Online Geographical Load Balancing for Energy-Harvesting Mobile Edge Computing

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Abstract

Mobile Edge Computing (MEC) (a.k.a. fog computing) has recently emerged to enable low-latency and location-aware data processing at the edge of mobile networks. Providing grid power supply in support of MEC, however, is costly and even infeasible, thus mandating on-site renewable energy as a major or even sole power supply in many scenarios. Nonetheless, the high intermittency and unpredictability of energy harvesting creates many new challenges of performing effective MEC. In this paper, we develop an algorithm called GLOBE that performs joint geographical load balancing (GLB) (for computation workload) and admission control (for communication data traffic), for optimizing the system performance of a network of MEC-enabled base stations. By leveraging the Lyapunov optimization with perturbation technique, GLOBE operates online without requiring future system information and addresses significant challenges caused by battery state dynamics and energy causality constraints. We prove that GLOBE achieves a close-to-optimal system performance compared to the offline algorithm that knows full future information, and present a critical tradeoff between battery capacity and system performance. Simulation results validate our analysis and demonstrate the superior performance of GLOBE compared to benchmark algorithms.

I. INTRODUCTION

Mobile computing and Internet of Things are driving the development of many new applications, turning data and information into actions that create new capabilities, richer experiences and unprecedented economic opportunities. Although cloud computing enables convenient access to a centralized pool of configurable and powerful computing resources, it often cannot meet
the stringent requirements of latency-sensitive or geographically constrained applications, such as mobile gaming, augmented reality, tactile Internet and connected cars, due to the often unpredictable network latency and expensive bandwidth [1], [2]. As a remedy to these limitations, Mobile Edge Computing (MEC) [3] (a.k.a. fog computing [4]) has recently emerged as a new computing paradigm to enable in-situ data processing at the network edge, in close proximity to mobile devices, sensors, actuators and connected things. In MEC, network edge devices, such as base stations (BSs) [2], are endowed with cloud-like functionalities to serve users’ requests as a substitute of clouds, while significantly reducing the transmission latency as they are just one wireless hop away from end users and data sources.

In increasingly many scenarios, BSs are primarily powered by renewable green energy (e.g. solar and wind), rather than the conventional electric grid, due to various reasons such as location, reliability, carbon footprint and cost. The high intermittency and unpredictability of energy harvesting (EH) [5] significantly exacerbates the challenge of the latency requirements of applications as the computing capacity of an individual MEC-enabled BS is significantly limited at any moment in time. Geographical load balancing (GLB) is a promising technique for optimizing MEC performance by exploiting the spatial diversity of the available renewable energy to re-shape the computation workload distribution among the distributed BSs. However, energy harvesting leads to extraordinary challenges that existing GLB approaches cannot address: not only the available energy in the batteries imposes a stringent energy constraint at any moment in time, but also the intrinsic evolution of these constraints couple the GLB decisions across time, and yet the decisions have to be made without foreseeing the future. Compared to existing GLB approaches for data center networks that solve time-decoupled problems, GLB for EH-powered MEC networks demands for a fundamentally new design that optimally manages limited energy, computing and radio access resources in both spatial and temporal domains.

In this paper, we study joint GLB (for computation workload) and admission control (for communication data traffic) among a network of EH-powered BSs (See Figure 1 for an illustration). We develop a novel online algorithm, called GLOBE (Geographical LOad Balancing with Energy-harvesting), for minimizing the system cost (due to violating the computation delay constraint and dropping data traffic). By extending the recently developed Lyapunov optimization with perturbation technique [6], we prove that GLOBE can achieve a close-to-minimum system cost, compared to the optimal offline algorithm that knows the complete information of future
system dynamics. Our result theoretically shows a critical tradeoff between the finite battery capacity and the achievable system cost: a larger battery capacity means that the system cost can be made closer to the minimum value achieved by the offline optimal algorithm. Simulation results validate our analysis and show that GLOBE tremendously improves the MEC performance compared to benchmark algorithms that do not perform GLB or only optimize the system myopically.

A. Related Work

GLB has been extensively studied in data center network (DCN) research [7], [8], [9], [10], [11]. Most of these works study load balancing problems that are independent across time and hence a myopic optimization problem is often formulated and solved to derive the GLB policy. Very few works consider temporally coupled GLB problems. In [7], the temporal dependency is due to the switching costs (turning on/off) of data center servers, which significantly differs from our considered problem and hence, different techniques are required. A temporally coupled GLB problem was studied under the framework of Lyapunov optimization in [11] considering a long-term water consumption constraint. However, firstly, the constraint in [11] is a long-term average constraint whereas our paper considers a much more complicated and stringent energy causality constraint, and secondly, the constraint in [11] is imposed on the entire network whereas in our paper, each individual BS is constrained by its own (time-varying) battery state. To address these new difficulties, we leverage the weighted perturbation technique [6] to develop our algorithm with provable performance guarantee.

GLB with renewables was studied in [7], [10], which show that GLB provides a huge opportunity by allowing for “follow the renewables” routing. Renewables in these works are
considered as a supplement to grid power. However, our considered problem uses renewables as the major power source. As a result, battery is used to balance supply and demand, and hence performing GLB needs careful consideration of the battery state dynamics and the energy causality constraint, which existing works ignore. Moreover, the GLB algorithms (e.g. Averaging Fixed Horizon Control [7]) in these works requires future information, whereas our algorithm only needs current information without foreseeing the far future.

Compared to the DCN literature, this paper optimizes the network performance by jointly considering both the computation and radio access aspects of MEC. Collaboration among BSs in MEC networks was recently studied. In [13], BS clustering algorithms are proposed to maximize users’ satisfaction ratio while keeping the communication power consumption low. In [14], coalitional game theory is applied to enable distributed formation of femto-clouds. These works study time-decoupled problems and do not consider energy-harvesting and hence, are very different from our paper.

II. System Model

We consider a network of $N$ base stations (e.g. macro or pico cells), indexed by $\mathcal{N} = \{1, 2, ..., N\}$, providing communication and edge computing services to users. Each BS is endowed with cloud-like computing and storage capabilities, and is powered by renewable energy harvested from wind and/or solar radiation. BSs can exchange workload with each other subject to a topological constraint. Let $\mathcal{M}_i \subseteq \mathcal{N}$ be the neighbor BSs that BS $i$ can communicate with (including itself). Time is discretized, with each time slot matching the timescale at which GLB decisions can be updated.

A. Communication Data Traffic and Cost Model

In each time slot $t$, each BS has to serve both uplink and downlink user data traffic in its coverage area. We assume that uplink and downlink transmisson operate on orthogonal channels and focus on the downlink traffic since energy consumption of BS is mainly due to downlink transmission. The downlink data traffic arrival at BS $i$ follows a Poisson process with rate $\mu_i^t \leq \mu^\text{max}$, where $\mu^\text{max}$ is the maximum arrival rate. The size of each data traffic is modeled as an exponential random variable with $\omega$. The expected energy consumption for transmitting each
data traffic by BS $i$ in time slot $t$ can be computed as

$$p^t_i = E \left[ \frac{P_{tx,i} \omega}{W \log_2(1 + \frac{H^t_i P_{tx,i}}{\sigma^2})} \right]$$  \hspace{1cm} (1)$$

where $W$ is the downlink bandwidth, $H^t_i$ is a random variable representing the downlink channel state, $P_{tx,i}$ is BS $i$’s transmitting power, $\sigma^2$ is the noise power, and the expectation is taken over the data size and the channel state. Since a BS may not have sufficient energy to support all downlink data transmission, each BS $i$ makes a traffic admission control decision, which decides the amount of data traffic $\alpha^t_i \leq \mu^t_i$ to serve. We collect the traffic admission control decisions in $\alpha^t = [\alpha^t_1, ..., \alpha^t_N]$. The transmission power consumption of BS $i$ in time slot $t$ is therefore

$$E_{tx,i}(\alpha^t) = p^t_i \alpha^t_i$$  \hspace{1cm} (2)$$

Dropping downlink data traffic incurs cost, which is

$$C_{tx,i}(\alpha^t) = c_{tx,i}(\mu^t_i - \alpha^t_i)$$  \hspace{1cm} (3)$$

where $c_{tx,i}$ is the unit data traffic dropping cost of BS $i$.

**Remark**: For analytical simplicity, in this paper, we simply assume that data traffic that cannot be supported by renewables is dropped. Nevertheless, our framework and technique can easily handle the scenario in which the leftover traffic is also served if backup brown energy supply (e.g. diesel generator or fuel cells) is available. Therefore, the cost due to dropping traffic becomes the cost of activating backup energy supply. Moreover, although the current model ignores the energy consumption due to load-independent basic operation of the BS, such cost can also be incorporated in our framework.

**B. Computation Tasks and Cost Model**

In each time slot $t$, each BS receives computation tasks from the users in its serving area, and when the computation is finished, the computation results are returned to the corresponding users. The computation task arrival at BS $i$ follows a Poisson process with rate $\lambda^t_i \leq \lambda^{max}$, where $\lambda^{max}$ is the maximum arrival rate. For each computation task, the required number of CPU cycles is an exponential random variable with mean $\rho$. The computation capability of BS $i$ is measured by its CPU speed (i.e. CPU cycles per second), denoted by $f_i$. Therefore, if BS $i$
processes all its workload $\lambda_i^t$ locally, the average computation delay (including the waiting time and the processing time) for a task, can be obtained as

$$d_i^t = \frac{1}{f_i/\rho - \lambda_i^t}$$

We consider delay-sensitive workload which must satisfy a maximum delay constraint $d^{max}$. If $\lambda_i^t$ is large, then the delay constraint can be easily violated. Therefore GLB is performed to exploit the under-used, otherwise wasted, computational resources on other BSs to improve the overall system performance. We assume that each workload can be offloaded only once and will not be offloaded to its originator to avoid offloading loops. BSs can also choose to drop some computation workload if the BS network collectively cannot support it. To simplify our analysis, we assume that computation delay dominates transmission delay, which is therefore ignored. Nevertheless, transmission delay can also be incorporated.

Let $\beta_t^i = \{\beta_{ij}^t\}_{j \in M_i}$ denote the offloading decision of BS $i$ in time slot $t$, where $\beta_{ij}^t$ is the amount of computation workload offloaded from BS $i$ to BS $j$. Note that $\beta_{ii}^t$ represents the workload that BS $i$ retains. A GLB strategy for the whole network is therefore $\beta^t = [\beta_1^t, ..., \beta_N^t]$. A feasible GLB strategy must satisfy the computation delay constraint, namely

$$\sum_{j \in M_i} \beta_{ji}^t \leq f_i/\rho - 1/d^{max}, \forall i$$

The computation energy consumption of BS $i$ is proportional to its workload $\sum_{j \in M_i} \beta_{ji}^t$ and the square of the CPU speed $(f_i)^2$ [2]. Therefore, the computation energy consumption of BS $i$ in time slot $t$ is

$$E_{com,i}(\beta^t) = \kappa(f_i)^2 \sum_{j \in M_i} \beta_{ji}^t$$

Dropping computation workload incurs cost, which is linear to the dropped computation workload as follows

$$C_{com,i}(\beta^t) = c_{com,i}(\lambda_i^t - \sum_{j \in M_i} \beta_{ij}^t)$$

where $c_{com,i}$ is the unit workload dropping cost for BS $i$. 
C. Energy Harvesting and Storage

BSs in the considered system are powered by renewable energy harvested from the environment, such as wind energy or solar energy. To capture the intermittent and unpredictable nature of the energy harvesting process, we model it as successive energy packet arrivals, i.e. at the beginning of each time slot \( t \), energy packets with amount \( E_i^t \leq E_{\text{max}}^i \) arrive at BS \( i \), where \( E_i^t \) is drawn from some unknown distribution upper bounded by \( E_{\text{max}}^i \). In each time slot \( t \), part of the arrived energy, denoted by \( e_i^t \), satisfying

\[
0 \leq e_i^t \leq E_i^t, \forall i
\]

will be harvested and stored in a battery, and it will be available for computation and communication from the next time slot on. We start by assuming that the battery capacity is sufficiently large. Later we will show that by picking the values of \( e_i^t \)'s, the battery energy levels are deterministically upper-bounded under the proposed algorithm, thus we only need finite-capacity batteries in the actual implementation. More importantly, including \( e_i^t \)'s as decision variables in the optimization facilitates the derivation and performance analysis of the proposed algorithm. Similar techniques were adopted in existing works [15], [16]. We collect the energy harvesting decisions of all BSs in the notation \( e^t = [e_1^t, ..., e_N^t] \).

The total energy consumption of BS \( i \) in time slot \( t \) includes both communication and computation energy consumption, which is

\[
E_i^t(\alpha^t, \beta^t) = E_{tx,i}^t(\alpha^t) + E_{\text{com},i}^t(\beta^t)
\]

Let \( B_i^t \) denote the available battery energy in time slot \( t \) for BS \( i \). Then \( B_i^t \) evolves as follows

\[
B_i^{t+1} = \min\{B_i^t - E_i^t(\alpha^t, \beta^t) + e_i^t, B_{\text{max}}\}
\]

where \( B_{\text{max}} \) is the battery capacity. Since the renewable energy that has not yet been harvested cannot be utilized, the energy causality constraint must be satisfied in every time slot

\[
E_i^t(\alpha^t, \beta^t) \leq B_i^t, \forall i \in \mathcal{N}
\]

D. Problem Formulation

The objective of the system is to minimize the total system cost due to dropping data traffic and computation workload, denoted by \( C_i(\alpha^t, \beta^t) \triangleq C_{tx,i}(\alpha^t) + C_{\text{com},i}(\beta^t) \), by jointly optimizing
the traffic admission control and GLB actions among the network of BSs. Formally, the problem is: formulated as follows

\[
\textbf{(P1)} \quad \min_{\alpha_t^t, \beta_t^t, e_t^t, \forall t} \lim_{T \to \infty} \frac{1}{T} \sum_{i \in \mathcal{N}} \mathbb{E} \left[ C_i^t(\alpha_t^t, \beta_t^t) \right]
\]

s.t. Constraints (5), (8), (11), \forall t,

Because of the battery state dynamics and energy causality constraints, the traffic admission control and GLB decisions are highly coupled across time slots. Let $C_1^*$ be the infimum time average system cost achievable by any policy that meets the required constraints in every time slot, possibly by an oracle algorithm that has complete future information of the data traffic arrival process, the computation workload arrival process, the energy harvesting process and the channel conditions. In the next sections, we will develop a practical algorithm that achieves $C_1^*$ within a bounded deviation without requiring future information.

III. Online GLB for EH-Powered MEC

A. Lyapunov Optimization based Online Algorithm

We note that the technique of conventional Lyapunov optimization [17] is not directly applicable for solving \textbf{P1} due to the presence of energy causality constraints (11). In order to circumvent this issue, we take an alternative approach based on the technique similar to [18], and formulate a slightly modified version of \textbf{P1} as follows:

\[
\textbf{(P2)} \quad \min_{\alpha_t^t, \beta_t^t, e_t^t, \forall t} \lim_{T \to \infty} \frac{1}{T} \sum_{i \in \mathcal{N}} \mathbb{E} \left[ C_i^t(\alpha_t^t, \beta_t^t) \right]
\]

\[
\text{s.t.} \quad \lim_{T \to \infty} \frac{1}{T} \sum_{i \in \mathcal{N}} \mathbb{E} \left[ E_i^t(\alpha_t^t, \beta_t^t) - e_t^i \right] = 0 \quad (12)
\]

Constraints (5), (8), \forall t

\textbf{P2} replaces the energy causality constraint (11) in \textbf{P1} with a long-term energy demand and supply clearance constraint (12). It can be shown that \textbf{P2} is a relaxed version of \textbf{P1}. Specifically, any feasible solution to \textbf{P1} would also satisfy \textbf{P2}. To see this, consider any policy that satisfies (8) and (11), then summing equation (10) over $t \in \{0, 1, \ldots, T - 1\}$, dividing by $T$ and taking limits as $T \to \infty$ yields (12). Let $C_2^*$ denote the optimal value of \textbf{P2}, we have $C_2^* \leq C_1^*$. 
We first show that the optimal solution to the relaxed problem can be obtained by the method of stationary randomized policy, stated in the following lemma.

**Lemma 1.** There exists a stationary and possibly randomized policy that achieves

$$\sum_{i \in \mathcal{N}} \mathbb{E} \left[ C_i(\alpha^{\Pi,t}, \beta^{\Pi,t}) \right] = C^*_2$$  \hspace{1cm} (13)

while satisfies the constraints (5), (8) in $P2$ and

$$\mathbb{E} \left[ E^t_i(\alpha^{\Pi,t}, \beta^{\Pi,t}) - e^{\Pi,t}_i \right] = 0$$  \hspace{1cm} (14)

**Proof.** The proof follows the framework in [17] and is omitted here for brevity. \qed

Now, we are ready to present the online GLB algorithm to solve the relaxed problem $P2$. We first define the perturbed battery queue for each BS.

**Definition 1.** The perturbed battery queue $\tilde{B}^t_i$ is defined as

$$\tilde{B}^t_i = B^t_i - \theta_i, \forall i \in \mathcal{N}$$  \hspace{1cm} (15)

where $\theta_i$ is the perturbation parameters for BS $i$.

The value of $\theta$ will be specified later when we analyze the algorithm performance. The proposed GLOBE algorithm minimizes the weighted sum of the traffic/workload dropping cost and the perturbed energy queue in each time slot, which shall stabilize $\tilde{B}^t_i$ around the perturbed energy level $\theta_i$ and meanwhile minimize the system cost. The GLOBE algorithm is summarized in Algorithm 1. In each time slot $t$, the admission control, the GLB and the energy harvesting actions are determined by solving the following optimization problem:

$$\begin{align*}
(P3) \quad \min_{\beta^t, \alpha^t, e^t} & \quad \sum_{i \in \mathcal{N}} \left( VC_i(\alpha^t, \beta^t) - \tilde{B}^t_i(E^t_i(\alpha^t, \beta^t) - e^t_i) \right) \\
\text{s.t.} & \quad \text{Constraints (5), (8)}
\end{align*}$$

which is parameterized by only current system state (i.e. workload arrival, unit offloading cost and energy packet arrival etc.). Therefore, our algorithm can work online without requiring future information of the system dynamics. At the end of each time slot, the battery states are updated depending on the harvested energy and the consumed energy, thereby linking per-time slot problems across time.
Algorithm 1 GLOBE algorithm

1: **Input**: $\theta$, $V$
2: **Output**: Admission control $\alpha_t$, GLB $\beta_t$ and energy harvesting $e_t$, for every time slot $t$
3: **for** every time slot $t$ **do**
4: Observe $\mu^t$, $\lambda^t$, $E^t$
5: Solve (P3) to get $\alpha_t$, $\beta_t$ and $e_t$
6: Update the battery state according to (10) $\forall i$
7: **end for**

B. Solving the Per-Time Slot Problem

Now, we solve the per-time slot problem P3. First, we realize that the objective function in P3 can be decomposed into four parts

$$
\sum_{i \in N} \left( VC_i(\alpha^t, \beta^t) - \tilde{B}_i(\alpha^t_i, \beta^t - e^t_i) \right)
= \sum_{i \in N} \left( V(c_{tx,i}(\mu^t_i - \alpha^t_i) + c_{com,i}(\lambda^t_i - \sum_{j \in M_i} \beta^t_{ji})) - \tilde{B}_i(p^t_i \alpha^t_i + \kappa(f_i)^2 \sum_{j \in M_i} \beta^t_{ji} - e^t_i) \right)
= \sum_{i \in N} \left( V(c_{tx,i}(\mu^t_i + c_{com,i}\lambda^t_i) - (Vc_{tx,i} + \tilde{B}_i p^t_i)\alpha^t_i - \sum_{j \in M_i} (Vc_{com,j} + \tilde{B}_i k(f_i)^2)\beta^t_{ji} + \tilde{B}_i e^t_i) \right)
$$

For each BS $i$, the first part $V(c_{tx,i}(\mu^t_i + c_{com,i}\lambda^t_i))$ is independent of the decision variables. The second part $(Vc_{tx,i} + \tilde{B}_i p^t_i)\alpha^t_i$ depends only on BS $i$’s traffic admission control decisions. The third part $\sum_{j \in M_i} (Vc_{com,j} + \tilde{B}_i k(f_i)^2)\beta^t_{ji}$ depends on the BS $i$’s incoming workload $\beta^t_{ji}$, $\forall j \in M_i$ from its neighbors. The fourth part $\tilde{B}_i e^t_i$ depends on BS $i$’s energy harvesting decision. We solve the optimal decisions as follows.

**Optimal Energy Harvesting**: The optimal energy harvesting decisions can be obtained by solving the following LP problem

$$
\min_{e_t} \sum_{i \in N} \tilde{B}_i e^t_i
$$

(16)
and its optimal solution is given by

\[ e_i^* = \mathcal{E}_i^t \cdot 1\{\bar{B}_i^t \leq 0\}, \forall i \]  \hspace{1cm} (17)

That is, BS \( i \) harvests all energy if its battery queue \( B_i^t \) is less than a threshold \( \theta \) and harvests no energy otherwise. We will show later that this strategy ensures that we only need a finite battery capacity for each BS.

**Optimal Admission Control:** The optimal data traffic admission control decisions can be obtained by solving the following LP problem

\[
\max_{\alpha} \sum_{i \in \mathcal{N}} (V_{tx,i} + \bar{B}_i^t p_i^t) \alpha_i^t
\]

and its optimal solution is given by

\[ \alpha_i^* = \mu_i^t \cdot 1\{V_{tx,i} + \bar{B}_i^t p_i^t \geq 0\} \]  \hspace{1cm} (19)

That is, BS \( i \) serves all its downlink data traffic if its battery queue \( B_i^t \) is larger than a threshold \( \theta - V_{tx,i}/p_i^t \) and serves no traffic otherwise. The threshold depends on the current time slot channel condition (thus transmission unit cost \( p_i^t \)). When the transmission unit cost \( p_i^t \) is larger, BS \( i \) requires more available battery energy to start serving data traffic.

**Optimal GLB:** The optimal GLB decisions decisions can be obtained by solving the following LP problem

\[
\max_{\beta} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{M}_i} (V_{com,j} + \bar{B}_i^t \kappa(f_i)^2) \beta_{ji}^t
\]

s.t. Constraint (5) and \( \sum_{j \in \mathcal{M}_i} \beta_{ji}^t \leq \lambda_i^t, \forall i \)

The optimal solution satisfies

\[ \beta_{ji}^t = 0, \text{ if } V_{com,j} + \bar{B}_i^t \kappa(f_i)^2 \leq 0 \]  \hspace{1cm} (21)

That is, BS \( i \) does not process any computation workload offloaded from BS \( j \) if its battery queue \( B_i^t \) is smaller than a threshold \( \theta - V_{com,j}/(\kappa(f_i)^2) \). Otherwise, the exact value of \( \beta_{ji}^t \) depends on the solution of the LP problem.
C. Performance Analysis

We analyze the performance of GLOBE in this subsection. To facilitate our exposition, we define

\[ c^{\text{max}} \triangleq \max \{ c^{\text{max}}_{\text{tx}}/p_{\text{min}}, c^{\text{max}}_{\text{com}}/(\kappa(f^{\text{min}})^2) \} \]  

(22)

**Lemma 2.** For any \( B^{\text{max}} > E^{\text{max}} + \mathcal{E}^{\text{max}} \), by choosing

\[ 0 \leq V \leq \frac{B^{\text{max}} - E^{\text{max}} - \mathcal{E}^{\text{max}}}{c^{\text{max}}} \]  

(23)

and \( \theta = V c^{\text{max}} + E^{\text{max}} \), the battery level \( B_i^t \) is bounded in \([0, B^{\text{max}}]\), \( \forall i \) and the energy causality constraint is satisfied in every time slot.

**Proof.** Let \( \tilde{\theta}_i^t = \theta - \max \{ V c_{\text{tx},i} / p_i^t, \max_j V c_{\text{com},j} / (\kappa(f_i))^2 \} \). We consider the following three cases depending on the value of \( B_i^t \).

- **Case 1:** \( B_i^t \in [\theta, B^{\text{max}}] \). In this case, we have \( e_i^{t^*} = 0 \), and hence \( B_i^{t+1} < B^{\text{max}} \). Because \( \theta > E^{\text{max}} \), the energy causality constraint is satisfied and we have

\[
B_i^{t+1} > \theta - E_{\text{tx}}^{\text{max}} - E_{\text{com}}^{\text{max}} > 0.
\]

- **Case 2:** \( B_i^t \in [\tilde{\theta}_i^t, \theta] \). In this case, we have \( e_i^{t^*} \leq \mathcal{E}^{\text{max}} \), \( E_{\text{tx},i}^{t^*} \leq E_{\text{tx}}^{\text{max}} \) and \( E_{\text{com},i}^{t^*} \leq E_{\text{com}}^{\text{max}} \). Therefore, \( B_i^{t+1} \leq \theta + \mathcal{E}^{\text{max}} = V c^{\text{max}} + E^{\text{max}} + \mathcal{E}^{\text{max}} \leq B^{\text{max}} \) where the last inequality follows from the chosen range of values of \( V \). Because \( \tilde{\theta}_i^t \geq E^{\text{max}} \), the energy causality constraint is satisfied and we have \( B_i^{t+1} \geq 0 \).

- **Case 3:** \( B_i^t \in [0, \tilde{\theta}_i^t] \). In this case, we have \( e_i^{t^*} \leq \mathcal{E}^{\text{max}} \), \( E_{\text{tx},i}^{t^*} = 0 \) and \( E_{\text{com},i}^{t^*} = 0 \). Clearly the energy causality constraint is satisfied, \( B_i^{t+1} \leq B^{\text{max}} \) and \( B_i^{t+1} \leq 0 \).

Lemma 2 is of significant importance because it shows that GLOBE not only yields a feasible solution to the relaxed problem \( P_2 \) but also a feasible solution to the original problem \( P_1 \) since the energy causality constraint in each time slot is actually satisfied by running GLOBE, provided that the battery capacity is sufficiently large and the algorithms parameters are carefully chosen.

Next we proceed to show the asymptotic optimality of the GLOBE algorithm, for which we first define the Lyapunov function as follows:

\[ \Psi^t \triangleq \frac{1}{2} \sum_{i \in \mathcal{N}} (\tilde{B}_i^t)^2 = \frac{1}{2} \sum_{i \in \mathcal{N}} (B_i^t - \theta)^2 \]  

(24)

The Lyapunov drift represents the expected change in the Lyapunov function from one time slot to the other, which is defined as

\[ \Delta^t = \mathbb{E} [\Psi^{t+1} - \Psi^t | B^t] \]  

(25)
where the expectation is with respect to the random process associated the system, given the battery state $B^t = [B^t_1, ..., B^t_N]$. Assuming that the battery capacity is infinite for now, the battery state dynamics yields

$$B^{i+1}_{t} - \theta = B^t_i - \theta - E^t_i(\beta^t_i) + \epsilon^t_i, \forall i$$  \hspace{1cm} (26)

Squaring both sides of the above equation, we obtain,

$$(B^{i+1}_{t} - \theta)^2 = (B^t_i - \theta)^2 + E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i$$

$$- 2(B^t_i - \theta)(E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i)$$  \hspace{1cm} (27)

Notice that the term $(E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i)^2 \leq (E^t_i(\alpha^t_i, \beta^t_i))^2 + (\epsilon^t_i)^2 \leq (E_{\text{tx}}^{\text{max}} + E_{\text{com}}^{\text{max}})^2 + (E_{\text{max}})^2 \equiv 2D/N$ is upper-bounded by a constant $2D/N$. Using this bound and rearranging the above equation, we have

$$2D/N - 2(B^t_i - \theta)(E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i)$$  \hspace{1cm} (28)

Using the above inequality and the definition of $\Delta^t$, we have

$$\Delta^t \leq D - \mathbb{E}\left[\sum_{i \in N}(B^t_i - \theta)(E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i)|B^t_i\right]$$  \hspace{1cm} (29)

Adding the system cost multiplied by $V$, namely $V\mathbb{E}\left[\sum_{i \in N} C_i(\alpha^t_i, \beta^t_i)|B^t_i\right]$, to both sides and denoting $\Delta^t_V = \Delta^t + V\mathbb{E}\left[\sum_{i \in N} C_i(\alpha^t_i, \beta^t_i)|B^t_i\right]$, we have

$$\Delta^t_V \leq D$$

$$+ \mathbb{E}\left[\sum_{i \in N}(VC_i(\alpha^t_i, \beta^t_i) - \tilde{B}^t_i(E^t_i(\alpha^t_i, \beta^t_i) - \epsilon^t_i)|B^t_i\right]$$  \hspace{1cm} (30)

According to the theory of Lyapunov optimization (drift-plus-penalty method), the control actions are chosen for each time slot $t$ to minimize the bound on the modified Lyapunov drift function $\Delta^t_V$. Therefore, in each time slot $t$, we solve the per-time slot optimization problem $P3$ to obtain the admission control and GLB decisions as in GLOBE.

Theorem 1 proves the performance guarantee of GLOBE.

**Theorem 1.** For any $V$, if the battery capacity satisfies $B^{\text{max}}_{\text{tx}} \geq Vc_{\text{com}}^{\text{max}} + E_{\text{max}}^{\text{trans}} + E_{\text{max}}^{\text{com}}$, then the proposed algorithm yields a feasible solution and the achievable time average system cost
satisfies
\[
\lim_{T \to \infty} \frac{1}{T} \sum_{i \in \mathcal{N}} \mathbb{E} \left[ C_i(\alpha^t, \beta^t) \right] \leq C^*_1 + D/V \tag{31}
\]
where \( D \) is a constant.

Proof. Consider the bound on the Lyapunov drift function (30). It is clear that the control actions \( \alpha^t, \beta^t, e^t \) by our algorithm minimizes the bound on the Lyapunov function over all possible control actions. Comparing it with the control actions chosen according to the optimal oracle policy that achieves \( C^* \), we have
\[
\Delta^t + V \mathbb{E} \left[ \sum_{i \in \mathcal{N}} C_i(\alpha^t, \beta^t) \right] B^t
\]
\[
\leq D + \mathbb{E} \left[ \sum_{i \in \mathcal{N}} \left( V C_i(\alpha^t, \beta^t) - \tilde{B}_i^t(E_i^t(\alpha^t, \beta^t) - e_i^t) \right) \right] B^t
\]
\[
\leq D + \mathbb{E} \left[ \sum_{i \in \mathcal{N}} \left( V C_i(\alpha^{\Pi,t}, \beta^{\Pi,t}) \right. \right.
\]
\[
- \tilde{B}_i^t(E_i^t(\alpha^{\Pi,t}, \beta^{\Pi,t}) - e_i^{\Pi,t}) \left. \right] B^t
\]
\[
= V \mathbb{E} \left[ \sum_{i \in \mathcal{N}} C_i(\alpha^{\Pi,t}, \beta^{\Pi,t}) \right] + D
\]
\[
- \mathbb{E} \left[ \tilde{B}_i^t(E_i^t(\alpha^{\Pi,t}, \beta^{\Pi,t}) - e_i^{\Pi,t}) \right] B^t
\]
Plugging in (13) and (14), taking the expectation on both sides and summing from \( t = 0, \ldots, T - 1 \), normalizing by \( T \) and taking the limit \( T \to \infty \), we have
\[
V \lim_{T \to \infty} \frac{1}{T} \sum_{i \in \mathcal{N}} \mathbb{E} \left[ C_i(\alpha^t, \beta^t) \right] \leq V C^*_2 + D
\tag{32}
\]
where \( D < \infty \) is a constant. The proof is completed with \( C^*_2 \leq C^*_1 \).

Theorem 1 proves that GLOBE can achieve the minimum cost achievable by the offline algorithm within a bounded deviation without foreseeing the future information. Moreover, it formalizes a critical tradeoff between the battery capacity and the achievable system performance: the achievable system performance improves with the increase of the battery capacity. In particular, the system performance can be made arbitrarily close to optimum if the battery capacity is large enough. This result provides profound guidelines for EH-powered MEC network design and deployment, especially on the its battery design.
IV. Simulation

In this section, we evaluate the performance of GLOBE through simulations. We consider \( N = 5 \) BSs who are able to perform computation offloading between one another, i.e. \( \mathcal{M}_i = \mathcal{N}, \forall i \). The downlink data traffic arrival at BS \( i \) is modeled by a Poisson process with \( \mu_i^t \in [0, 10] \) unit/sec. The expected size of each data traffic \( \mathbb{E}[\omega] \) is set as 100 Mbits. The transmitting power of BS \( i \) is \( P_{tx,i} = 1 \) W, the noise power is \( \sigma^2 = 0.01 \) W/Hz, and the bandwidth is \( W = 20 \) MHz. The downlink traffic dropping costs are \( c_{tx,i} = 10, \forall i \). The computation task arrival at BS \( i \) is modeled as a Poisson process with \( \lambda_i^t \in [0, 10] \) with the mean task size of 1 Mbit. The CPU speed is \( f_i = 2.4 \) GHz and the mean required number of CPU cycles for each computation task is \( \rho = 8 \times 10^5 \). The computation constraint is \( d_{\text{max}} = 1 \) ms. The energy consumption parameter is chosen as \( \kappa = 2.5 \times 10^{-22} \). The cost of dropping one unit of computation task is \( c_{\text{com},i} = 0.01 \).

The harvested energy is modeled as a uniform distribution and satisfies \( E \in [0, 10] \).

The proposed GLOBE are compared with three benchmarks: **LyO without GLB** minimizes the long-term system cost considering the energy harvesting constraints (i.e. battery dynamics and energy causality) by leveraging the Lyapunov technique. However, in this case, GLB is not performed; **Myopic with GLB** performs GLB and admission control to minimize the system cost in the current time slot by performing myopic optimization without considering the energy harvesting constraints. **Myopic without GLB** is the most naive scheme which does not perform GLB or consider the energy harvesting constraints. Each BS simply tries to serve all computation workload and data traffic given the available energy and drops whatever cannot be fulfilled.

![Fig. 2. Performance comparison with benchmarks](image-url)
A. Performance Comparison

Fig. 2 shows the time-average system costs and the stabilized battery levels of GLOBE and the three benchmarks. It can be observed from Fig. 2(a) that GLOBE achieves the lowest system cost compared to the benchmarks. Specifically, GLOBE reduces the system cost by nearly 50% compared to the second-best scheme LyO without GLB. Fig. 2(b) compares the stabilized battery levels of the four schemes. As can be seen, the stabilized battery level is bounded in GLOBE and LyO without GLB, the two schemes that are built on the Lyapunov with perturbation technique. By contrast, the two myopic benchmarks may require a very large battery capacity.

B. Impact of Control Parameter $V$

Fig. 3 shows the system cost and the stabilized battery level over time for various values of $V$ in GLOBE. Consistent to our analysis, the system cost decreases with a larger $V$. However, a lower system cost is achieved at the price of a higher battery capacity and longer convergence time. Fig. 4 further shows the tradeoff between battery capacity and system performance as a function of $V$. As can be seen, the system cost obeys the $1/V$ relation with the control parameter $V$ as claimed in Theorem 1. It shows that a better system performance requires a larger battery capacity.

V. Conclusion

In this paper, we proposed an online algorithm to perform GLB and traffic admission control in EH-powered MEC networks. We demonstrated that a fundamentally new design that manages the limited energy, computing and radio access resources in both spatial and temporal domains is
Fig. 4. Relations among $V$, cost, battery states

key to fully reap the benefits of EH-power MEC. Our algorithm is simple and easy to implement in practical deployment scenarios, yet provides provable performance guarantee.

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