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ADMM-Based Distributed Online Algorithm for Energy Management in Hybrid Energy Powered Cellular Networks

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ABSTRACT Energy harvesting has been considered as a promising technique to decrease the conventional grid energy expenditure. However, most renewable energy sources are unreliable and random. To overcome these drawbacks, besides the commonly adopted approaches such as purchasing power from the grid and deploying batteries, energy cooperation is an appealing solution. In this paper, we investigate the energy management problem by jointly optimizing the data admission rate, transmit power, energy sharing among base stations (BSs), battery charging and discharging rate, and the energy purchased from the grid in hybrid energy powered cellular networks. First, the long-term average total cost minimization problem under the constraints on limited battery size and users' data rate requirements is formulated as a stochastic optimization problem. Employing the Lyapunov optimization technique and alternating direction method of multipliers (ADMM), we propose an online distributed algorithm, referred to as distributed online energy management algorithm (DOEMA), where the current system states are needed, without requiring the system statistic or future information. Furthermore, the proposed algorithm can be implemented in a parallel and completely distributed fashion, which could provide more engineering guidelines for practical communication protocols compared with the centralized algorithm. The extensive simulation results are conducted to demonstrate the correctness of the theoretical analysis and validate the performance improvement against other algorithms in terms of system total cost reduction.

INDEX TERMS Multi-cell networks, renewable energy, energy cooperation, stochastic optimization, ADMM, distributed online algorithm.

I. INTRODUCTION

Energy harvesting, which collects cheap and clean renewable energy from ambient environment, has been recognized as a promising technology to prolong the lifetime of energy constrained networks in a sustainable way. Whereas, most renewable energy sources are unreliable and random, which increases the energy management complexity. To tackle these challenges, three approaches are commonly used. One is that each base station (BS) can purchase back-up power from the traditional grid to ensure a reliable service for the users [1]. Furthermore, deploying batteries to store the surplus energy, and to discharge when the electricity price is high [2]. Moreover, exploiting the geographical diversity of renewable energy can further utilize the limited renewable energy effectively, and thus reduce the grid energy expenditure significantly [3]. As a consequence, it is of great importance to apply these three approaches comprehensively to exploit the limited available renewable energy effectively in hybrid energy powered cellular networks.

Abundant works have devoted to investigating the energy management problem in cellular networks with hybrid energy supply, which can be mainly classified into two categories, namely the energy management policies without energy cooperation, and the energy cooperation enabled strategies. The former studied the system with only a single BS or several BSs operating independently without energy cooperation [4]–[11]. Based on the non-causal renewable energy and traffic information, the authors in [4] proposed an offline

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energy allocation algorithm with infinite battery capacity to reduce the total on-grid energy consumption. By leveraging the priori distributions of the renewable energy arrival and data arrival, an optimal deterministic offline resource scheduling policy was exhibited in [5] to minimize the energy consumption. Assuming the availability of non-causal information, the authors in [6] devised an offline resource allocation algorithm for the system power costs minimization. While, it is hard to obtain the exact non-causal information during the time-varying energy harvesting process in real-world applications and the capacity of the battery is limited as well. Without requiring the prior knowledge of channel and harvested energy information, an online resource allocation algorithm was developed in [7] to fully exploit the harvested energy. Aiming at the system energy consumption minimization, three online energy management strategies were presented in [8], [9] and [10], respectively. Exploiting the traffic load and harvested energy forecasts, the work [11] proposed an online energy aware and adaptive management algorithm to make the renewable energy self-sufficiency possible. Although different energy management schemes were presented in the aforementioned works [7]–[11], the minimum and maximum energy level of BSs' battery have rarely been studied. In addition, energy cooperation among BSs was neglected as well, which may result in a suboptimal configuration between the renewable energy and the arrived traffic load.

To exploit the geographical energy diversity, many researches have devoted to developing the energy cooperation among the BSs [12]–[17]. In order to minimize the grid energy expenditure, two static cost-efficient resource allocation algorithms were presented in [12] to reshape the spatial renewable energy and mobile traffic. Besides, through jointly optimizing the user association and spatial distribution of renewable energy, the work [13] developed the optimal offline energy management algorithm to minimize the grid energy expenditure of heterogeneous networks. Aiming at the amount of conventional energy consumed minimization, the authors in [14] proposed the optimal offline energy cooperation policy under known the renewable energy profile and energy demand profile at all BSs, and then developed an online energy cooperation algorithm when the renewable energy and demand profiles are stochastic and only causally known at each BS. Considering the harvested energy transferred between BSs, the authors in [15] devised an online power allocation algorithm in millimeter wave networks to alleviate the harvested energy imbalance problem and reduce the energy waste. A model predictive based online power management strategy was presented in [16] for the computation of energy allocation and transfer across BSs to compensate the imbalance in the harvested energy. Taking the noncooperative energy-harvesting BSs into account, the work [17] designed two novel online energy trading approaches to minimize the nonrenewable energy consumption. Nevertheless, the energy management problems formulated in the aforementioned works [12]–[17] were solved in a centralized manner with high computational complexity, as there is a large amount of data/information exchanged among BSs. Compared with the centralized algorithm, the distributed control policy can provide more engineering guidelines for practical communication protocols. Although a distributed energy-bandwidth allocation algorithm was presented in [18], the results were based on the impractical assumption that the harvested energy and channel state information are known non-causally before scheduling.

The above observations give rise to the need for an online distributed energy management policy which should be capable of efficiently exploiting the limited available renewable energy with the dynamic of the electricity price taking into account. Specifically, we investigate the energy management problem by jointly considering the data admission control, power allocation, energy exchanging among BSs, battery charging and discharging, and energy purchased from the grid in cellular networks with hybrid energy supply. Firstly, we formulate it as a stochastic optimization problem to minimize the long term system cost with the users' data rate requirements and the battery time-coupling constraints taken into consideration. Then, an online distributed algorithm, named distributed online energy management algorithm (DOEMA), is proposed to solve this problem employing the Lyapunov optimization technique and alternating direction method of multipliers (ADMM).

Our major contributions are summarized as follows:

- A stochastic programming problem is formulated to minimize the time averaged total cost of the system with the considerations of many practical factors, e.g., the users' data rate requirements, the limited battery capacity, the dynamic of the electricity price, the stochastic data arrivals, the time-varying wireless channels, and the intermittent energy harvesting.
- Employing the Lyapunov optimization technique and ADMM, an online algorithm is proposed to solve the formulated problem, which is a fully distributed algorithm where each BS can make decisions on their own at each time slot requiring only the knowledge of instantaneous system state.
- The asymptotic optimality of the proposed algorithm is analyzed in detail by selecting an appropriate value of the control parameter V. Moreover, extensive simulation results are conducted to demonstrate the correctness of the theoretical analysis and exhibit the performance improvement against other algorithms without energy cooperation or batteries in terms of long term system cost reduction.

The rest of this paper is structured as follows. In Section II, the system model is described in detail, and then a stochastic programming problem is formulated. Section III devises a distributed online energy management algorithm to settle the formulated problem. The theoretical results are presented in Section IV. The performance of the proposed algorithms is evaluated by simulation in Section V. Finally, we conclude our paper in Section VI.

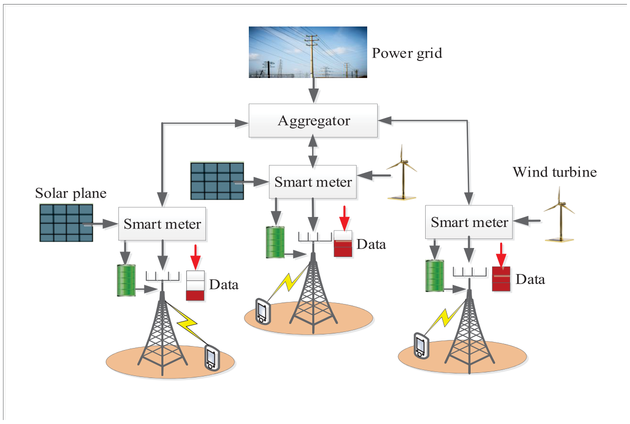

FIGURE 1. Topology example of the hybrid energy powered cellular network.

II. SYSTEM MODEL

In this section, we first describe the network model, the energy supply model, and the battery model. Then, based on these aforementioned models, the energy management problem is formulated.

A. NETWORK MODEL

As illustrated in Fig. 1, we consider a multi-cell downlink system consisting of M cells. Each cell is comprised of one BS, which is equipped with N antennas and serves only one single-antenna user. Then, we denote the set of M pairs of BSs and its corresponding user by $\mathcal{M}$, i.e., $\mathcal{M} = \{1, \cdots, M\}$. The network is assumed to operate in slotted time and time slot t refers to the interval $[t, t+1)$, $t \in \{1, 2, \cdots, +\infty\}$. For notational convenience, we also assume the length of each time slot is normalized to unity and thus we will utilize the terms "energy" and "power" interchangeably throughout this paper. Additionally, the network is a queuing system and each BS i maintains the data queue $Q_i(t)$ for its corresponding user. The process of random data arrival is represented by $(A_i(t))$, where $A_i(t)$ denotes the amount of data destined for user i at time slot t. Through the data admission control, the newly arrived data $(A_i(t))$ is stored into the data queue $(Q_i(t))$. Let $a_i(t)$ indicate the data rate admission control of each BS at time slot t, where $0 \leqslant a_i(t) \leqslant A_i(t)$.

The channel vector from BS i to its corresponding user at time slot t is denoted by $\mathbf{h}_i(t) \in \mathbb{C}^{N\times 1}$ and the associated information signal is represented by $s_i(t)$. As in [19], we apply the ZF beamforming strategy and only optimize the transmit power of each BS. Let $\mathbf{w}_i(t)$ denote the associated normalized ZF beamforming vector for user i. As such, the transmitted signal for user i is

$$\mathbf{x}_i(t) = \sqrt{P_i(t)}\mathbf{w}_i(t)s_i(t), \tag{1}$$

where the information signal $s_i(t)$ is assumed to be a complex random variable with zero mean and unit variance. Consequently, the received signal at user i is

$$y_i(t) = \mathbf{h}_i^H(t)\mathbf{x}_i(t) + \nu_i(t), \tag{2}$$

where the intercell interference is assumed to be completely removed by adopting the ZF beamforming, and $\nu_i(t)$ indicates the additive circular complex Gaussian noise with zero mean and variance σ_i^2.

Employing the ZF beamforming, the achievable data rate of user i at time slot t is calculated by

$$R_i(t) = W\log\left(1 + P_i(t)g_i(t)\right), \tag{3}$$

where $g_i(t) = |\mathbf{h}_i^H(t)\mathbf{w}_i(t)|^2/\sigma_i^2$, and W is the allocated bandwidth for each user.

Given the amount of the admitted data $a_i(t)$ and the transmission rate $R_i(t)$, each BS's data queue $Q_i(t)$ evolves according to

$$Q_i(t+1) = [Q_i(t) - R_i(t)]^+ + a_i(t), \tag{4}$$

where $[y]^+ = \max\{y, 0\}$.

B. ENERGY SUPPLY MODEL

Each BS has access to both the energy from the energy harvesting device and the energy from the conventional main grid. To be specific, each BS is equipped with an energy harvester that is capable of collecting renewable energy through solar panels and/or wind turbines. The amount of harvested energy at BS i at time slot t is denoted by $H_i(t)$, $H_i(t) \leqslant H_i^{\max}$, which is an independent and identically distributed (i.i.d.) process across different BSs and time slots. In addition, we consider a linear time-varying energy cost model for the conventional energy purchased from the main grid. Let $G_i(t)$ represent the amount of conventional energy drawn from the grid to BS i at time slot t, then the energy cost is

$$C_g(t) = p_g(t)\sum_{i\in\mathcal{M}} G_i(t), \tag{5}$$

where $p_g(t)$ indicates the price of purchasing one unit of power from the grid at time slot t. As in [21]–[26], we assume that $p_g(t)$ is an i.i.d. process across different slots and bounded by $p_g(t) \in \left[p_g^{\min}, p_g^{\max}\right]$.

We further assume that the energy can be exchanged among BSs, which can for instance happen through a power grid or as a wireless power transfer [12], [18]. Let $E_{k,i}(t)$ denote the amount of energy that BS i exchanges with BS k at time slot t. If BS i draw energy from BS k in time slot t, then $E_{k,i}(t) > 0$; otherwise, BS i distributes energy to BS k and $E_{k,i}(t) < 0$. Similarity to [21] and [27], the energy sharing balance should be satisfied, then we have

$$E_{k,i}(t) + E_{i,k}(t) = 0. \tag{6}$$

C. BATTERY MODEL

In the following, we describe the battery model in detail. Let $B_i(t)$ denote the amount of energy stored in the rechargeable battery of BS i at time slot t. Then, we have

$$B_i^{\min} \leqslant B_i(t) \leqslant B_i^{\max}, \quad i \in \mathcal{M}, \tag{7}$$

where $B_{\min}$ is the minimum bound of the battery level to avoid battery sulfation, while $B_{\max}$ indicates the maximum capacity of the battery.

Let $E_i^c(t)$ and $E_i^d(t)$ denote the amount of charged energy and discharged energy at time slot t, respectively. Similarity to [20] and [21], the battery level $B_i(t)$ evolves as

$$B_i(t+1) = \left[B_i(t) - E_i^d(t)\right]^+ + E_i^c(t). \tag{8}$$

To indicate whether the rechargeable battery of BS i is charged or discharged at time slot t, we introduce two indicator functions, i.e., $I_i^c(t) = 1\left(E_i^c(t) > 0\right)$ and $I_i^d(t) = 1\left(E_i^d(t) > 0\right)$. Without loss of generality, we assume that charging and discharging cannot be done simultaneously. As a consequence, we have

$$I_i^c(t) + I_i^d(t) \leqslant 1, \tag{9}$$

$$0 \leqslant E_i^c(t) \leqslant E_i^{c\max} I_i^c(t), \tag{10}$$

$$0 \leqslant E_i^d(t) \leqslant \min\left[B_i(t), E_i^{d\max} I_i^d(t)\right], \tag{11}$$

where $E_i^{c\max}$ and $E_i^{d\max}$ are the maximum charging and discharging power for the battery of BS i, respectively.

Due to the fact that the rechargeable battery usually has a certain number of operation times, cost would be incurred during the procurement and maintenance of battery [21]. Therefore, we introduce $C_b(t)$ as the amortized cost of charging and discharging over the lifetime, and model the cost of energy charging and discharging operations as

$$C_b(t) = \sum_{i\in\mathcal{M}} p_b \left(E_i^c(t) + E_i^d(t)\right), \tag{12}$$

where p_b is the fixed cost resulted from the every charging or discharging operation.

D. PROBLEM FORMULATION

With the aforementioned models, we address the energy management problem by jointly optimizing the admitted data rate $\{a_i(t)\}$, and that the transmit power of each BS $\{P_i(t)\}$, and that the conventional energy drawn from the main grid $\{G_i(t)\}$, and that exchanged between BSs $\{E_{k,i}(t)\}$, and that charged/discharged to/from the battery of each BS $\{E_i^c(t), E_i^d(t)\}$ to minimize the time averaged total system cost, while satisfying the constraints of users' required data rate and the limited battery size. Thus, the optimization problem is formulated as

$$\mathcal{P}_1: \ \min \overline{C} \triangleq \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \left(C_g(t) + C_b(t)\right) \tag{13}$$

$$\begin{aligned}
\text{s.t.}\ \ & (C1): \overline{a}_i \geqslant a_i^{req}, \quad \forall i \in \mathcal{M},\\
& (C2): B_i^{\min} \leqslant B_i(t) \leqslant B_i^{\max}, \quad \forall i \in \mathcal{M}, t\\
& (C3): E_{k,i}(t) + E_{i,k}(t) = 0, \quad \forall i, k \in \mathcal{M},\ t,\\
& (C4): P_i(t) + E_i^c(t) \leqslant G_i(t) + H_i(t) + E_i^d(t)\\
& \quad + \sum_{k\in\mathcal{M}, k\neq i} E_{k,i}(t), \quad \forall i,\ k \in \mathcal{M},\ t,\\
& (C5): I_i^c(t) + I_i^d(t) \leqslant 1, \quad \forall i \in \mathcal{M}, t,\\
& (C6): 0 \leqslant E_i^c(t) \leqslant E_i^{c\max} I_i^c(t), \forall i \in \mathcal{M}, t,\\
& (C7): 0 \leqslant E_i^d(t) \leqslant \min\left[B_i(t),\ \ E_i^{d\max} I_i^d(t)\right],\\
& \qquad \forall i \in \mathcal{M}, t,\\
& (C8): 0 \leqslant a_i(t) \leqslant A_i(t), \quad \forall i \in \mathcal{M}, t,\\
& (C9): 0 \leqslant P_i(t) \leqslant P_i^{\max}, \quad \forall i \in \mathcal{M}, t,\\
& (C10): 0 \leqslant G_i(t) \leqslant G_i^{\max}, \quad \forall i \in \mathcal{M}, t,\\
& (C11): Q_i(t) \text{ is mean rate stable}, \quad \forall i \in \mathcal{M}, t.
\end{aligned}$$

In $\mathcal{P}_1$, $\overline{a}_i = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} a_i(t)$, a_i^{req} is the required data rate for user i, while $P_i^{\max}$ and $G_i^{\max}$ are the maximum transmit power and energy purchased from the grid of BS i. (C1) represents the constraint of long-term average data rate, which guarantees the QoS requirement of each user. (C3) guarantees the energy sharing must be balanced in the system. (C4) is the energy neutralization constraint of each BS, which presents that the expenditure energy of each BS and battery charged energy are satisfied by (i) the harvested energy and/or (ii) the drawing energy from other BSs and/or (iii) the discharging from the battery and/or (iv) the drawing energy from the main grid. (C2), (C6) − (C10) denote the bounds of energy level in the battery, charging rate and discharging rate, data admission rate, transmit power, and energy purchased from the grid of BS i.

Problem $\mathcal{P}_1$ is a long-term optimization problem and the minimization of the objective function relies on the decisions over the whole operation time. Accordingly, the lack of future system state information hinders the network to obtain the minimum system cost. Although this problem can be settled by employing the traditional dynamic programming, the curse of dimensionality will make the computational complexity too high. What's more, it requires to have the knowledge of the future system state information. Therefore, we exploit the Lyapunov optimization framework to deal with problem $\mathcal{P}_1$.

III. LYAPUNOV OPTIMIZATION AND DISTRIBUTED ONLINE ALGORITHM

In this section, we first introduce two virtual queues to tackle constraints (C1) and (C2). Then, we apply the Lyapunov optimization and the ADMM technique to develop the distributed online energy management algorithm (DOEMA), which is a fully distributed algorithm that each BS makes optimal decisions at each time slot and only requires knowledge of the instantaneous system state.

A. TWO VIRTUAL QUEUES

1) VIRTUAL QUEUE FOR USERS' DATA RATE REQUIREMENT

The constraint (C1) in $\mathcal{P}_1$ is a long-term average constraint, which makes problem $\mathcal{P}_1$ intractable. To settle it, we employ the queuing theory to transform all these inequality constraints into queue stability problems [7]. More specifically, we define the virtual queue $Z_i(t)$, which evolves according to

$$Z_i(t+1) = \left[Z_i(t) - a_i(t) + a_i^{req}\right]^+. \tag{14}$$

As shown in [7], $Z_i(t)$ is mean rate stable if

$$\lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{Z_i(t)\} < +\infty. \tag{15}$$

Then, we give the following lemma.

Lemma 1: If $Z_i(t)$ is mean rate stable, the long-term average rate constraint of user i can be satisfied.

2) VIRTUAL QUEUE FOR BATTERY LEVEL

It can be observed that the battery level constraint (C2) couples the current charging and discharging strategy and that in future. For instance, an aggressive charging decision currently may cause the short of available capacity to store energy in future even if the electricity price is lower. To eliminate the temporal correlation of the charging and discharging, we construct the virtual queue $Y_i(t)$ as

$$Y_i(t) = B_i(t) - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}, \tag{16}$$

with update equation as follows

$$Y_i(t+1) = Y_i(t) + E_i^c(t) - E_i^d(t). \tag{17}$$

B. LYAPUNOV OPTIMIZATION

Similarity to [22] and [23], we apply the Lyapunov optimization technique to design an online policy to settle problem $\mathcal{P}_1$. Let $\Theta(t) \triangleq [Q(t), Y(t), Z(t)]$ represent the concatenated vector of all $Q_i(t)$ and $Y_i(t)$, and $Z_i(t)$. Thus, the Lyapunov function is defined as

$$L(\Theta(t)) \triangleq \frac{1}{2}\sum_{i\in\mathcal{M}} \left\{Q_i^2(t) + Y_i^2(t) + Z_i^2(t)\right\}.$$

Then, the conditional Lyapunov drift at time slot t is

$$\Delta(\Theta(t)) \triangleq \mathbb{E}\{L(\Theta(t+1)) - L(\Theta(t))|\Theta(t)\}.$$

Employing the Lyapunov optimization technique, the policy is to make decisions for minimizing the bound of the following "drift-plus-penalty" expression $\Delta_V(t)$ at each time slot

$$\Delta_V(t) \triangleq \Delta(\Theta(t)) + V\left(C_g(t) + C_b(t)\right),$$

where V is a non-negative control parameter, which can be tuned to control $\overline{C}$ arbitrarily close to the optimal value with a corresponding tradeoff with the data queue size.

In the following, we will present the upper bound of $\Delta_V(t)$ through Lemma 2.

Lemma 2: Suppose the system state information $\mathbf{A}$, $\mathbf{h}$, $\mathbf{H}$ and $\mathbf{p}_g$ are i.i.d. over different time slots. For $V \geqslant 0$, all possible values of $\Theta(t)$, and any feasible energy management decisions made at each time slot t, the upper bound of the $\Delta_V(t)$ is given by

$$\begin{aligned}\Delta_V(t) \leqslant D &+ \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Q_i(t)\left(a_i(t) - R_i(t)\right)|\Theta(t)\right\}\\ &+ \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Y_i(t)\left(E_i^c(t) - E_i^d(t)\right)|\Theta(t)\right\}\\ &+ \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Z_i(t)\left[a_i^{req} - a_i(t)\right]|\Theta(t)\right\}\\ &+ V\mathbb{E}\left\{\left(C_g(t) + C_b(t)\right)|\Theta(t)\right\},\end{aligned}$$

where D is a positive constant and satisfies

$$D \geqslant \frac{1}{2}M\left\{\left(A_i^{\max}\right)^2 + \max\left[\left(E_i^{c\max}\right)^2, \left(E_i^{d\max}\right)^2\right] + \max\left[\left(a_i^{req}\right)^2, \left(A_i^{\max} - a_i^{req}\right)^2\right]\right\}.$$

Proof: See Appendix A. □

Following the general Lyapunov optimization framework, we observe the current queue values $\Theta(t) \triangleq [Q(t), Y(t), Z(t)]$, and then make decisions for $\mathbf{a}_i = \{a_i(t)\}$, $\mathbf{P}_i = \{P_i(t)\}$, $\mathbf{G}_i = \{G_i(t)\}$, $\mathbf{E}_{k,i} = \{E_{k,i}(t)\}$, $\mathbf{E}_i^c = \{E_i^c(t)\}$, and $\mathbf{E}_i^d = \{E_i^d(t)\}$ to minimize the upper bound of $\Delta_V(t)$ at each time slot. Then, we have the following problem $\mathcal{P}_2$

$$\begin{aligned}\mathcal{P}_2: \ \min \ &\sum_{i\in\mathcal{M}} U_i(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i})\\ \text{s.t.}\ &(\text{C3}) - (\text{C10}),\end{aligned} \tag{18}$$

where $U_i\left(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}\right) = Q_i(t)\left(a_i(t) - R_i(t)\right) + Y_i(t)\left(E_i^c(t) - E_i^d(t)\right) + Z_i(t)\left[a_i^{req} - a_i(t)\right] + Vp_g(t)G_i(t) + Vp_b\left(E_i^c(t) + E_i^d(t)\right)$.

C. DISTRIBUTED ONLINE ALGORITHM

It is obvious that $\mathcal{P}_2$ is not strictly convex since both the objective function and the constraints are linear functions. Consequently, the traditional dual decomposition cannot be utilized here due to the fact that it needs the problem to be strictly convex. As shown in [24]–[27], ADMM can be adopted to settle a large-scale convex optimization problem without assuming strict convexity of the separable objective function. What's more, the distributed algorithm can be implemented in a parallel and completely distributed fashion and thus provide more engineering guidelines for practical communication protocols compared with the centralized algorithm. Motivated by this analysis, we propose an online ADMM-based distributed algorithm.

1) ADMM-BASED DISTRIBUTED ENERGY MANAGEMENT ALGORITHM

Since ADMM is applied to a large-scale convex optimization problem with separable objective function and linear equality constraints, we transform $\mathcal{P}_2$ into the following problem $\mathcal{P}_3$ by introducing auxiliary variables $e_{k,i}(t)$ for the energy sharing decisions to replace constraint (C3) as in [25] and [27]. Accordingly, we have

$$\mathcal{P}_3: \min_{\mathbf{a}_i,\mathbf{P}_i,\mathbf{G}_i,\mathbf{E}_i^c,\mathbf{E}_i^d,\mathbf{E}_{k,i},\mathbf{e}_{k,i}} \sum_{i\in\mathcal{M}} U_i(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}) \tag{19}$$

$$\text{s.t. } (\text{C4}) - (\text{C10}),$$

$$e_{k,i}(t) = E_{k,i}(t), \quad \forall i,k\in\mathcal{M},\ k\neq i, \tag{20}$$

$$e_{k,i}(t) + e_{i,k}(t) = 0, \quad \forall i,k\in\mathcal{M},\ k\neq i. \tag{21}$$

$$L_1 = \sum_{i\in\mathcal{M}} \left[U_i(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}) + \sum_{k\in\mathcal{M},k\neq i} \left(\frac{\rho}{2} \left(e_{k,i}(t) - E_{k,i}(t)\right)^2 + \lambda_{k,i}(t) \left(e_{k,i}(t) - E_{k,i}(t)\right) \right) \right], \quad (22)$$

$$L_2 = \sum_{i\in\mathcal{M}} \left[U_i(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}) + \sum_{k\in\mathcal{M},k\neq i} \left(\frac{\rho}{2} \left(e_{k,i}(t) - E_{k,i}(t)\right)^2 + \lambda_{k,i}(t) \left(e_{k,i}(t) - E_{k,i}(t)\right) \right) \right]$$
$$+ \mu_i(t) \left[P_i(t) + E_i^c(t) - G_i(t) - H_i(t) - E_i^d(t) - \sum_{k\in\mathcal{M},k\neq i} E_{k,i}(t) \right]. \quad (28)$$

To deal with problem $\mathcal{P}_3$, we adopt $\{\lambda_{k,i}(t)\}$ as the dual variables with respect to constraint (20), and thus the augmented Lagrangian for problem $\mathcal{P}_3$ is given by (22), as shown at the top of this page, where $\rho > 0$ is a parameter for the quadratic penalty of constraint.

By employing the ADMM to the problem $\mathcal{P}_3$, we first minimize the augmented Lagrangian in (22) over the local decision variables $\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}$, then over the global energy sharing variables $\{e_{k,i}(t)\}$, and finally update the dual variables $\{\lambda_{k,i}(t)\}$. In the following, we describe the problem solution procedure in detail.

It is noteworthy that the first step of the ADMM to problem $\mathcal{P}_3$ is completely decentralized. More specifically, BSs solve their local optimization problems in parallel based on fixed dual variables $\lambda_{k,i}^n(t)$ and auxiliary variables $e_{k,i}^n(t)$, where n is the iteration index.

Local optimization problem:

$$\min_{\mathbf{a}_i,\mathbf{P}_i,\mathbf{G}_i,\mathbf{E}_i^c,\mathbf{E}_i^d,\mathbf{E}_{k,i}} U_i(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i})$$
$$+ \sum_{k\in\mathcal{M},k\neq i} \left(\frac{\rho}{2} \left(e_{k,i}^n(t) - E_{k,i}(t)\right)^2 - \lambda_{k,i}^n(t) E_{k,i}(t) \right)$$
$$\text{s.t. (C4)} - \text{(C10)}, \quad (23)$$

Now, let us focus on the second step of the ADMM to problem $\mathcal{P}_3$. Based on the obtained energy sharing decisions $E_{k,i}^{n+1}(t)$ from the above local optimization problem, the higher level global optimization problem updates the auxiliary variables $e_{k,i}^{n+1}(t)$ and dual variables $\lambda_{k,i}^{n+1}(t)$ is given by

$$\min_{e_{k,i}(t)} \sum_{i\in\mathcal{M}} \sum_{k\neq i} \left(\frac{\rho}{2} \left(e_{k,i}(t) - E_{k,i}^{n+1}(t)\right)^2 + \lambda_{k,i}^n(t) e_{k,i}(t) \right)$$
$$\text{s.t. } e_{k,i}(t) + e_{i,k}(t) = 0, \quad \forall i,\ k \in \mathcal{M},\ k \neq i. \quad (24)$$

It is observed that the auxiliary variables are only coupled between each pair of exchanging BSs, we can settle the higher level optimization problem by the following problem

$$\min_{e_{k,i}(t),e_{i,k}(t)} \frac{\rho}{2} \left(e_{k,i}(t) - E_{k,i}^{n+1}(t)\right)^2 + \lambda_{k,i}^n(t) e_{k,i}(t)$$
$$+ \frac{\rho}{2} \left(e_{i,k}(t) - E_{i,k}^{n+1}(t)\right)^2 + \lambda_{i,k}^n(t) e_{i,k}(t)$$
$$\text{s.t. } e_{k,i}(t) + e_{i,k}(t) = 0, \quad \forall i,\ k \in \mathcal{M},\ k \neq i, \quad (25)$$

and achieve the optimal closed-form solution as

$$e_{k,i}^{n+1}(t) = \frac{\rho \left(E_{k,i}^{n+1}(t) - E_{i,k}^{n+1}(t)\right) - \left(\lambda_{k,i}^n(t) - \lambda_{i,k}^n(t)\right)}{2\rho}. \quad (26)$$

The final step of the ADMM to problem $\mathcal{P}_3$ is the dual variable update. Based on the obtained $e_{k,i}^{n+1}(t)$ and $E_{k,i}^{n+1}(t)$, the dual variables are updated according to

$$\lambda_{k,i}^{n+1}(t) = \lambda_{k,i}^n(t) + \rho \left(e_{k,i}^{n+1}(t) - E_{k,i}^{n+1}(t)\right). \quad (27)$$

In the following, we present the detailed solution procedure of the local optimization problem (23).

2) THE SOLUTION PROCEDURE OF THE LOCAL OPTIMIZATION PROBLEM

It can be easily derived that the objective function is jointly concave over $\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}$ and all the constraints are convex sets by definition. Relaxing constraint (C4) by adopting Lagrangian multiplier $\mu_i(t)$ at time slot t, it makes sense to form the Lagrangian as (28), as shown at the top of this page.

Then, the Lagrangian dual problem can be given by

$$\mathcal{F}(\mu_i) = \max \min L_2 \left(\mathbf{a}_i, \mathbf{P}_i, \mathbf{G}_i, \mathbf{E}_i^c, \mathbf{E}_i^d, \mathbf{E}_{k,i}, \mu_i\right)$$
$$\text{s.t. } \mu_i(t) \geqslant 0.$$

We solve the above dual problem via the projected subgradient approach and achieve the following subproblems:

a: DATA ADMISSION RATE CONTROL SUBPROBLEM

$$\min \ [Q_i(t) - Z_i(t)]\, a_i(t). \quad (29)$$
$$\text{s.t.} \quad \text{(C8)}.$$

Given Lagrangian multiplier $\mu_i(t)$, we obtain the optimal data admission rate of BS i as

$$a_i(t) = \begin{cases} A_i(t), & \textit{if } Q_i(t) \leqslant Z_i(t), \\ 0, & \text{otherwise}. \end{cases} \quad (30)$$

b: TRANSMIT POWER CONTROL SUBPROBLEM

$$\min \ \mu_i(t) P_i(t) - Q_i(t) W \log\left(1 + P_i(t) g_i(t)\right) \quad (31)$$
$$\text{s.t.} \quad \text{(C9)}.$$

Given the Lagrangian multiplier $\mu_i(t)$, we obtain the optimal transmit power of BS i as

$$P_i(t) = \left[\frac{WQ_i(t)\ln 2}{\mu_i(t)} - \frac{1}{g_i(t)}\right]_0^{P_i^{\max}}. \quad (32)$$

c: BATTERY CHARGING AND DISCHARGING SUBPROBLEM

$$\min\, [Y_i(t)+Vp_b+\mu_i(t)]E_i^c(t)+[Vp_b-Y_i(t)-\mu_i(t)]E_i^d(t) \quad (33)$$

$$\text{s.t.}\quad (C5), (C6), (C7).$$

Given the Lagrangian multiplier $\mu_i(t)$, we obtain the optimal battery charging rate and discharging rate of BS i as

$$E_i^c(t) = \begin{cases} E_i^{c\max}, & \text{if } Y_i(t) \leqslant -Vp_b - \mu_i(t), \\ 0, & \text{otherwise.} \end{cases} \quad (34)$$

$$E_i^d(t) = \begin{cases} \min\left[B_i(t), E_i^{d\max}\right], & \text{if } Y_i(t) \geqslant Vp_b - \mu_i(t), \\ 0, & \text{otherwise.} \end{cases} \quad (35)$$

d: GRID ENERGY PURCHASE SUBPROBLEM

$$\min\ \left[Vp_g(t) - \mu_i(t)\right)]G_i(t)$$
$$\text{s.t.}\quad (C10). \quad (36)$$

Given the Lagrangian multiplier $\mu_i(t)$, we obtain the optimal energy purchased from the main grid of BS i as

$$G_i(t) = \begin{cases} G_i^{\max}, & \text{if } Vp_g(t) \leqslant \mu_i(t), \\ 0, & \text{otherwise.} \end{cases} \quad (37)$$

e: ENERGY SHARING RATE CONTROL SUBPROBLEM

$$\min \sum_{k\in\mathcal{M},k\neq i} \left(\frac{\rho}{2}\left(e_{k,i}^n(t)-E_{k,i}(t)\right)^2 - \left(\lambda_{k,i}^n(t)+\mu_i(t)\right)E_{k,i}(t)\right) \quad (38)$$

Given the Lagrangian multiplier $\mu_i(t)$, we obtain the optimal energy sharing rate of BS i as

$$E_{k,i}^{n+1}(t) = e_{k,i}^n(t) + \frac{1}{\rho}\left(\lambda_{k,i}^n(t) + \mu_i(t)\right). \quad (39)$$

The dual variables are updated at each iteration m with the projected subgradient methods as

$$\mu_i^{m+1}(t) = \mu_i^m(t) + \delta^m \Bigg[P_i(t) + E_i^c(t) - G_i(t) - H_i(t) - E_i^d(t) - \sum_{k\in\mathcal{M},k\neq i} E_{k,i}(t)\Bigg], \quad (40)$$

where δ^m is the stepsize of BS i at iteration k.

The specifical distributed online energy management algorithm procedure, which is referred to as DOEMA, is described in **Algorithm 1**. The computational complexity of the proposed DOEMA is $\mathcal{O}(\frac{6M^3}{\epsilon_1^2})$, which comprises of two parts: the outer global optimization loop $\mathcal{O}(M^2)$ and the inner local optimization loop $\mathcal{O}(\frac{6M}{\epsilon_1^2})$, where ϵ_1 denotes the maximum error tolerance. More specifically, the iteration number of the outer global optimization loop is $\mathcal{O}(M^2)$ [18], while the iteration number of the inner local optimization loop is $\mathcal{O}(\frac{6M}{\epsilon_1^2})$ because that the adopted subgradient method converges to the desired state only after $\mathcal{O}(\frac{1}{\epsilon_1^2})$ iterations.

Algorithm 1 Distributed Online Energy Management Algorithm (DOEMA)

Initialization: At every time slot t, observe the system state $\Theta(t) = [Q(t), Y(t), Z(t)]$, $A(t)$, $h(t)$, $H(t)$, $P_g(t)$. Set the iteration index $n = 0$, error tolerance $\epsilon_2 > 0$, and $\rho = 1$, initial the multipliers $\lambda_{k,i}^0(t) = 0$.

Step1: Solve the local optimization problem:

Initialization: Set the iteration index $m = 0$, error tolerance $\epsilon_1 > 0$, $\delta = 2$, and $\mu_i^0(t) = 0$.

Repeat the following steps a)-c):

a): At m-th iteration, based on the current value of dual variables $\mu_i^m(t)$, $\lambda_{k,i}^n(t)$, and the auxiliary variables $e_{k,i}^n(t)$, each BS calculates $a_i(t)$, $P_i(t)$, $E_i^C(t)$, $E_i^D(t)$, $G_i(t)$, and $\mu_i^{m+1}(t)$ according to Eqs. (30), (32), (34), (35), (37), and (39), respectively;

b): Each BS updates the Lagrange multiplier $\mu_i^{m+1}(t)$ according to Eq. (40).

c): Set the iteration index $m = m+1$, and then repeat steps a) and b) until the terminal condition is satisfied, i.e., $\sum_{i\in\mathcal{M}} \left|\mu_i^{m+1}(t) - \mu_i^m(t)\right| \leqslant \epsilon_1$

Step2: Solve the global problem: based on the energy sharing rate $E_{k,i}^{n+1}(t)$ obtained in Step 1, each BS updates $e_{k,i}^{n+1}(t)$ and $\lambda_{k,i}^{n+1}(t)$ according to Eq. (26) and Eq. (27).

Step3: Set $n = n+1$ and go to Step1 until satisfying the termination criterion, i.e., $\sum_{i\in\mathcal{M}}\sum_{k\in\mathcal{M},k\neq i}\left|\left(e_{k,i}^n(t) - E_{k,i}^n(t)\right)\right| \leqslant \epsilon_2$.

Step4: Update $Q_i(t)$, $Y_i(t)$, and $Z_i(t)$ according to Eqs. (4), (16), and (14), respectively.

IV. PERFORMANCE ANALYSIS

In this section, the performance of the proposed algorithm is analyzed.

We firstly demonstrate that the battery energy level $B_i(t)$ is always in the range $[B_i^{\min}, B_i^{\max}]$ for all time slots through the following Lemma 3.

Lemma 3: Sine the energy level of BS i's battery is bounded by $B_i^{\min} \leqslant B_i(t) \leqslant B_i^{\max}$ with respect to the virtual queue definition in Eq. (16), $Y_i(t)$ is bounded by $V \in [0, V_{\max}]$, then, we have

$$Y_i(t) \leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}, \quad (41)$$

$$Y_i(t) \geqslant -E_i^{d\max} - Vp_g^{\max}, \quad (42)$$

where $V_{\max} = \min_i \left[\frac{B_i^{\max}-B_i^{\min}-E_i^{c\max}(t)-E_i^{d\max}(t)}{p_g^{\max}}\right]$, which can guarantee the constraint of the battery energy level.

Proof: See Appendix B. □

Next, we present the performance guarantees of our proposed algorithm when the system state information is i.i.d. over different time slots.

Theorem 1: Let U^{opt} denote the optimal value of problem $\mathcal{P}_1$ and U^{pro} be the time-averaged value obtained through the proposed algorithm. When the system state information $\mathbf{A}$, $\mathbf{h}$, $\mathbf{H}$ and $\mathbf{p}_g$ are i.i.d across different time slots, we can prove that the following inequality is valid:

$$0 \leqslant \lim_{T\to\infty} U^{pro} - \lim_{T\to\infty} U^{opt} \leqslant \frac{D}{V}. \tag{43}$$

Proof: See Appendix C. □

V. SIMULATION RESULTS

In this section, extensive experiments are conducted to verify the theoretical results derived in Section IV and demonstrate the performance improvement against other algorithms in terms of system total cost reduction.

The common simulation parameters are listed as follows, unless otherwise specified. We have conducted a set of simulations on a scenario which consists of three BSs as shown in Fig. 1. As in [12], [18] and [19], the maximum transmission power of each BS is 40 W, and the energy-harvesting rate $H_i(t)$ are distributed within [5, 20] W. Similarity to [19], we adopt the complex Gaussian distributed channel with zero mean and unit variance. Additionally, the signal-noise-ratio (SNR) g is uniformly distributed with the interval $[g_{\min}, g_{\max}]$, where $g_{\min} = 5$ and $g_{\max} = 15$. The positive stepsize of the Lagrange multiplier μ in Eq. (40) is set as $\delta = 2$ in our simulations. In addition, the maximum tolerances are set to $\epsilon_1 = \epsilon_2 = 0.001$. Similarity to [7], the rate requirement of each user is set to 200 kbps and the traffic arrival rate ($A_i(t)$) is assumed to be randomly distributed within a range of [200, 256] kbps. All the initial queue sizes are set to be zero and several other parameters are given as follows: $W = 10^4$ Hz, $B^{\min} = 20$ W, $B^{\max} = 50$ W, $\rho = 1$, $p_b = 0.01$.

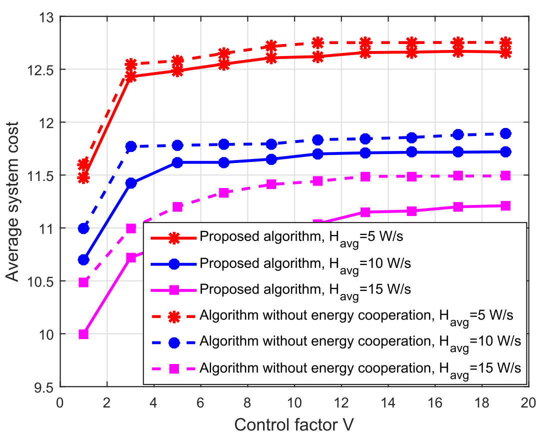

FIGURE 2. The average system cost of different algorithms versus V.

Fig. 2 depicts that the time averaged system cost $\overline{C}$ obtained by the proposed algorithm DOEMA versus the control parameter V. It is seen from Fig. 2 that the time averaged system cost $\overline{C}$ under proposed algorithm increases as the control parameter V increases and that it increases to the optimum at the speed of $1/V$. This consolidates the theoretical analysis in *Theorem 1*. Hence, we can conclude that the $\overline{C}$ eventually converges to the optimal value of problem $\mathcal{P}_2$ with a sufficiently large V, which verifies the asymptotic optimality of the proposed algorithm DOEMA. As shown in Fig. 2, the proposed algorithm outperforms the strategy without energy cooperation, which enhances the importance of exploiting the geographical energy diversity. This also demonstrates that the proposed algorithm can significantly decrease the long term system cost.

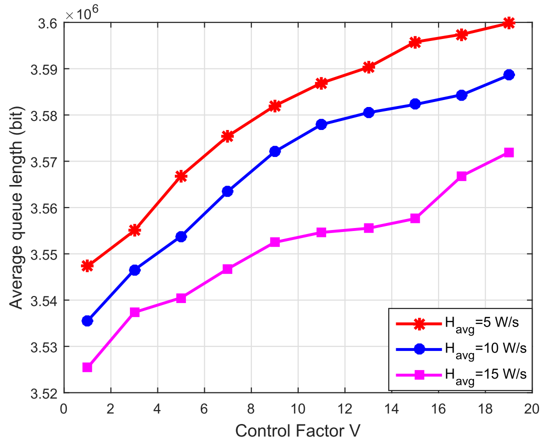

FIGURE 3. The average queue length versus V.

Fig. 3 plots the average data queue length of the first BS with respect to the control parameter V. We can observe that the average data queue length under the proposed algorithm increases when V increases and it grows linearly with V, and thus validates *Theorem 1*. Combining Fig. 2 and Fig. 3, we conclude that the proposed algorithm can guarantee different performance requirements by adjusting V to strike a balance between the queue backlog and the system cost. Hence, it quantitatively provides insights into the crucial tradeoff between the system cost and the data queue length, which presents a significant approach to control the network utility and the needed storage capacities of data buffers in practical system design.

Fig. 4 depicts the energy level of different batteries within the 100 time slots. We can observe that each battery energy level $B_i(t)$ is always in the range $[B^{\min}, B^{\max}]$ for all time slots, which verifies the theoretical analysis in *Lemma 3* and further suggests that the proposed algorithm can be implemented into practical networks with limited battery size.

We also study the long term average system cost performance versus the average electricity price for the three algorithms, namely the proposed algorithm, the algorithm without energy cooperation or battery, in Fig. 5 and Fig. 6, respectively. It is readily observed from Fig. 5 that the curve of the proposed algorithm is strictly lower than the scheme without energy cooperation. As the average electricity price $\overline{p_g}$ increases, the performance gap between the proposed algo-

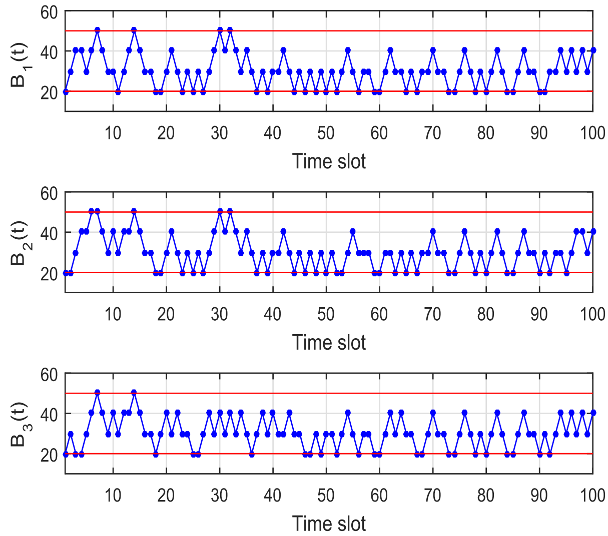

FIGURE 4. The energy level of different batteries at each time slot.

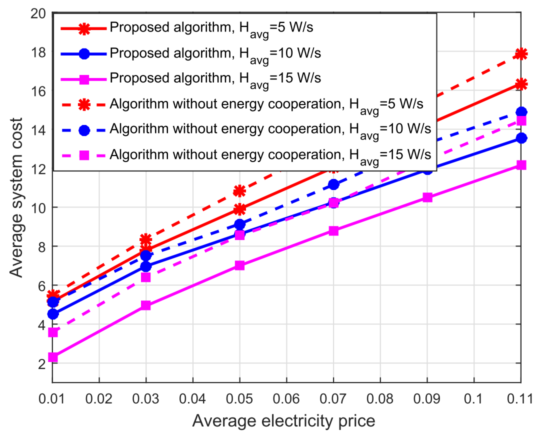

FIGURE 5. The average system cost of different algorithms versus the average electricity price $\overline{p_g}$.

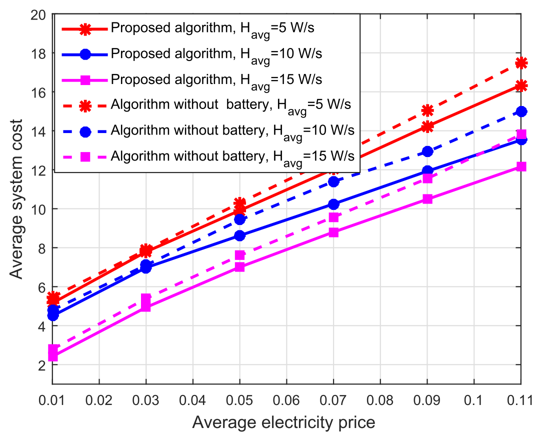

FIGURE 6. The average system cost of different algorithms versus the average electricity price $\overline{p_g}$.

rithm and the scheme without energy cooperation becomes larger. This can be accounted by the fact that the energy cooperation will bring in more benefit when the electricity price is higher. Furthermore, the performance gap will become larger when the average harvested energy rate is higher. Additionally, it can be observed from Fig. 6 that the performance of the proposed algorithm is superior to the algorithm without battery. This further verifies that the algorithm presented in the paper can decrease the system cost of the hybrid energy powered cellular networks.

VI. CONCLUSION

In this paper, we have formulated a stochastic optimization problem taking into account of the limited battery size and users' data rate requirements to minimize the long term system total cost in hybrid energy powered cellular networks by jointly optimizing the data admission rate, transmit power, energy exchanging among BSs, battery charging and discharging rate, and energy purchased from the grid. Correspondingly, we have devised an online distributed algorithm, referred to DOEMA, to settle this problem with the aid of the Lyapunov optimization and ADMM technique. We have conducted extensive simulation to demonstrate the advantages of the proposed algorithm.

APPENDIX

This section contains the proofs of the lemmas and theorems in this paper.

A. PROOF OF LEMMA 2

According to the inequality $(\max[x-y,0]+a)^2 \leqslant x^2+a^2+2x(a-y)$, we square both sides of Eq. (4), and then apply $a_i^2(t) \leqslant \left(A_i^{\max}\right)^2$. Hence, we have the following

$$Q_i^2(t+1) \leqslant Q_i^2(t) + \left(A_i^{\max}\right)^2 + 2Q_i(t)\left(a_i(t) - R_i(t)\right).$$

Analogously, for $Y_i(t)$, we can obtain

$$Y_i^2(t+1) \leqslant Y_i^2(t) + \left(E_i^c(t) - E_i^d(t)\right)^2 + 2Y_i(t)\left(E_i^c(t) - E_i^d(t)\right).$$

Squaring both sides of Eq. (14), we have

$$Z_i^2(t+1) \leqslant Z_i^2(t) + \left[a_i^{req} - a_i(t)\right]^2 + 2Z_i(t)\left[a_i^{req} - a_i(t)\right].$$

Based on the above inequality, we can obtain

$$\Delta_V(t) \leqslant D + \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Q_i(t)\left(a_i(t) - R_i(t)\right)|\Theta(t)\right\} + \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Z_i(t)\left[a_i^{req} - a_i(t)\right]|\Theta(t)\right\} + V\mathbb{E}\left\{\left(C_g(t) + C_b(t)\right)|\Theta(t)\right\}.$$

where D is a positive constant and satisfies

$$D \geqslant \frac{1}{2}M\left\{\left(A_i^{\max}\right)^2 + \max\left[\left(E_i^{c\max}\right)^2, \left(E_i^{d\max}\right)^2\right] + \max\left[\left(a_i^{req}\right)^2, \left(A_i^{\max} - a_i^{req}\right)^2\right]\right\}.$$

B. PROOF OF LEMMA 3

The mathematical induction is applied to demonstrate Lemma 3.

It is obvious that all the constraints can be satisfied when the time slot $t = 0$. According to Eq. (16), we have

$$-E_i^{d\max} - Vp_g^{\max} \leqslant Y_i(0) \leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}.$$

If we assume that the constraints hold when $t = t_0$, i.e.,

$$-E_i^{d\max} - Vp_g^{\max} \leqslant Y_i(t_0) \leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}.$$

Then, we will demonstrate that all the constraints can be guaranteed when $t = t_0 + 1$ as well.Firstly, we demonstrate that constraint (41) is guaranteed when $t = t_0 + 1$.

a) If $Y_i(t) \leqslant -Vp_b - \mu_i(t)$, we have $E_i^d(t) = 0$. According to (17), we have

$$Y_i(t_0 + 1) = Y_i(t_0) + E_i^{c\max} - E_i^d(t) \leqslant Y_i(t_0) + E_i^{c\max}.$$

Based on the inequation that $Y_i(t_0) < 0$, $Y_i(t_0 + 1) < E_i^{c\max}$, and the definition of $V_{\max}$, we can achieve

$$\begin{aligned} E_i^{c\max} &\leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - V_{\max} p_g^{\max} \\ &\leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}. \end{aligned}$$

Then, we have the following inequation

$$Y_i(t_0 + 1) \leqslant Y_i(t_0) + E_i^{c\max} \leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}.$$

b) If $Y_i(t) \geqslant -Vp_b(t) - \mu_i(t)$, we have $E_i^c(t) = 0$. Based on (17), we have

$$\begin{aligned} Y_i(t_0 + 1) &= Y_i(t_0) - E_i^d(t) \leqslant Y_i(t_0) \\ &\leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}. \end{aligned}$$

To sum up, the demonstration of inequation (41) is completed now.

As for the inequation (42), if $Y_i(t) \leqslant -Vp_b - \mu_i(t)$, we have $E_i^d(t) = 0$. According to (17), we can obtain $Y_i(t_0+1) = Y_i(t_0) + E_i^{c\max}(t)$. Then, we have

$$Y_i(t_0 + 1) \geqslant Y_i(t_0) \geqslant -E_i^{d\max} - Vp_g^{\max}.$$

If $Y_i(t) \geqslant -Vp_b - \mu_i(t)$, we have $E_i^c(t) = 0$, and combining (17), we can obtain

$$\begin{aligned} Y_i(t_0 + 1) &= Y_i(t_0) - E_i^d(t) \\ &\geqslant Y_i(t_0) - E_i^{d\max} \\ &\geqslant -Vp_g(t) - E_i^{d\max} \\ &\geqslant -Vp_g^{\max} - E_i^{d\max}. \end{aligned}$$

As a consequence, the proof of inequation (42) is completed.

C. PROOF OF THEOREM 1

It can be easily derived that the feasibility can be guaranteed. It should be noticed that the values obtained from the proposed algorithm can guarantee all the constraints in $\mathcal{P}_2$. As such, what we should do is to demonstrate that these values also guarantee the constraints for $\mathcal{P}_1$. Hence, these values can satisfy constraint (C2). According to Lemma 2 and (41), we have

$$\begin{aligned} -Vp_g^{\max} - E_i^{d\max} &\leqslant B_i(t) - B_i^{\min} - E_i^{d\max} - Vp_g^{\max} \\ &\leqslant B_i^{\max} - B_i^{\min} - E_i^{d\max} - Vp_g^{\max}, \end{aligned}$$

and we can obtain that $B_i^{\min} \leqslant B_i(t) \leqslant B_i^{\max}$, then constraint (C2) is satisfied.

In the following, we present the suboptimality of the proposed algorithm. The proposed algorithm is obtained by minimizing the upper bound of the $\Delta_V(t)$, and the proposed algorithm would greedily explore all control policies. Taking the control decisions refer to the stationary, randomized strategy in $\mathcal{P}_2$ into account, we have the following

$$\begin{aligned} &\Delta(\Theta(t)) + V\left(C_g(t) + C_b(t)\right) \\ &\quad\leqslant D + \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Q_i(t)\left(a_i(t) - R_i(t)\right)|\Theta(t)\right\} \\ &\qquad + \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Y_i(t)\left(E_i^c(t) - E_i^d(t)\right)|\Theta(t)\right\} \\ &\qquad + \sum_{i\in\mathcal{M}} \mathbb{E}\left\{Z_i(t)\left[a_i^{req} - a_i(t)\right]|\Theta(t)\right\} \\ &\qquad + V\mathbb{E}\left\{\left(C_g(t) + C_b(t)\right)|\Theta(t)\right\} \\ &\quad= D + VU^{pro} \leqslant D + VU^{opt}. \end{aligned}$$

Summing over $t \in \{0, 1, \ldots, T-1\}$ for the above equation, we have

$$\begin{aligned} V\sum_{t=0}^{T-1} \mathbb{E}\{\left(C_g(t) + C_b(t)\right)\} + \mathbb{E}\{L(\Theta(T-1))\} - \mathbb{E}\{L(\Theta(0))\} \\ \leqslant TD + TVU^{opt}. \end{aligned}$$

Dividing by TV and utilizing the fact that both $\mathbb{E}\{L(\Theta(T-1))\}$ and $\mathbb{E}\{L(\Theta(0))\}$ are finite constant, we have

$$U^{pro} = \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{\left(C_g(t) + C_b(t)\right)\} \leqslant \frac{D}{V} + U^{opt}.$$

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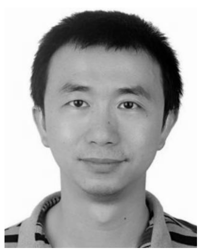

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