which $\frac{\lambda_k(t)}{\alpha} > 0$. We will prove that the data is transmitted on or before time $t + \delta_{\max}$ by contradiction.

Suppose the data $\frac{\lambda_k(t)}{\alpha} > 0$ is not served on or before time $t + \delta_{\max}$, then during slots $\tau \in \{t+1, \ldots, t+\delta_{\max}\}$, it must be that $D_k(\tau) > 0$. Thus, we have $1_{\{D_k(t)\}} = 1$ for all $\tau \in \{t+1, \ldots, t+\delta_{\max}\}$. With the update (14) of $Z_k(t)$, for all $\tau \in \{t+1, \ldots, t+\delta_{\max}\}$, we have:

$$Z_k(\tau+1) \geqslant Z_k(\tau) - \frac{\mu(P_k(\tau), H_k(\tau))}{\alpha} + \xi.$$

Summing the above inequality over $\tau \in \{t+1, \ldots, t+\delta_{\max}\}$ yields

$$Z_k(t+\delta_{\max}+1) - Z_k(t+1) \geqslant -\sum_{\tau=t+1}^{t+\delta_{\max}} \frac{\mu(P_k(\tau), H_k(\tau))}{\alpha} + \xi\delta_{\max}.$$

Rearranging the terms and using the facts that $0 \leqslant Z_k(t+1)$ and $Z_k(t+\delta_{\max}+1) < Z_{\max}$ yields

$$\sum_{\tau=t+1}^{t+\delta_{\max}} \frac{\mu(P_k(\tau), H_k(\tau))}{\alpha} \geqslant \xi\delta_{\max} - Z_{\max}.$$

Since the $\frac{\lambda_k(t)}{\alpha}$ are queued in FIFO manner and $D_k(t) \leqslant D_{\max}$, it must be that $\sum_{\tau=t+1}^{t+\delta_{\max}} \frac{\mu(P_k(\tau), H_k(\tau))}{\alpha} \leqslant D_{\max}$ as we have assumed that the data $\frac{\lambda_k(t)}{\alpha}$ are not served by time $t + \delta_{\max}$. Therefore, we have

$$\xi\delta_{\max} - Z_{\max} < D_{\max},$$

which implies that $\delta_{\max} < \frac{D_{\max}+Z_{\max}}{\xi}$, contradicting the definition of $\delta_{\max}$ in (15). □

Finally, we define another variable $Y(t)$ as a shifted version of battery level $B(t)$ as follows to ensure that the constraints (4) and (5) on $B(t)$, which are ignored in **P2**, are still satisfied in our algorithm:

$$Y(t) = B(t) - VC_{\max} - Q_{\min}, \quad (16)$$

where V is another control parameter. The intuition behind $Y(t)$ is to construct the algorithm based on a quadratic Lyapunov function, but carefully perturb the weights used for decision making, so as to push the battery level toward certain nonzero values to avoid underflow. According to (3), we have the same update equation for $Y(t)$ as follows:

$$Y(t+1) = Y(t) + Q(t) + \gamma(t)E(t). \quad (17)$$

3.3. Optimal control policy

With the above modified data queues $\vec{D}(t)$, virtual queues $\vec{Z}(t)$ and shifted version of battery level $Y(t)$ in the previous subsection, our proposed algorithm is shown in Algorithm 1. The algorithm is designed based on the Lyapunov optimization technique developed in [17]. The idea of the algorithm is to greedily minimize a upper bound of the drift-plus-penalty function in (B.5).

Algorithm 1. Proposed algorithm based on the Lyapunov theory.

1: **for** each time period t **do**
2: Measure the system states $Y(t)$, $\vec{D}(t)$, $\vec{Z}(t)$, $\vec{H}(t)$, $E(t)$, $\vec{\lambda}(t)$, and $C(t)$;
3: Choose control decisions $Q^{PA}(t)$, $\gamma^{PA}(t)$ and $\vec{P}^{PA}(t)$ as the solution to the following optimization problem, called **P3**:

$$\underset{Q(t),\vec{P}(t),\gamma(t)}{\text{minimize}}\, f(t) \triangleq = (Y(t) + VC(t))Q(t) + Y(t)\gamma(t)E(t) - \sum_{k=1}^{K} \left\{ (D_k(t) + Z_k(t)) \frac{\mu(P_k(t), H_k(t))}{\alpha} + aVC(t)P_k(t) \right\}$$

subject to constraints (1), (2), (8), (11);
4: Update the system states as (13), (14) and (17).
5: **end for**

As shown in Algorithm 1, we just need to measure the system states $Y(t)$, $\vec{D}(t)$, $\vec{Z}(t)$, $\vec{H}(t)$, $E(t)$, $\vec{\lambda}(t)$, and $C(t)$, without knowledge of future information. $Y(t)$, $\vec{D}(t)$ and $\vec{Z}(t)$ are the queues managed by the BS, thus they are known and identified for the BS. $E(t)$ and $C(t)$ are the current harvested energy and opened price information, thus they also can be known by the BS. $\vec{H}(t)$ and $\vec{\lambda}(t)$ are the channel condition and arrived data, which can be achieved with the beacon signal. In this paper, we assume that $\vec{H}(t)$ and $\vec{\lambda}(t)$ are error-free. If $\vec{H}(t)$ and $\vec{\lambda}(t)$ are not error-free, Algorithm 1 can be still applied through replacing them with estimated values, which may affect the performance to some extent.

We can find that all the constraints of **P3** are affine functions. Besides, the object function is convex function. Thus, for each time slot t, **P3** is a convex optimization problem, which can be solved easily by some standard convex optimization techniques with low complexity [20]. Here, we give out some important features of the optimal solution in the following Lemma, which will be used in the performance analysis in next section.

Lemma 3. *The solution to* **P3** *has the following features:*

(1) *When* $Y(t) > 0$, *the solution always chooses* $\gamma^{PA}(t) = 0$; $\gamma^{PA}(t) = 1$ *otherwise;*
(2) *When* $Y(t) > -VC_{\min}$, *the solution always chooses* $Q^{PA}(t) \leqslant 0$; *When* $Y(t) < -VC_{\max}$, *the optimal solution always choose* $Q^{PA}(t) \geqslant 0$;
(3) *When* $\frac{W(D_k(t)+Z_k(t))}{\alpha aVC(t)} - \frac{1}{H_k(t)} \geqslant P_{\max}$, *the solution always chooses* $P_k^{PA}(t) = P_{\max}$.

Proof. (1) It is straightforward from the object function of **P3** and the constraint $0 \leqslant \gamma(t) \leqslant 1$.

(2) When $Y(t) > -VC_{\min}$, suppose the solution is $\vec{P}^{PA}(t)$, $\gamma(t)$, and $Q^{PA}(t)$, where $Q^{PA}(t) > 0$. This solution satisfies the constraints of **P3**. We can keep the same $\vec{P}^{PA}(t)$, $\gamma^{PA}(t)$ and set $Q^{PA'}(t) = 0$ which also satisfy the constraints of **P3** and achieve a smaller objective because $Y(t) + VC(t) > 0$. Hence, when $Y(t) > -VC_{\min}$, we have $Q^{PA}(t) \leqslant 0$. Similarly, we can prove that when $Y(t) < -VC_{\max}$, we have $Q^{PA}(t) \geqslant 0$.

(3) The Lagrangian of **P3** is

$$L = f(t) + \varphi_1(-Q_{\min} - Q(t)) + \varphi_2(Q(t) - Q_{\max}) - \sum_{k=1}^{K}\varphi_{3,k}P_k(t) + \sum_{k=1}^{K}\varphi_{4,k}(P_k(t) - P_{\max}) + \varphi_5\left(-a\sum_{k=1}^{K}P_k(t) - b - Q(t)\right), \quad (18)$$

where φ_1, φ_2, $\vec{\varphi}_3$, $\vec{\varphi}_4$ and φ_5 are Lagrangian multipliers and greater than or equal 0. We obtain part of Karush–Kuhn–Tucker (KKT) conditions as:

$$\frac{\partial L}{\partial P_k(t)} = -\frac{WH_k(t)(D_k(t)+Z_k(t))}{\alpha\cdot(1+P_k(t)H_k(t))} + aVC(t) - \varphi_{3,k} + \varphi_{4,k} - \varphi_5 a = 0, \quad (19)$$

$$\varphi_{4,k}(P_k(t) - P_{\max}) = 0. \quad (20)$$

From (19), we have

$$P_k(t) = \frac{W(D_k(t)+Z_k(t))}{\alpha\cdot(aVC(t) - \varphi_{3,k} + \varphi_{4,k} - \varphi_5 a)} - \frac{1}{H_k(t)}. \quad (21)$$

When $\frac{W(D_k(t)+Z_k(t))}{\alpha aVC(t)} - \frac{1}{H_k(t)} \geqslant P_{\max}$, we should set $\varphi_{4,k} > 0$ to ensure $P_k(t)$ in (21) satisfy the constraint $P_k(t) \leqslant P_{\max}$. With $\varphi_{4,k} > 0$ and (20), we have $P_k(t) = P_{\max}$. □

From (21), we find that $P_k(t)$ is monotonically increasing in $D_k(t)$, $Z_k(t)$ and $H_k(t)$, and monotonically decreasing in $C(t)$. It is intuitive because we should increase the transmission power when the queue length increases, the channel quality becomes better or the electricity price is low.

4. Performance analysis and discussions

In this section, we analyze the delay, feasibility and cost saving performance of our algorithm, which are given by Theorem 1–3, respectively. Besides, the impacts of three control parameters α, ξ and V on the performance are discussed.

4.1. Performance analysis

Theorem 1. (Worst delay performance). *Denote $H_{\min}$ as the minimum value of all the acquired channel state and assume that $\mu(P_{\max}, H_{\min}) \geqslant \lambda_{\max}$ is satisfied to provide steady service. If $D_k(0) = Z_k(0) = 0$, then for any fixed parameter $0 < \xi \leqslant \frac{\lambda_{\max}}{\alpha}$, our control algorithm can make sure that:*

(1) *The queues $D_k(t)$ and $Z_k(t)$ are deterministically upper bounded by the following expressions at each slot:*

$$D_k(t) \leqslant D_{\max} \triangleq \frac{\alpha}{W}aVC_{\max}P_{\max}\frac{2^{\lambda_{\max}/W}}{2^{\lambda_{\max}/W}-1} + \frac{\lambda_{\max}}{\alpha},$$
$$Z_k(t) \leqslant Z_{\max} \triangleq \frac{\alpha}{W}aVC_{\max}P_{\max}\frac{2^{\lambda_{\max}/W}}{2^{\lambda_{\max}/W}-1} + \xi. \quad (22)$$

(2) *The worst case delay for any data in queue is given by*

$$\delta_{\max} \triangleq \left\lceil \frac{2\frac{\alpha}{W}aVC_{\max}P_{\max}\frac{2^{\lambda_{\max}/W}}{2^{\lambda_{\max}/W}-1} + \frac{\lambda_{\max}}{\alpha} + \xi}{\xi} \right\rceil. \quad (23)$$

Proof. Based on (1) and Lemma 2, (2) is straightforward. Now, we prove (1) with induction method.

We first prove that $D_k(t) \leqslant \frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right) + \frac{\lambda_{\max}}{\alpha}$ for all time slot t. Obviously, $D_k(0) = 0 \leqslant \frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right) + \frac{\lambda_{\max}}{\alpha}$. Suppose it holds at time slot t, we need to show that it also holds at time slot $t+1$. According to (13), if $D_k(t) \leqslant \frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right)$, then we have $D_k(t+1) \leqslant \frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right) + \frac{\lambda_{\max}}{\alpha}$ because the maximum amount of data arrival is $\frac{\lambda_{\max}}{\alpha}$; if $\frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right) \leqslant D_k(t) \leqslant \frac{\alpha}{W}aVC_{\max}\left(P_{\max} + \frac{1}{H_{\min}}\right) + \frac{\lambda_{\max}}{\alpha}$, then $\frac{WD_k(t)}{\alpha aVC(t)} - \frac{1}{H_k(t)} \geqslant P_{\max}$. Due to $Z_k(t) \geqslant 0$, we have $\frac{W(D_k(t)+Z_k(t))}{\alpha aVC(t)} - \frac{1}{H_k(t)} \geqslant P_{\max}$. From (3) in Lemma 3, we have $P_k^{PA}(t) = P_{\max}$, thus, $\frac{\mu(P_k^{PA}(t), H_k(t))}{\alpha} = \frac{W\log(1+P_{\max}H_k(t))}{\alpha} \geqslant \frac{\lambda_{\max}}{\alpha}$. According to (13), we have $D_k(t+1) \leqslant D_k(t) \leqslant \frac{\alpha}{W}aVC_{\max}(P_{\max} + \frac{1}{H_{\min}}) + \frac{\lambda_{\max}}{\alpha}$.

Then combining the assumption $W\log(1 + P_{\max}H_{\min}) \geqslant \lambda_{\max}$, we have $D_k(t) \leqslant D_{\max}$.

Similarly, we can prove the second part of (22). □.

The above Theorem shows that our algorithm can make sure worst case delay is controlled within acceptable limits through setting fit control parameters. It should be noted that, the assumption $\mu(P_{\max}, H_{\min}) \geqslant \lambda_{\max}$ is usually satisfied in practical deployed system. Otherwise, the system may not be stable with any scheme.

Theorem 2. (Feasibility). *For any*

$$0 < V \leqslant V^{\max} \triangleq \min\left\{\frac{B_{\max} - Q_{\min} - Q_{\max} - E_{\max}}{C_{\max} - C_{\min}}, \frac{B_{\max} - Q_{\min} - E_{\max}}{C_{\max}}\right\},$$

our algorithm can make sure:

(1) $B_{\max} - VC_{\max} - Q_{\min} \geqslant Y(t) \geqslant -VC_{\max} - Q_{\min}$, that is, $B_{\max} \geqslant B(t) \geqslant 0$ for all time slot t.
(2) All control decisions can be feasible with a fit ξ.

The proof is given in Appendix A.

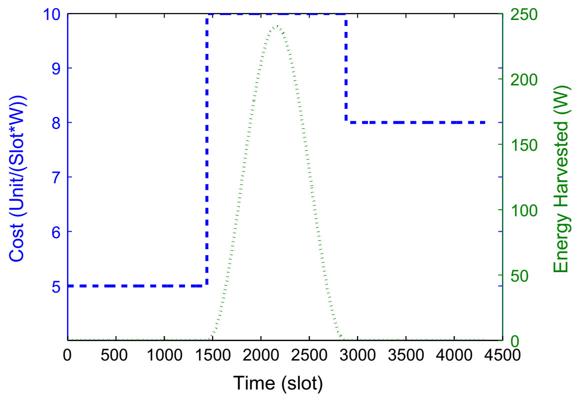


Fig. 2. Daily electricity price and renewable energy profile in scenario 2.

Theorem 3. (Cost saving performance). *If* $\vec{\lambda}(t)$, $\vec{H}(t)$, $E(t)$ *and* $C(t)$ *are i.i.d. over slots, then for any fixed parameter* $0 \leqslant \xi \leqslant \mathbb{E}\left\{\frac{\min_k\{\lambda_k(t)\}}{\alpha}\right\}$, *the time-average expected electricity cost under our algorithm is within bound of the optimal value, i.e.,*

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{C(t)G^{PA}(t)\} \leqslant R^*_{ori} + A/V, \tag{24}$$

where V is control parameter and

$$A = \frac{1}{2}\max\left[(Q_{\max}+E_{\max})^2, Q_{\min}^2\right] + \frac{K}{2}\max\left[\left(\frac{\mu_{\max}}{\alpha}\right)^2, \xi^2\right] + \frac{K}{2}\left(\left(\frac{\lambda_{\max}}{\alpha}\right)^2 + \left(\frac{\mu_{\max}}{\alpha}\right)^2\right). \tag{25}$$

The proof is given in Appendix B.

4.2. Discussions on the impact of control parameters

There are three control parameters in our algorithm: α, ξ and V, all of which are important in the system performance.

From Theorem 3, it reveals that with larger V, the electricity cost is closer to the optimal value. However, as shown in Theorem 2, V has a maximum value to make sure our solution is feasible. Thus, we suggest $V = V^{\max}$.

From Theorem 1, it reveals that with larger ξ, our proposed algorithm will suffer smaller worst delay. However, as shown in Theorem 3, larger ξ may bring a higher electricity cost. Thus, ξ has an influence on the tradeoff between the worst delay and cost saving performance. Besides, as indicated in Theorem 2 and Theorem 3, we should ensure

$$0 \leqslant \xi \leqslant \min\left\{\mathbb{E}\left\{\frac{\min_k\{\lambda_k(t)\}}{\alpha}\right\}, \frac{\lambda_{\max}}{\alpha}\right\}. \tag{26}$$

Similarly to ξ, α also affects the tradeoff between worst delay and cost saving performance as shown in (23) and (25). What's more, we can find that A in (25) consists of two part: energy part and data part. Therefore, α builds the bridge between energy and data. To make sure the two parts have the same order of magnitude, we propose that α uses the following order of magnitude:

$$\alpha_0 = \sqrt{\frac{W\lambda_{\max}}{aP_{\max}P_{\max}}}. \tag{27}$$

Finally, we can ensure the average or worst delay constraint $\delta_{\max} \leqslant d$ is satisfied via setting fit α and ξ.

5. Simulations

In this section, we evaluate our proposed algorithm (denoted as PA) by comparing it with the following existing work: (1) The online adaptive water filling algorithm in [12], denoted as AWFA; (2) The throughput optimal algorithm in [13], denoted as TOA; (3) The traditional schemes without consideration of variable cost [9–11], denoted as TA.

5.1. Simulation setup

We consider a multiuser system with 1 BS and 20 UEs. All the UEs are uniformly distributed in a 1200 m × 1200 m region centered at the BS. The parameters of channel are configured as: $H_k(t) = \frac{h_k(t)l_k^{-\beta}}{\delta^2}$, where

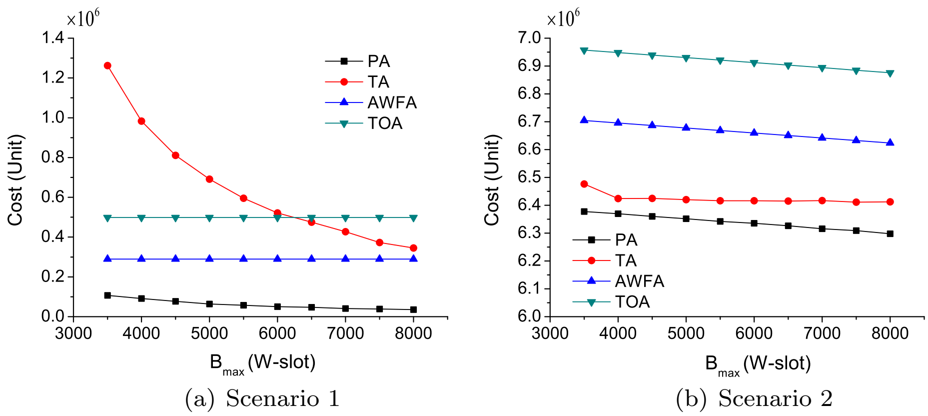
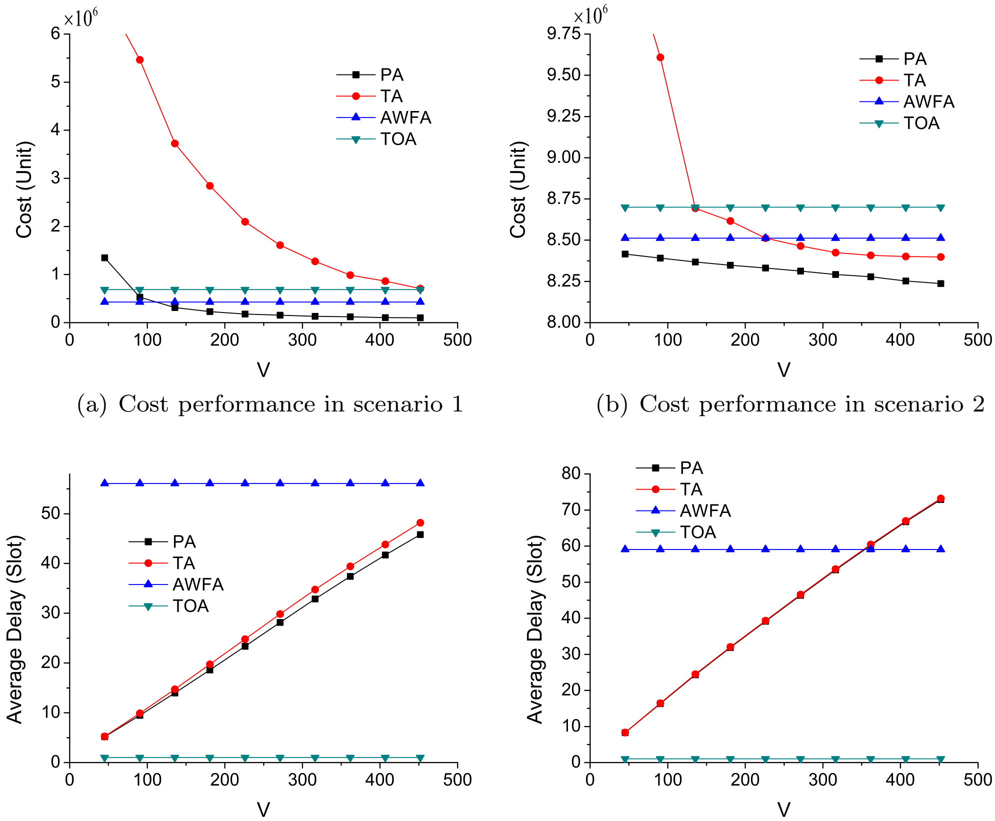


Fig. 3. Total cost performance of different algorithms with different battery capacity $B_{\max}$ settings.



(a) Cost performance in scenario 1 (b) Cost performance in scenario 2

(c) Delay performance in scenario 1 (d) Delay performance in scenario 2

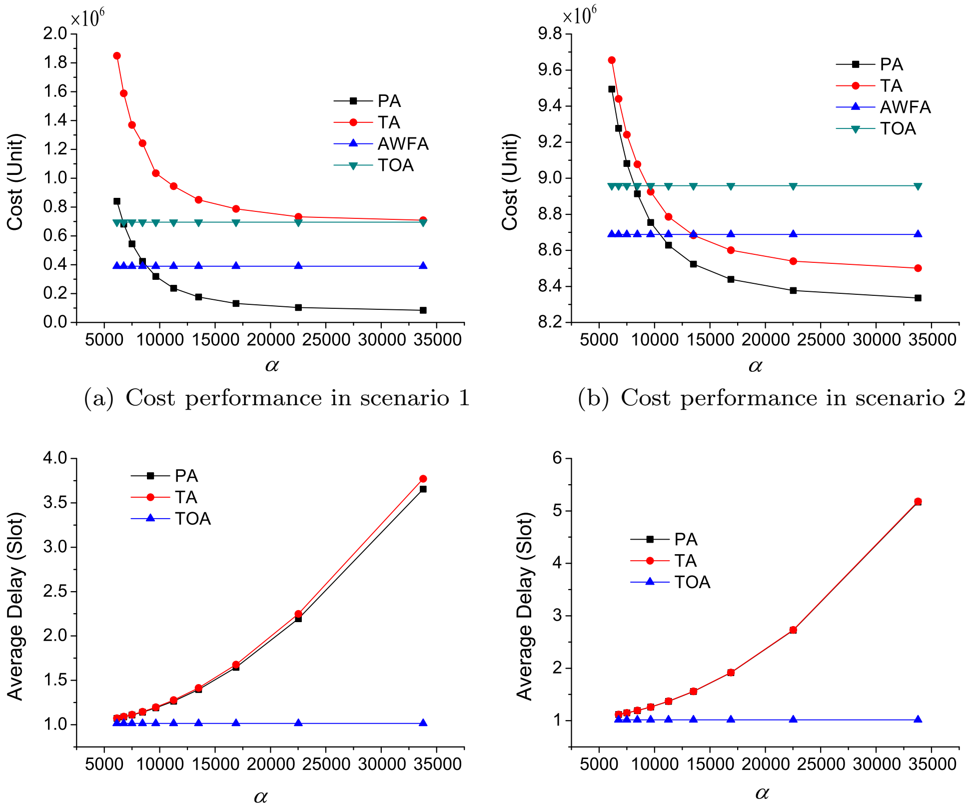
Fig. 4. Performance results of different algorithms with different control parameter V settings. ($\alpha = \alpha_0$).

the random variable $h_k(t)$ follows an exponential distribution with mean 1, $\beta = 4$ is the pathloss exponent, l_k is the distance between UE k and BS, and $\delta^2 = -100$ dBm is the additive noise power. The BS is configured with 5 MHz carrier bandwidth which is evenly divided into 20 subchannels, to serve UEs. The parameters related to power consumption are $a = 2.66$, $b = 118.7$ W, and $P_{\max} = 1.6$ W [21]. We fix the parameters $Q_{\min} = Q_{\max} = 240$ W-slot. In our simulations, the data arrival of each UE during each time slot t is uniformly distributed in the interval $[0, 1080]$ Kb/s. We consider two scenarios where different price functions $C(t)$ and energy profile functions $E(t)$ are used: (1) Scenario 1: The random functions are applied, i.e., we assume the electricity price $C(t)$ and energy profile $E(t)$ during each time slot t are uniformly distributed in the interval $[5, 10]$ Unit/(slot*W) and $[0, 240]$ W, respectively. (2) Scenario 2: As shown in Fig. 2, the common peak-valley electricity price is used where $C(t)$ can take three possible values in $\{C_{low} = 5,\ C_{mid} = 8,\ C_{high} = 10\}$ Unit/(slot*W). Besides, we model $E(t)$ with the practical energy profile in Fig. 2, similarly to [16]. The simulation time is set to 3 days, i.e., 12960 slots.

5.2. Results and analysis

First, we study the impact of storage capacity $B_{\max}$ on cost saving performance by varying $B_{\max}$ from 3500 to 8000 *W-slot*. In this part, we set $\alpha = \alpha_0,\ \xi = \mathbb{E}\left\{\frac{\min_k\{\lambda_k(t)\}}{\alpha}\right\}$ and $V = V^{\max}$. The results in two scenarios are illustrated in Fig. 3. From the figure, it is clear that the performance of PA is superior to that of TA, AWFA and TOA in both scenario 1 and scenario 2. The gain comes from two aspects: (1) PA stores excessive renewable energy harvested in current time slot for use at later time when renewable energy generation is insufficient, charges the battery when the price is low while discharges it when the price is high; (2) PA saves the BS's transmission energy by sacrificing some delay performance, i.e., delaying data to be transmitted when the link quality is good enough, the electricity price is low or the available harvested energy is much enough. As a comparison, TA, AWFA and TOA do not consider the price factor. Besides, TOA just maximizes the throughput instead of delaying the data to be transmitted when the link quality is good enough. What's more, we can find that the larger $B_{\max}$ is, the less cost PA needs. The reason is that with larger $B_{\max}$, we can store more renewable energy harvested for use at later time when renewable energy generation is insufficient or the price is high.

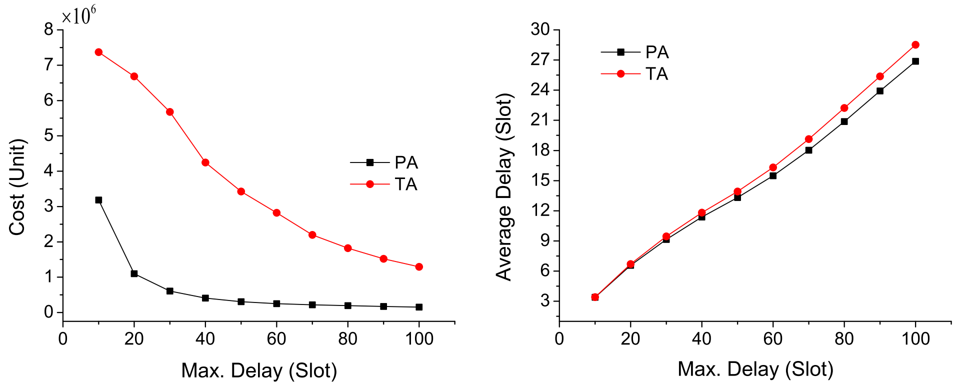
Next, we investigate the effects of control parameters V and α on the system cost and average delay performance. In this part, we set $B_{\max} = 5000$ *W-slot* and $\xi = \mathbb{E}\left\{\frac{\min_k\{\lambda_k(t)\}}{\alpha}\right\}$. The effects of V and α are shown in



(a) Cost performance in scenario 1 (b) Cost performance in scenario 2

(c) Delay performance in scenario 1 (d) Delay performance in scenario 2

Fig. 5. Performance results of different algorithms with different control parameter α settings. ($V = V^{\max}$).



(a) Cost vs. Max. delay (b) Ave. Delay vs. Max. delay

Fig. 6. The trade-off between delay performance and energy cost (scenario 1).

Figs. 4 and 5, respectively. It is obvious that the larger α and V are, the more cost saving PA and TA can obtain and the larger delay PA and TA suffer. It demonstrates that α and V play an important role in the tradeoff between the delay and cost saving performance which corroborates the accuracy of our theoretical analysis. Besides, we can find that only if α and V are not too small, PA has the best cost performance. For the delay performance, TOA performs best because it always tries to maximize the throughput which also brings a high cost. Furthermore, Fig. 5 shows that through adjusting α and V to some fit values, we can achieve a low cost while suffering the acceptable delay. For example, when $V = V^{\max}$ and $\alpha = 22,500$, the delay of PA are 2.19 and 2.72 slot in scenario 1 and scenario 2, respectively, while the cost are 1×10^5 and 8.37×10^6 Unit in scenario 1 and scenario 2, respectively, which are much lower than TA, AWFA and TOA.

Last, we study the trade-off between delay performance and energy cost through varying the maximum delay constraints. The results are illustrated in Fig. 6. The results show that with a more relaxed constraint, we can sacrifice more delay performance to achieve a lower cost performance. What's more, the curves in Fig. 6a shows that with the increase of maximum delay, the cost gain PA and TA achieved by sacrificing delay decreases. For example, when we adjust the maximum delay from 10 to 20 slots, the cost of PA is decreased from 3.15×10^6 to 1.09×10^6 Unit. However, when we adjust the maximum delay from 60 to 70 slots, the cost of PA is decreased from 3×10^5 to 2.4×10^5 Unit. Besides, all the curves show that PA is always superior to TA since it considers the price factor.

It should be mentioned that although Lemma 1 and Theorem 3 holds with the i.i.d. assumption (i.e., scenario 1), all the results in scenario 2 (which does not have i.i.d. assumption and thus is more practical), i.e., Figs. 3–5, show that PA still works well in practical system.

6. Conclusions

In this paper, we have studied the joint power allocation and battery management approach to reducing the electricity cost for cellular networks with hybrid energy sources. Based on the Lyapunov optimization techniques, we design an online algorithm to approximately obtain the optimal cost. Theoretical analysis shows that our algorithm can achieve the cost deviated no more than $O(1/V)$ from the optimal cost where V is a control parameter determined by the battery capacity. Furthermore, our algorithm can guarantee the worst case delay for any UE's data by using the virtual queue technique. Numerical simulation results confirm that (1) our algorithm is superior to some existing work in terms of electricity cost; (2) the larger delay can be tolerated, the more cost can be saved by our algorithm.

Although this paper just considers the single-cell system, our proposed algorithm and results can be directly applied in the noise-limited multi-cell system. As future work, we will focus on the multi-cell system with the consideration of inter-cell interference and energy cooperation.

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Appendix A. Proof of Theorem 2

Proof. (1) We prove this result by induction. When $t = 0$, $Y(0) = B(0) - VC_{\max} - Q_{\min}$ and $0 \leqslant B(0) \leqslant B_{\max}$, thus we have $B_{\max} - VC_{\max} - Q_{\min} \geqslant Y(0) \geqslant -VC_{\max} - Q_{\min}$. Now suppose that $B_{\max} - VC_{\max} - Q_{\min} \geqslant Y(t) \geqslant -VC_{\max} - Q_{\min}$ is satisfied for time slot t. We need to show that it also holds for time slot $t+1$:

If $-VC_{\max} - Q_{\min} \leqslant Y(t) < -VC_{\max}$, from (2) in Lemma 3 we know that $Q^{PA}(t) \geqslant 0$. According to (17), we have $Y(t+1) \geqslant Y(t) \geqslant -VC_{\max} - Q_{\min}$; Besides, we have $Y(t+1) \leqslant Y(t) + Q_{\max} + E_{\max} \leqslant -VC_{\max} + Q_{\max} + E_{\max} \leqslant -VC_{\min} + Q_{\max} + E_{\max}$. With $V \leqslant V^{\max}$, we have $Y(t+1) \leqslant -VC_{\min} + Q_{\max} + E_{\max} \leqslant B_{\max} - VC_{\max} - Q_{\min}$.

If $-VC_{\max} \leqslant Y(t) \leqslant -VC_{\min}$, according to (17), we have $Y(t+1) \geqslant Y(t) - Q_{\min} \geqslant -VC_{\max} - Q_{\min}$; Besides, we have $Y(t+1) \leqslant Y(t) + Q_{\max} + E_{\max} \leqslant -VC_{\min} + Q_{\max} + E_{\max}$. With $V \leqslant V^{\max}$, we have $Y(t+1) \leqslant -VC_{\min} + Q_{\max} + E_{\max} \leqslant B_{\max} - VC_{\max} - Q_{\min}$.

If $-VC_{\min} < Y(t) \leqslant 0$, according to (17), we have $Y(t+1) \geqslant Y(t) - Q_{\min} \geqslant -VC_{\min} - Q_{\min} \geqslant -VC_{\max} - Q_{\min}$; Besides, from (2) in Lemma 3 we know that $Q^{PA}(t) \leqslant 0$, thus we have $Y(t+1) \leqslant E_{\max} \leqslant B_{\max} - VC_{\max} - Q_{\min}$. With $V \leqslant V^{\max}$, we have $Y(t+1) \leqslant E_{\max} \leqslant B_{\max} - VC_{\max} - Q_{\min}$.

If $0 < Y(t) \leqslant B_{\max} - VC_{\max} - Q_{\min}$, from (1) and (2) in Lemma 3 we know that $\gamma^{PA}(t) = 0$ and $Q^{PA}(t) \leqslant 0$. According to (17), we have $Y(t+1) = Y(t) + Q^{PA}(t) \leqslant Y(t) \leqslant B_{\max} - VC_{\max} - Q_{\min}$ and $Y(t+1) = Y(t) + Q(t) \geqslant -Q_{\min} \geqslant -VC_{\max} - Q_{\min}$.

(2) From (1), the constraints on $B(t)$ are satisfied. Besides, from Theorem 1, we can make sure the delay constraint with the fit control parameter ξ and α. Further, we choose our control policy to satisfy all constraints in **P3**. Combining them together, all constraints of **P1** can be satisfied. Therefore, our control decisions are feasible to the original problem. □

Appendix B. Proof of Theorem 3

Proof. We make use of Lyapunov optimization techniques to derive this result. Denote the system queue states $\vec{K}(t) \triangleq (\vec{D}(t), \vec{Z}(t), Y(t))$. Define the Lyapunov function as $L(\vec{K}(t)) \triangleq \frac{1}{2}\left(\sum_{k=1}^{K} D_k^2(t) + \sum_{k=1}^{K} Z_k^2(t) + Y^2(t)\right)$ and the conditional 1-slot Lyapunov drift as follows:

$$\Delta(\vec{K}(t)) = \mathbb{E}\{L(\vec{K}(t+1)) - L(\vec{K}(t)) | \vec{K}(t)\}.$$

From the update (17), we obtain the following results by squaring both sides:

$$\frac{Y^2(t+1) - Y^2(t)}{2} = \frac{(Q(t) + \gamma(t)E(t))^2}{2} + Y(t)(Q(t) + \gamma(t)E(t))$$

As $-Q_{\min} \leqslant Q(t) \leqslant Q_{\max}$ and $0 \leqslant \gamma(t)E(t) \leqslant E_{\max}$, we have

$$\frac{(Q(t) + \gamma(t)E(t))^2}{2} \leqslant \frac{1}{2} \max\left[(Q_{\max} + E_{\max})^2, Q_{\min}^2\right].$$

Thus, we can get the following upper bound for the Lyapunov drift $Y(t)$:

$$\frac{Y^2(t+1) - Y^2(t)}{2} \leqslant \frac{1}{2} \max\left[(Q_{\max} + E_{\max})^2, Q_{\min}^2\right] + Y(t)(Q(t) + \gamma(t)E(t)). \quad \text{(B.1)}$$

Similarly, from the update (14) and (13), we can obtain the following inequalities:

$$\frac{Z_k^2(t+1)-Z_k^2(t)}{2} \leqslant \frac{1}{2}\max\left[\left(\frac{\mu_{\max}}{\alpha}\right)^2, \xi^2\right] + Z_k(t)\left(\xi - \frac{\mu(P_k(t),H_k(t))}{\alpha}\right), \quad (B.2)$$

$$\frac{D_k^2(t+1)-D_k^2(t)}{2} \leqslant \frac{\left(\frac{\lambda_{\max}}{\alpha}\right)^2+\left(\frac{\mu_{\max}}{\alpha}\right)^2}{2} + D_k(t)\left(\frac{\lambda(t)}{\alpha} - \frac{\mu(P_k(t),H_k(t))}{\alpha}\right). \quad (B.3)$$

Combining these three bounds (B.1)–(B.3) together and taking the expectation w.r.t. on both sides, we have

$$\begin{aligned}\Delta(\vec{K}(t)) \leqslant A &+ \mathbb{E}\{Y(t)(Q(t)+\gamma(t)E(t))|\vec{K}(t)\} \\ &+ \sum_{k=1}^{K}\mathbb{E}\{Z_k(t)\left(\xi - \frac{\mu(P_k(t),H_k(t))}{\alpha}\right)|\vec{K}(t)\} \\ &+ \sum_{k=1}^{K}\mathbb{E}\{D_k(t)\left(\frac{\lambda_k(t)}{\alpha} - \frac{\mu(P_k(t),H_k(t))}{\alpha}\right)|\vec{K}(t)\},\end{aligned} \quad (B.4)$$

where A is expressed as (25).

Adding penalty term $V\mathbb{E}\{C(t)G(t) \mid \vec{K}(t)\}$ to both sides of (B.4), we obtain the following inequality:

$$\begin{aligned}&\Delta(\vec{K}(t)) + V\mathbb{E}\{C(t)G(t)|\vec{K}(t)\} \\ &\leqslant A + Y(t)\mathbb{E}\{Q(t)+\gamma(t)E(t)|\vec{K}(t)\} \\ &\quad + \sum_{k=1}^{K} Z_k(t)\mathbb{E}\left\{\xi - \frac{\mu(P_k(t),H_k(t))}{\alpha}|\vec{K}(t)\right\} \\ &\quad + \sum_{k=1}^{K} D_k(t)\mathbb{E}\left\{\frac{\lambda_k(t)}{\alpha} - \frac{\mu(P_k(t),H_k(t))}{\alpha}|\vec{K}(t)\right\} \\ &\quad + V\mathbb{E}\{C(t)G(t)|\vec{K}(t)\}.\end{aligned} \quad (B.5)$$

Plugging $G(t) = a\sum_{k=1}^{K}P_k(t) + b + Q(t)$ into (B.5) and comparing with objective of **P3**, it is obvious that our algorithm always attempts to greedily minimize the right hand side of the above inequality for each time slot t over all possible feasible control policies including the optimal, stationary policy given in Lemma 1. Therefore,

$$\begin{aligned}&\Delta(\vec{K}(t)) + V\mathbb{E}\{C(t)G^{PA}(t)|\vec{K}(t)\} \\ &\leqslant A + Y(t)\mathbb{E}\{\hat{Q}^{stat}(t)+\hat{\gamma}^{stat}(t)E(t)|\vec{K}(t)\} \\ &\quad + \sum_{k=1}^{K} Z_k(t)\mathbb{E}\left\{\xi - \frac{\mu(\hat{P}_k^{stat}(t),H_k(t))}{\alpha}|\vec{K}(t)\right\} \\ &\quad + \sum_{k=1}^{K} D_k(t)\mathbb{E}\left\{\frac{\lambda_k(t)}{\alpha} - \frac{\mu(\hat{P}_k^{stat}(t),H_k(t))}{\alpha}|\vec{K}(t)\right\} \\ &\quad + V\mathbb{E}\{C(t)\hat{Q}^{stat}(t)|\vec{K}(t)\} \\ &\leqslant A + VR_{rel}^* \leqslant A + VR_{ori}^*,\end{aligned} \quad (B.6)$$

where the following facts have been used:

$$\begin{aligned}&\mathbb{E}\{C(t)\hat{G}^{stat}(t)|\vec{K}(t)\} = R_{rel}^*, \mathbb{E}\{\hat{Q}^{stat}(t)+\hat{\gamma}^{stat}(t)E(t)|\vec{K}(t)\} = 0, \\ &\mathbb{E}\left\{\lambda_k(t) - \mu\left(\hat{P}_k^{stat}(t),H_k(t)\right)|\vec{K}(t)\right\} \leqslant 0, \\ &\mathbb{E}\left\{\xi - \frac{\mu\left(\hat{P}_k^{stat}(t),H_k(t)\right)}{\alpha}|\vec{K}(t)\right\} \leqslant 0.\end{aligned} \quad (B.7)$$

The first three equations follow from Lemma 1 and the last one follows from the third equations and $\xi \leqslant \mathbb{E}\left\{\frac{\min_k\{\lambda_k(t)\}}{\alpha}\right\}$. Taking the expectation on both sides, using the law of iterative expectation and summing over $t \in \{0,1,2,\ldots,T-1\}$, we obtain

$$V\sum_{t=0}^{T-1}\mathbb{E}\{C(t)G^{PA}(t)\} \leqslant AT + VR_{ori}^* - \mathbb{E}\{L(\vec{K}(T))\} + \mathbb{E}\{L(\vec{K}(0))\}. \quad (B.8)$$

Dividing both sides by T and letting $T \to \infty$, we arrive at the following result for our proposed algorithm because $\mathbb{E}\{L(\vec{K}(0))\}$ are finite and $\mathbb{E}\{L(\vec{K}(T))\}$ are nonnegative:

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{C(t)G^{PA}(t)\} \leqslant R_{ori}^* + A/V,$$

where R_{ori}^* is the optimal objective value of original problem **P1**, A is a constant given by (25) and V is a control parameter which has a maximum value given in Theorem 2. □

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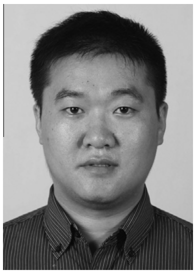

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